Consumption Inequality across Heterogeneous Families

Online Appendix, Not for Publication

Alexandros Theloudis*

A Taylor Approximations of First-Order Conditions and Lifetime Budget Constraint

Suppose the household utility function takes the form

$$U_{it}(C_{it}, H_{1it}, H_{2it}; \mathbf{Z}_{it}) = \beta_{it}(\mathbf{Z}_i) U_i(C_{it}, H_{1it}, H_{2it}; \mathbf{Z}_{it}) \equiv \widetilde{\beta}_{it} \widetilde{U}_i(\widetilde{C}_{it}, \widetilde{H}_{1it}, \widetilde{H}_{2it})$$

where $\widetilde{\beta}_{it} = \beta_{it}(\mathbf{Z}_i)$, $\widetilde{C}_{it} = C_{it} \exp(-\mathbf{Z}'_{it}\boldsymbol{\alpha}_C)$, $\widetilde{H}_{jit} = H_{jit} \exp(-\mathbf{Z}'_{it}\boldsymbol{\alpha}_{H_j})$ for $j = \{1, 2\}$, and $\mathbf{Z}_i$ is the time invariant portion of $\mathbf{Z}_{it}$. Normalizing the price of consumption at $P_t = 1$ $\forall t$, and assuming an interior solution and geometric discounting ($\widetilde{\beta}_{it} = \widetilde{\beta}_i^t$), the first-order conditions of household problem (1) *s.t.* (2) are

$$\begin{aligned}
[C_{it}]: \quad & \widetilde{U}_{iC}(\widetilde{C}_{it}, \widetilde{H}_{1it}, \widetilde{H}_{2it}) \exp(-\mathbf{Z}'_{it}\boldsymbol{\alpha}_C) = \lambda_{it} \\
[H_{jit}]: \quad & -\widetilde{U}_{iH_j}(\widetilde{C}_{it}, \widetilde{H}_{1it}, \widetilde{H}_{2it}) \exp(-\mathbf{Z}'_{it}\boldsymbol{\alpha}_{H_j}) = \lambda_{it} W_{jit}, \quad j = \{1, 2\} \\
[A_{it+1}]: \quad & \widetilde{\beta}_i (1 + r_{t+1}) \mathbb{E}_t \lambda_{it+1} = \lambda_{it}.
\end{aligned}$$

$\widetilde{U}_{iC}$ is the marginal utility of consumption and $\widetilde{U}_{iH_j}$ the marginal utility of hours of spouse j; λ_{it} is the marginal utility of wealth (the Lagrange multiplier on the sequential budget constraint). Subsequently I follow steps similar to Blundell et al. (2013) and BPS (Blundell et al., 2016).

Approximation of intra-temporal first-order conditions. Applying logs to the intra-temporal first-order conditions and taking a first difference in time yields

$$\begin{aligned}
[C_{it}]: \quad & \Delta \ln \widetilde{U}_{iC}(\widetilde{C}_{it}, \widetilde{H}_{1it}, \widetilde{H}_{2it}) - \Delta (\mathbf{Z}'_{it}\boldsymbol{\alpha}_C) = \Delta \ln \lambda_{it} \\
[H_{jit}]: \quad & \Delta \ln \left(-\widetilde{U}_{iH_j}(\widetilde{C}_{it}, \widetilde{H}_{1it}, \widetilde{H}_{2it}) \right) - \Delta \left(\mathbf{Z}'_{it}\boldsymbol{\alpha}_{H_j} \right) = \Delta \ln \lambda_{it} + \Delta \ln W_{jit}, \quad j = \{1, 2\}.
\end{aligned}$$

*Alexandros Theloudis: Luxembourg Institute for Socio-Economic Research, and Department of Econometrics and Operations Research, Tilburg University (email: a.theloudis@gmail.com).

A first-order approximation of $\ln \widetilde{U}_{iC}(\widetilde{C}_{it}, \widetilde{H}_{1it}, \widetilde{H}_{2it})$ around $\widetilde{C}_{it-1}$, $\widetilde{H}_{1it-1}$, and $\widetilde{H}_{2it-1}$ yields

$$\begin{aligned}\Delta \ln \widetilde{U}_{iC}(\widetilde{C}_{it}, \widetilde{H}_{1it}, \widetilde{H}_{2it}) \approx \widetilde{U}_{iC}^{-1}(\widetilde{C}_{it-1}, \widetilde{H}_{1it-1}, \widetilde{H}_{2it-1}) \times \Big(& \widetilde{U}_{iCC}(\widetilde{C}_{it-1}, \widetilde{H}_{1it-1}, \widetilde{H}_{2it-1})\widetilde{C}_{it-1}\Delta \ln C_{it} \\ & + \widetilde{U}_{iCH_1}(\widetilde{C}_{it-1}, \widetilde{H}_{1it-1}, \widetilde{H}_{2it-1})\widetilde{H}_{1it-1}\Delta \ln H_{1it} \\ & + \widetilde{U}_{iCH_2}(\widetilde{C}_{it-1}, \widetilde{H}_{1it-1}, \widetilde{H}_{2it-1})\widetilde{H}_{2it-1}\Delta \ln H_{2it}\Big)\end{aligned}$$

where $\widetilde{U}_{iCC}$ denotes the derivative of $\widetilde{U}_{iC}$ with respect to consumption C, etc. The approximation of $-\widetilde{U}_{iH_j}(\widetilde{C}_{it}, \widetilde{H}_{1it}, \widetilde{H}_{2it})$ follows similarly. Replacing $\Delta \ln \widetilde{U}_{iC}$ and $\Delta \ln \left(-\widetilde{U}_{iH_j}\right)$ with their approximation counterparts yields a system of three equations in the growth rates of outcomes $\Delta \ln C_{it}$, $\Delta \ln H_{1it}$, and $\Delta \ln H_{2it}$. Solving the system and rearranging so that all outcome variables and observable taste shifters are on the left results in system (4) in the text. Note that the Frisch elasticities are defined on the basis of first & second order derivatives of the utility function, as well as of levels of consumption and hours (see appendix B for definitions). Given the nature of the approximation, these derivatives and outcome levels concern period $t-1$. The relevant Frisch elasticities in this system thus also concern period $t-1$.

Approximation of Euler equation. The approximation of the inter-temporal first-order condition involves future expectations. Suppose $\exp(\Gamma_{it+1}) = {}^{1}/_{\widetilde{\beta}_i(1+r_{t+1})}$ for some Γ_{it+1}. I apply a second-order approximation of $\exp(\ln \lambda_{it+1})$ around $\ln \lambda_{it} + \Gamma_{it+1}$ to get

$$\exp(\ln \lambda_{it+1}) \approx \exp(\ln \lambda_{it} + \Gamma_{it+1}) \left(1 + (\Delta \ln \lambda_{it+1} - \Gamma_{it+1}) + \frac{1}{2}(\Delta \ln \lambda_{it+1} - \Gamma_{it+1})^2\right).$$

Taking expectations at time t and noting that $\mathbb{E}_t \lambda_{it+1} = \lambda_{it} \exp(\Gamma_{it+1})$ yields

$$\mathbb{E}_t \left(\Delta \ln \lambda_{it+1} - \Gamma_{it+1} + \frac{1}{2}(\Delta \ln \lambda_{it+1} - \Gamma_{it+1})^2\right) \approx 0$$

which in turn implies

$$\begin{aligned}\mathbb{E}_t \Delta \ln \lambda_{it+1} &\approx \Gamma_{it+1} - \frac{1}{2}\mathbb{E}_t(\Delta \ln \lambda_{it+1} - \Gamma_{it+1})^2 \\ \Delta \ln \lambda_{it+1} &\approx \omega_{it+1} + \varepsilon_{it+1}. \qquad \text{(A.1)}\end{aligned}$$

The first term $\omega_{it+1} = \Gamma_{it+1} - \frac{1}{2}\mathbb{E}_t(\Delta \ln \lambda_{it+1} - \Gamma_{it+1})^2$ captures the impact of interest rate r_{t+1}, impatience $\widetilde{\beta}_i$ and precautionary motives on consumption growth (Blundell et al., 2013). To maintain tractability, I fix $\mathbb{E}_t(\Delta \ln \lambda_{it+1})^2$ (precautionary motive) in the cross-section. ω_{it} is heterogeneous across households due to Γ_{it+1} -the anticipated gradient of outcome growth- but non-stochastic. The second term is an expectation error with $\mathbb{E}_t(\varepsilon_{it+1}) = 0$; it captures idiosyncratic revisions to λ upon arrival of new information, namely of wage shocks.

Approximation of lifetime budget constraint (draws on Campbell (1993)'s log-linearization of the intertemporal budget constraint)**.** Normalizing the price of consumption at $P_t = 1$, $\forall t$,

the general form of household i's lifetime budget constraint is

$$A_{it} + \mathbb{E}_t \sum_{s=0}^{T-t} \sum_{j=1}^{2} \frac{W_{jit+s} H_{jit+s}}{(1+r)^s} = \mathbb{E}_t \sum_{s=0}^{T-t} \frac{C_{it+s}}{(1+r)^s}.$$

To ease the notation I will temporarily suppress cross-sectional subscript i.

Let $G(\boldsymbol{\xi}) = \ln \sum_{s=0}^{T-t} \exp \xi_s$ for $\boldsymbol{\xi} = (\xi_0, \xi_1, \ldots, \xi_{T-t})'$. Applying a first-order approximation of $G(\boldsymbol{\xi})$ around a deterministic $\boldsymbol{\xi}^0$, and taking expectations conditional on some information set $\mathcal{I}$, yields

$$\mathbb{E}_{\mathcal{I}} G(\boldsymbol{\xi}) \approx G(\boldsymbol{\xi}^0) + \sum_{s=0}^{T-t} \frac{\exp \xi_s^0}{\sum_{\kappa=0}^{T-t} \exp \xi_\kappa^0} \left(\mathbb{E}_{\mathcal{I}} \xi_s - \xi_s^0 \right). \tag{A.2}$$

The logarithm of the *right* hand side of the budget constraint, assuming expectations away, is

$$G^{RH}(\boldsymbol{\xi}) = \ln \sum_{s=0}^{T-t} \exp \left(\ln \frac{C_{t+s}}{(1+r)^s} \right)$$

for $\xi_s = \ln C_{t+s} - s \ln(1+r)$. Suppose $\xi_s^0 = \mathbb{E}_{t-1} \ln C_{t+s} - s \ln(1+r)$. Following (A.2) I write

$$\mathbb{E}_{\mathcal{I}} G^{RH}(\boldsymbol{\xi}) \approx G^{RH}(\boldsymbol{\xi}^0) + \sum_{s=0}^{T-t} \theta_{t+s} \left(\mathbb{E}_{\mathcal{I}} \ln C_{t+s} - \mathbb{E}_{t-1} \ln C_{t+s} \right)$$

where $\theta_{t+s} = \frac{\exp(\mathbb{E}_{t-1} \ln C_{t+s} - s \ln(1+r))}{\sum_{\kappa=0}^{T-t} \exp(\mathbb{E}_{t-1} \ln C_{t+\kappa} - \kappa \ln(1+r))}$ is approximately equal to the expected share of time $t+s$ consumption in total lifetime consumption. θ_{t+s} is known at any $t+s \geq t$ because it pertains to expectations at $t-1$ (before time t shocks realize).

Defining the information set to contain information known at time t, that is $\mathcal{I} := t$, and replacing $\ln C_{t+s}$ consecutively by the analytical expression in (4) yields

$$\sum_{s=0}^{T-t} \theta_{t+s} \left(\mathbb{E}_t \ln C_{t+s} - \mathbb{E}_{t-1} \ln C_{t+s} \right) \approx \bar{\eta}_{c(t-1)} \varepsilon_t + \sum_{j=1}^{2} \eta_{c,w_j(t-1)} v_{jt} + \sum_{j=1}^{2} \theta_t \eta_{c,w_j(t-1)} u_{jt}$$

where $\bar{\eta}_c = \eta_{c,p} + \eta_{c,w_1} + \eta_{c,w_2}$ (ω_{t+s} is non-stochastic and disappears in the first difference). If the share of a period's consumption in total lifetime consumption is negligible, i.e. $\theta_t \approx 0$, then taking a first difference in expectations between t and $t-1$ and reinstating i yields

$$\mathbb{E}_t G^{RH}(\boldsymbol{\xi}) - \mathbb{E}_{t-1} G^{RH}(\boldsymbol{\xi}) \approx \bar{\eta}_{c(i,t-1)} \varepsilon_{it} + \sum_{j=1}^{2} \eta_{c,w_j(i,t-1)} v_{jit}.$$

Applying similar arguments to the *left* hand side of the budget constraint yields

$$\mathbb{E}_t G^{LH}(\boldsymbol{\xi}) - \mathbb{E}_{t-1} G^{LH}(\boldsymbol{\xi}) \approx (1-\pi_{it}) \sum_{j=1}^{2} \left\{ s_{jit} \bar{\eta}_{h_j(i,t-1)} \varepsilon_{it} + \left(s_{jit} (1 + \eta_{h_j,w_j(i,t-1)}) + s_{-jit} \eta_{h_{-j},w_j(i,t-1)} \right) v_{jit} \right\}$$

where $\bar{\eta}_{h_j} = \eta_{h_j,p} + \eta_{h_j,w_1} + \eta_{h_j,w_2}$, $-j$ denotes the spouse, and

$$G^{LH}(\boldsymbol{\xi}) = \ln \left(\exp(\ln A_t) + \sum_{s=1}^{T-t+1} \exp \left(\ln \sum_{j=1}^{2} \frac{W_{jt+s-1} H_{jt+s-1}}{(1+r)^{s-1}} \right) \right)$$

$$\xi_s = \begin{cases} \ln A_{t+s} & \text{for } s = 0 \\ \ln \sum_{j=1}^{2} W_{jt+s-1} H_{jt+s-1} - (s-1)\ln(1+r) & \text{for } s = 1, \ldots, T-t+1 \end{cases}$$

$$\xi_s^0 = \begin{cases} \mathbb{E}_{t-1} \ln A_{t+s} & \text{for } s = 0 \\ \mathbb{E}_{t-1} \ln \sum_{j=1}^{2} W_{jt+s-1} H_{jt+s-1} - (s-1)\ln(1+r) & \text{for } s = 1, \ldots, T-t+1. \end{cases}$$

The rest of the notation is as follows: $\pi_t = \frac{Q_{1t}}{Q_{1t}+Q_{2t}}$, with $Q_{1t} = \exp\left(\mathbb{E}_{t-1} \ln A_t\right)$ and $Q_{2t} = \sum_{\kappa=0}^{T-t} \exp\left(\mathbb{E}_{t-1} \ln \sum_j W_{jt+\kappa} H_{jt+\kappa} - \kappa \ln(1+r)\right)$, is the 'partial insurance' coefficient: it is approximately equal to the share of financial wealth in the household's total financial and human wealth at t. $s_{jt} = \sum_{s=0}^{T-t} \vartheta_{t+s} \widetilde{q}_{jt+s}$, with $\vartheta_{t+s} = \exp\left(\mathbb{E}_{t-1} \ln \sum_{j=1}^{2} W_{jt+s} H_{jt+s} - s \ln(1+r)\right)/Q_{2t}$ and $\widetilde{q}_{jt+s} = \frac{\mathbb{E}_{t-1} W_{jt+s} H_{jt+s}}{\sum_{\iota=1}^{2} \mathbb{E}_{t-1} W_{\iota t+s} H_{\iota t+s}}$, is approximately equal to the share of spouse j's human wealth (expected lifetime earnings) in the household's total human wealth at t. ϑ_{t+s} and $\widetilde{q}_{jt+s}$ are known at $t+s \geq t$ (they pertain to $t-1$ expectations before shocks at t realize) and $\vartheta_{t+s} \approx 0$ if the share of a period's earnings in the household's total lifetime earnings is negligible.

I bring the two sides together following Blundell et al. (2013) and solve for ε_{it} to get

$$\varepsilon_{it} \approx \varepsilon_1(\pi_{it}, \mathbf{s}_{it}; \boldsymbol{\eta}_{it-1}) v_{1it} + \varepsilon_2(\pi_{it}, \mathbf{s}_{it}; \boldsymbol{\eta}_{it-1}) v_{2it} \tag{A.3}$$

where

$$\begin{aligned} \varepsilon_1(\pi_{it}, \mathbf{s}_{it}; \boldsymbol{\eta}_{it-1}) &= \frac{(1-\pi_{it})\left(s_{1it}(1+\eta_{h_1,w_1(i,t-1)}) + s_{2it}\eta_{h_2,w_1(i,t-1)}\right) - \eta_{c,w_1(i,t-1)}}{\bar{\eta}_{c(i,t-1)} - (1-\pi_{it})\left(s_{1it}\bar{\eta}_{h_1(i,t-1)} + s_{2it}\bar{\eta}_{h_2(i,t-1)}\right)} \\ \varepsilon_2(\pi_{it}, \mathbf{s}_{it}; \boldsymbol{\eta}_{it-1}) &= \frac{(1-\pi_{it})\left(s_{1it}\eta_{h_1,w_2(i,t-1)} + s_{2it}(1+\eta_{h_2,w_2(i,t-1)})\right) - \eta_{c,w_2(i,t-1)}}{\bar{\eta}_{c(i,t-1)} - (1-\pi_{it})\left(s_{1it}\bar{\eta}_{h_1(i,t-1)} + s_{2it}\bar{\eta}_{h_2(i,t-1)}\right)} \end{aligned}$$

and $\mathbf{s}_{it} = (s_{1it}, s_{2it})'$ with $s_{1it} + s_{2it} = 1$ by construction. $\boldsymbol{\eta}$ is the 9×1 vector of household-specific Frisch elasticities presented in table 1 and defined in appendix B.

Estimable equations. Combining the approximations of the intra-temporal first-order conditions in (4), the Euler equation in (A.1), and the lifetime budget constraint in (A.3), I obtain

$$\begin{aligned} \Delta c_{it} &\approx \bar{\eta}_{c(i,t-1)}\omega_{it} + \eta_{c,w_1(i,t-1)}\Delta u_{1it} + \eta_{c,w_2(i,t-1)}\Delta u_{2it} \\ &\quad + \left(\eta_{c,w_1(i,t-1)} + \bar{\eta}_{c(i,t-1)}\varepsilon_1(\pi_{it}, \mathbf{s}_{it}; \boldsymbol{\eta}_{it-1})\right) v_{1it} + \left(\eta_{c,w_2(i,t-1)} + \bar{\eta}_{c(i,t-1)}\varepsilon_2(\pi_{it}, \mathbf{s}_{it}; \boldsymbol{\eta}_{it-1})\right) v_{2it} \\ \Delta h_{jit} &\approx \bar{\eta}_{h_j(i,t-1)}\omega_{it} + \eta_{h_j,w_1(i,t-1)}\Delta u_{1it} + \eta_{h_j,w_2(i,t-1)}\Delta u_{2it} \\ &\quad + \left(\eta_{h_j,w_1(i,t-1)} + \bar{\eta}_{h_j(i,t-1)}\varepsilon_1(\pi_{it}, \mathbf{s}_{it}; \boldsymbol{\eta}_{it-1})\right) v_{1it} + \left(\eta_{h_j,w_2(i,t-1)} + \bar{\eta}_{h_j(i,t-1)}\varepsilon_2(\pi_{it}, \mathbf{s}_{it}; \boldsymbol{\eta}_{it-1})\right) v_{2it}. \end{aligned}$$

The intercepts $\bar{\eta}_{c(i,t-1)}\omega_{it}$ and $\bar{\eta}_{h_j(i,t-1)}\omega_{it}$ reflect the gradient of outcome growth in the absence of shocks. As shown above, these are functions of the interest rate, the discount factor and precautionary motives, and they also depend on the past levels of consumption and hours through $\bar{\eta}_{c(i,t-1)}$ and $\bar{\eta}_{h_j(i,t-1)}$. Identification of moments of the intercepts is straightforward. However, this does not identify moments of the discount factor $\widetilde{\beta}_i$ because two consecutive moments of $\widetilde{\beta}_i$ appear additively in any moment of ω_{it} and separating them is impossible.

Therefore I absorb $\bar{\eta}_{c(i,t-1)}\omega_{it}$ and $\bar{\eta}_{h_j(i,t-1)}\omega_{it}$ into the intercepts of the first-stage regression of consumption and hours growth on observables, including on past levels of consumption and hours, resulting in the main estimating equations (5)-(7).

Approximation with heterogeneous wage process. Following similar steps but replacing the permanent-transitory wage process (3) with the $ARMA(1,1)$ process (11) yields

$$\mathbb{E}_t G^{RH}(\boldsymbol{\xi}) - \mathbb{E}_{t-1} G^{RH}(\boldsymbol{\xi}) \approx \bar{\eta}_{c(i,t-1)}\varepsilon_{it} + \sum_{j=1}^{2} \eta_{c,w_j(i,t-1)} f_c(\rho_{ji}) v_{jit}$$

$$\begin{aligned}\mathbb{E}_t G^{LH}(\boldsymbol{\xi}) - \mathbb{E}_{t-1} G^{LH}(\boldsymbol{\xi}) \approx{}& (1-\pi_{it})\left(s_{1it}\bar{\eta}_{h_1(i,t-1)} + s_{2it}\bar{\eta}_{h_2(i,t-1)}\right)\varepsilon_{it} \\ &+ (1-\pi_{it})\sum_{j=1}^{2}\left(f_{h_j}(s_{jit},\rho_{ji})(1+\eta_{h_j,w_j(i,t-1)}) + f_{h_{-j}}(s_{-jit},\rho_{ji})\eta_{h_{-j},w_j(i,t-1)}\right) v_{jit}\end{aligned}$$

where $f_c(\rho_{ji}) = 1 + \sum_{s=1}^{T-t}\theta_{it+s}(\rho_{ji}^s - 1)$, $f_{h_{j'}}(s_{j'it},\rho_{ji}) = s_{j'it} + \sum_{s=1}^{T-t}\vartheta_{it+s}\widetilde{q}_{j'it+s}(\rho_{ji}^s - 1)$ with $f_c(\rho_{ji}=1) = 1$, $f_{h_{j'}}(s_{j'it},\rho_{ji}=1) = s_{j'it}$ and $j,j' = \{1,2\}$. Bringing the two sides together yields

$$\varepsilon_{it} \approx \widetilde{\varepsilon}_1(\pi_{it}, \mathbf{s}_{it}; \boldsymbol{\eta}_{it-1}, \rho_{1i}) v_{1it} + \widetilde{\varepsilon}_2(\pi_{it}, \mathbf{s}_{it}; \boldsymbol{\eta}_{it-1}, \rho_{2i}) v_{2it}$$

where $\widetilde{\varepsilon}_j(\pi_{it}, \mathbf{s}_{it}; \boldsymbol{\eta}_{it-1}, \rho_{ji})$ equals

$$\frac{(1-\pi_{it})\left(f_{h_j}(s_{jit},\rho_{ji})(1+\eta_{h_j,w_j(i,t-1)}) + f_{h_{-j}}(s_{-jit},\rho_{ji})\eta_{h_{-j},w_j(i,t-1)}\right) - f_c(\rho_{ji})\eta_{c,w_j(i,t-1)}}{\bar{\eta}_{c(i,t-1)} - (1-\pi_{it})\left(s_{1it}\bar{\eta}_{h_1(i,t-1)} + s_{2it}\bar{\eta}_{h_2(i,t-1)}\right)}$$

and $\widetilde{\varepsilon}_j(\pi_{it}, \mathbf{s}_{it}; \boldsymbol{\eta}_{it-1}, \rho_{ji}=1) = \varepsilon_j(\pi_{it}, \mathbf{s}_{it}; \boldsymbol{\eta}_{it-1})$. Combining this with previous results yields the equation for consumption growth in the presence of a heterogeneous wage process.

B Frisch Elasticities

Period preferences $U_i(C_{it}, H_{1it}, H_{2it})$ are described ordinally by 9 Frisch elasticities. There are 9 elasticities because there are 3 goods (C, H_1, H_2) and 3 prices (P, W_1, W_2); consequently there are 3 own-price and 6 cross-price elasticities. Their analytical expressions are

$$\begin{aligned}
\eta_{c,w_j(i,t)} &= \frac{\partial C}{\partial W_j}\frac{W_j}{C}\bigg|_{\lambda\text{-const.}}^{i,t} &&= Det^{-1}\frac{U_{H_j}}{C}(U_{CH_{-j}}U_{H_1H_2} - U_{CH_j}U_{H_{-j}H_{-j}}) \\
\eta_{c,p(i,t)} &= \frac{\partial C}{\partial P}\frac{P}{C}\bigg|_{\lambda\text{-const.}}^{i,t} &&= Det^{-1}\frac{U_C}{C}(U_{H_1H_1}U_{H_2H_2} - U_{H_1H_2}^2) \\
\eta_{h_j,w_j(i,t)} &= \frac{\partial H_j}{\partial W_j}\frac{W_j}{H_j}\bigg|_{\lambda\text{-const.}}^{i,t} &&= Det^{-1}\frac{U_{H_j}}{H_j}(U_{CC}U_{H_{-j}H_{-j}} - U_{CH_{-j}}^2) \\
\eta_{h_j,w_{-j}(i,t)} &= \frac{\partial H_j}{\partial W_{-j}}\frac{W_{-j}}{H_j}\bigg|_{\lambda\text{-const.}}^{i,t} &&= Det^{-1}\frac{U_{H_{-j}}}{H_j}(U_{CH_1}U_{CH_2} - U_{CC}U_{H_1H_2}) \\
\eta_{h_j,p(i,t)} &= \frac{\partial H_j}{\partial P}\frac{P}{H_j}\bigg|_{\lambda\text{-const.}}^{i,t} &&= Det^{-1}\frac{U_C}{H_j}(U_{CH_{-j}}U_{H_1H_2} - U_{CH_j}U_{H_{-j}H_{-j}})
\end{aligned}$$

where $j = \{1, 2\}$, $-j$ denotes the spouse, U_o the marginal utility with respect to outcome variable $o = \{C, H_1, H_2\}$ and $U_{o\chi}$ the derivative of U_o with respect to $\chi = \{C, H_1, H_2\}$. $Det = U_{CC}U_{H_1H_1}U_{H_2H_2} + 2U_{CH_1}U_{CH_2}U_{H_1H_2} - U_{CC}U_{H_1H_2}^2 - U_{H_1H_1}U_{CH_2}^2 - U_{H_2H_2}U_{CH_1}^2$ is the determinant of the Hessian matrix of preferences. All partial derivatives, outcome variables, and the determinant are i- and t-specific but I suppress these subscripts to ease the notation. The partial effects are calculated at the household level holding λ constant in expectation.

From Phlips (1974), section 2.4, the matrix of substitution effects after a marginal-utility-of-wealth-compensated price change is

$$\begin{pmatrix} \frac{dC}{dP} & -\frac{dC}{dW_1} & -\frac{dC}{dW_2} \\ \frac{dH_1}{dP} & -\frac{dH_1}{dW_1} & -\frac{dH_1}{dW_2} \\ \frac{dH_2}{dP} & -\frac{dH_2}{dW_1} & -\frac{dH_2}{dW_2} \end{pmatrix} = \lambda_i \mathbf{H}_i^{-1} \mathbf{I}_3 \tag{B.1}$$

where $\mathbf{H}_i$ is the Hessian of U_i and $\mathbf{I}_3$ is a 3×3 identity matrix. I obtain (B.1) by totally differentiating the intra-temporal first-order conditions of the household problem with respect to prices and noting that $\Delta\lambda_{it} = 0$ in expectation. As the right hand side of (B.1) is a symmetric matrix (the Hessian is symmetric by Young's theorem and standard regularity conditions on U_i), it follows that $\frac{dH_j}{dP} = -\frac{dC}{dW_j}$ and $\frac{dH_1}{dW_2} = \frac{dH_2}{dW_1}$. Simple manipulations of these restrictions translate into restrictions on the corresponding cross-price Frisch elasticities.

C Identification Details

C.1 Wage Process

Second moments. There are 6 parameters for the cross-sectional dispersion of shocks at t, namely $\sigma^2_{v_j(t)}$, $\sigma^2_{u_j(t)}$, $\sigma_{v_1v_2(t)}$ and $\sigma_{u_1u_2(t)}$ for $j = \{1, 2\}$. Identification requires second moments of the joint distribution of spouses' wages across households. Consider wage process (3) and assume measurement error away for now. The covariance between consecutive wage growths $\mathbb{E}\left(\Delta w_{jit}\Delta w_{jit+1}\right)$ identifies the variance of the transitory shock due to mean reversion. The covariance between contemporaneous wage growth and a sum of three consecutive wage growths $\mathbb{E}\left(\Delta w_{jit}\sum_{\varsigma=-1}^{\varsigma=1}\Delta w_{jit+\varsigma}\right)$ identifies the variance of the permanent shock as the sum strips Δw_{jit} of the time-t transitory shock. Formally

$$\begin{aligned} \sigma^2_{v_j(t)} &= \mathbb{E}\left(\Delta w_{jit}(\Delta w_{jit-1} + \Delta w_{jit} + \Delta w_{jit+1})\right) \\ \sigma^2_{u_j(t)} &= -\mathbb{E}\left(\Delta w_{jit}\Delta w_{jit+1}\right) \\ \sigma_{v_1v_2(t)} &= \mathbb{E}\left(\Delta w_{1it}(\Delta w_{2it-1} + \Delta w_{2it} + \Delta w_{2it+1})\right) \\ \sigma_{u_1u_2(t)} &= -\mathbb{E}\left(\Delta w_{1it}\Delta w_{2it+1}\right). \end{aligned}$$

Third moments. There are 8 parameters for the cross-sectional skewness of shocks at t, namely $\gamma_{v_j(t)}$, $\gamma_{u_j(t)}$, $\gamma_{v_1v_2^2(t)}$, $\gamma_{v_1^2v_2(t)}$, $\gamma_{u_1u_2^2(t)}$ and $\gamma_{u_1^2u_2(t)}$ for $j = \{1, 2\}$. Identification parallels

that for the second moments; formally

$$\begin{aligned}
\gamma_{v_j(t)} &= \mathbb{E}\left((\Delta w_{jit})^2(\Delta w_{jit-1} + \Delta w_{jit} + \Delta w_{jit+1})\right) \\
\gamma_{u_j(t)} &= -\mathbb{E}\left((\Delta w_{jit})^2 \Delta w_{jit+1}\right) \\
\gamma_{v_1 v_2^2(t)} &= \mathbb{E}\left((\Delta w_{2it})^2(\Delta w_{1it-1} + \Delta w_{1it} + \Delta w_{1it+1})\right) \\
\gamma_{v_1^2 v_2(t)} &= \mathbb{E}\left((\Delta w_{1it})^2(\Delta w_{2it-1} + \Delta w_{2it} + \Delta w_{2it+1})\right) \\
\gamma_{u_1 u_2^2(t)} &= -\mathbb{E}\left((\Delta w_{2it})^2 \Delta w_{1it+1}\right) \\
\gamma_{u_1^2 u_2(t)} &= -\mathbb{E}\left((\Delta w_{1it})^2 \Delta w_{2it+1}\right).
\end{aligned}$$

Higher moments. Generalization to the n^{th} moment ($n > 1$) is straightforward. The n^{th} moment of permanent shocks is identified through $\mathbb{E}\left((\Delta w_{jit})^{n-1}(\Delta w_{jit-1} + \Delta w_{jit} + \Delta w_{jit+1})\right)$ (own moments) and $\mathbb{E}\left((\Delta w_{2it})^{n-\nu}\left(\Delta w_{1it-1} + \Delta w_{1it} + \Delta w_{1it+1}\right)^{\nu}\right)$ (cross-moments) with $\nu = \{1, \ldots, n-1\}$. These moments convey information on $\mathbb{E}(v_{jit}^n)$ and $\mathbb{E}(v_{1it}^{\nu} v_{2it}^{n-\nu})$ respectively *plus* a sum of products of lower-order moments (up to $n-2 \geq 2$) of the spouses' permanent and transitory shocks between $t-2$ and $t+1$. Such lower-order moments are identified sequentially relying on results for the variance and skewness and then moving up, if required, until reaching moments of order $n-2$.

The n^{th} moment of transitory shocks is identified through the n^{th} covariance of wages; namely $\mathbb{E}\left((\Delta w_{jit})^{n-1}\Delta w_{jit+1}\right)$ (own moments) and $\mathbb{E}\left((\Delta w_{2it})^{n-\nu}(\Delta w_{1it+1})^{\nu}\right)$ (cross-moments). The covariances convey information on $\mathbb{E}(u_{jit}^n)$ and $\mathbb{E}(u_{1it}^{\nu} u_{2it}^{n-\nu})$ respectively *plus*, like previously, a sum of products of lower-order moments (order up to $n-2 \geq 2$) of the spouses' permanent and transitory wage shocks between $t-1$ and $t+1$.

Three remarks are in order. First, unlike the variance and skewness, it is not possible to identify higher than third moments without previously identifying lower-order moments. Second, no generic formulas exist for $\mathbb{E}(v_{jit}^n)$, $\mathbb{E}(u_{jit}^n)$ etc, *for every* n. The reason is the accompanying sum of products of lower-order moments in each case. Such term depends on (and increases with) n; lower-order sums are not nested within higher-order sums thus ruling out a generic formula *for every* n. Third, over-identifying restrictions exist for all own- and cross-moments of order higher than 2.

Measurement error. Identification so far assumes measurement error away. If wages are contaminated with error, then identification requires moments of the error up to order n. In the permanent-transitory specification the variance of the transitory shock is not separately identified from the variance of measurement error (Meghir and Pistaferri, 2011). However, information on the variance of wage error in survey data is often available through validation studies (Bound et al., 1994, for the PSID). The previous identifying equations can be easily adapted for an external estimate of the error variance.

It is not possible to separate higher moments of wage measurement error from those of the transitory shock. Moreover, there are no validation studies (at least not for the PSID) with

Table C.1 – Second Moments of Preference Distribution $F_{\boldsymbol{\eta}_t|\mathbf{O}_t}$

	Consumption elasticities			*Male labor supply elasticities*			*Female labor supply elasticities*		
	$\eta_{c,w_1(i,t)}$	$\eta_{c,w_2(i,t)}$	$\eta_{c,p(i,t)}$	$\eta_{h_1,w_1(i,t)}$	$\eta_{h_1,w_2(i,t)}$	$\eta_{h_1,p(i,t)}$	$\eta_{h_2,w_1(i,t)}$	$\eta_{h_2,w_2(i,t)}$	$\eta_{h_2,p(i,t)}$
$\eta_{c,w_1(i,t)}$	$\mathrm{V}(\eta_{c,w_1})$	$\mathrm{C}\begin{pmatrix}\eta_{c,w_1}\\ \eta_{c,w_2}\end{pmatrix}$	$\mathrm{C}\begin{pmatrix}\eta_{c,w_1}\\ \eta_{c,p}\end{pmatrix}$	$\mathrm{C}\begin{pmatrix}\eta_{c,w_1}\\ \eta_{h_1,w_1}\end{pmatrix}$	$\mathrm{C}\begin{pmatrix}\eta_{c,w_1}\\ \eta_{h_1,w_2}\end{pmatrix}$	$\mathrm{C}\begin{pmatrix}\eta_{c,w_1}\\ \eta_{h_1,p}\end{pmatrix}$	$\mathrm{C}\begin{pmatrix}\eta_{c,w_1}\\ \eta_{h_2,w_1}\end{pmatrix}$	$\mathrm{C}\begin{pmatrix}\eta_{c,w_1}\\ \eta_{h_2,w_2}\end{pmatrix}$	$\mathrm{C}\begin{pmatrix}\eta_{c,w_1}\\ \eta_{h_2,p}\end{pmatrix}$
$\eta_{c,w_2(i,t)}$		$\mathrm{V}(\eta_{c,w_2})$	$\mathrm{C}\begin{pmatrix}\eta_{c,w_2}\\ \eta_{c,p}\end{pmatrix}$	$\mathrm{C}\begin{pmatrix}\eta_{c,w_2}\\ \eta_{h_1,w_1}\end{pmatrix}$	$\mathrm{C}\begin{pmatrix}\eta_{c,w_2}\\ \eta_{h_1,w_2}\end{pmatrix}$	$\mathrm{C}\begin{pmatrix}\eta_{c,w_2}\\ \eta_{h_1,p}\end{pmatrix}$	$\mathrm{C}\begin{pmatrix}\eta_{c,w_2}\\ \eta_{h_2,w_1}\end{pmatrix}$	$\mathrm{C}\begin{pmatrix}\eta_{c,w_2}\\ \eta_{h_2,w_2}\end{pmatrix}$	$\mathrm{C}\begin{pmatrix}\eta_{c,w_2}\\ \eta_{h_2,p}\end{pmatrix}$
$\eta_{c,p(i,t)}$			$\mathrm{V}(\eta_{c,p})$	$\mathrm{C}\begin{pmatrix}\eta_{c,p}\\ \eta_{h_1,w_1}\end{pmatrix}$	$\mathrm{C}\begin{pmatrix}\eta_{c,p}\\ \eta_{h_1,w_2}\end{pmatrix}$	$\mathrm{C}\begin{pmatrix}\eta_{c,p}\\ \eta_{h_1,p}\end{pmatrix}$	$\mathrm{C}\begin{pmatrix}\eta_{c,p}\\ \eta_{h_2,w_1}\end{pmatrix}$	$\mathrm{C}\begin{pmatrix}\eta_{c,p}\\ \eta_{h_2,w_2}\end{pmatrix}$	$\mathrm{C}\begin{pmatrix}\eta_{c,p}\\ \eta_{h_2,p}\end{pmatrix}$
$\eta_{h_1,w_1(i,t)}$				$\mathrm{V}(\eta_{h_1,w_1})$	$\mathrm{C}\begin{pmatrix}\eta_{h_1,w_1}\\ \eta_{h_1,w_2}\end{pmatrix}$	$\mathrm{C}\begin{pmatrix}\eta_{h_1,w_1}\\ \eta_{h_1,p}\end{pmatrix}$	$\mathrm{C}\begin{pmatrix}\eta_{h_1,w_1}\\ \eta_{h_2,w_1}\end{pmatrix}$	$\mathrm{C}\begin{pmatrix}\eta_{h_1,w_1}\\ \eta_{h_2,w_2}\end{pmatrix}$	$\mathrm{C}\begin{pmatrix}\eta_{h_1,w_1}\\ \eta_{h_2,p}\end{pmatrix}$
$\eta_{h_1,w_2(i,t)}$					$\mathrm{V}(\eta_{h_1,w_2})$	$\mathrm{C}\begin{pmatrix}\eta_{h_1,w_2}\\ \eta_{h_1,p}\end{pmatrix}$	$\mathrm{C}\begin{pmatrix}\eta_{h_1,w_2}\\ \eta_{h_2,w_1}\end{pmatrix}$	$\mathrm{C}\begin{pmatrix}\eta_{h_1,w_2}\\ \eta_{h_2,w_2}\end{pmatrix}$	$\mathrm{C}\begin{pmatrix}\eta_{h_1,w_2}\\ \eta_{h_2,p}\end{pmatrix}$
$\eta_{h_1,p(i,t)}$						$\mathrm{V}(\eta_{h_1,p})$	$\mathrm{C}\begin{pmatrix}\eta_{h_1,p}\\ \eta_{h_2,w_1}\end{pmatrix}$	$\mathrm{C}\begin{pmatrix}\eta_{h_1,p}\\ \eta_{h_2,w_2}\end{pmatrix}$	$\mathrm{C}\begin{pmatrix}\eta_{h_1,p}\\ \eta_{h_2,p}\end{pmatrix}$
$\eta_{h_2,w_1(i,t)}$							$\mathrm{V}(\eta_{h_2,w_1})$	$\mathrm{C}\begin{pmatrix}\eta_{h_2,w_1}\\ \eta_{h_2,w_2}\end{pmatrix}$	$\mathrm{C}\begin{pmatrix}\eta_{h_2,w_1}\\ \eta_{h_2,p}\end{pmatrix}$
$\eta_{h_2,w_2(i,t)}$								$\mathrm{V}(\eta_{h_2,w_2})$	$\mathrm{C}\begin{pmatrix}\eta_{h_2,w_2}\\ \eta_{h_2,p}\end{pmatrix}$
$\eta_{h_2,p(i,t)}$									$\mathrm{V}(\eta_{h_2,p})$

Notes: The table lists the 45 parameters that characterize the second moment of the conditional distribution of preferences $F_{\boldsymbol{\eta}_t|\mathbf{O}_t}$ for a given value for $\mathbf{O}_t = (C_t, H_{1t}, H_{2t})'$. Parameters that refer exclusively to wage elasticities appear without shade. These are all identified from panel data on consumption, hours, and wages. Parameters that involve moments of the labor supply elasticities with respect to the price of consumption (own moments and cross-moments with wage elasticities) appear in light gray. These are linear transformations of the previous moments, thus identified. Moments of the consumption elasticity with respect to its price appear in dark gray; these are not identified. V denotes the cross-sectional variance and C the covariance.

information on the error's distributional aspects. This thus necessitates additional assumptions, for example the Gaussian assumption in proposition 1 of section 3.1.

C.2 Preferences

Outline. There are 9 parameters for the first moment of the conditional joint distribution $F_{\boldsymbol{\eta}_t|\mathbf{O}_t}$ of Frisch elasticities across households, given a value for $\mathbf{O}_t = (C_t, H_{1t}, H_{2t})'$. These are $\mathbb{E}(\eta_{c,w_j(i,t)}|\mathbf{O}_t)$, $\mathbb{E}(\eta_{c,p(i,t)}|\mathbf{O}_t)$, $\mathbb{E}(\eta_{h_{j'},w_j(i,t)}|\mathbf{O}_t)$, and $\mathbb{E}(\eta_{h_{j'},p(i,t)}|\mathbf{O}_t)$ for $j, j' = \{1, 2\}$. There are 45 parameters for the conditional second moment; table C.1 lists these parameters. In general, there are $\prod_{i=1}^{8}(n+i)/8!$ parameters for the conditional $n^{\text{th}} = \{1, 2, 3, \dots\}$ moment, assuming that such moment exists and is finite.

I group these parameters into three categories. The first involves exclusively moments of *wage elasticities*. The second involves moments of the labor supply elasticities *with respect to the price of consumption* $\eta_{h_j,p}$, including their cross-moments with wage elasticities. The third includes all other parameters, namely moments of the consumption elasticity *with respect to its price* $\eta_{c,p}$. In table C.1, second moments belonging to the first category appear without shade, those in the second appear in light gray, and those in the third appear in dark gray.

Detailed derivation of consumption autocovariance. Abstracting from measurement

error for now, the first-order consumption autocovariance that appears in the text is given by

$$\begin{aligned} m_{cc(t)} &= \mathbb{E}(\Delta c_{it}\Delta c_{it+1}|\mathbf{O}_{t-1},\mathbf{O}_t) \\ &= -\mathbb{E}(\eta^2_{c,w_1(i,t)}|\mathbf{O}_{t-1},\mathbf{O}_t)\sigma^2_{u_1(t)} - \mathbb{E}(\eta^2_{c,w_2(i,t)}|\mathbf{O}_{t-1},\mathbf{O}_t)\sigma^2_{u_2(t)} \\ &\quad - 2\mathbb{E}(\eta_{c,w_1(i,t)}\eta_{c,w_2(i,t)}|\mathbf{O}_{t-1},\mathbf{O}_t)\sigma_{u_1u_2(t)}. \end{aligned} \tag{C.1}$$

I condition this moment on both $\mathbf{O}_{t-1}$ and $\mathbf{O}_t$ because, by the nature of the approximation, Δc_{it} is a function of $\boldsymbol{\eta}_{it-1}$ while Δc_{it+1} is a function of $\boldsymbol{\eta}_{it}$. As these $\boldsymbol{\eta}$'s depend on outcome levels at $t-1$ and t, the appropriate conditioning variables given identifying *assumption 1b* are both $\mathbf{O}_{t-1}$ and $\mathbf{O}_t$.

I will now show in detail how I obtain expression (C.1). To simplify the illustration I assume temporarily that female shocks $v_{2it} = u_{2it} = 0, \forall t$, so as per (5), $\Delta c_{it} \approx \eta_{c,w_1(i,t-1)}\Delta u_{1it} + g(\pi_{it},\mathbf{s}_{it},\boldsymbol{\eta}_{it-1})v_{1it}$ where $g(\pi_{it},\mathbf{s}_{it},\boldsymbol{\eta}_{it-1}) = \eta_{c,w_1(i,t-1)} + \bar{\eta}_{c(i,t-1)}\varepsilon_1(\pi_{it},\mathbf{s}_{it};\boldsymbol{\eta}_{it-1})$. Using expressions (3) and (5), assumptions 1a and 1b, and results from Bohrnstedt and Goldberger (1969) for the covariance of products of random variables, one can show

$$\begin{aligned} m_{cc(t)} &= \mathbb{E}\big\{\big(\eta_{c,w_1(i,t-1)} \times \Delta u_{1it} + g(\pi_{it},\mathbf{s}_{it},\boldsymbol{\eta}_{it-1}) \times v_{1it}\big) \\ &\quad \times \big(\eta_{c,w_1(i,t)} \times \Delta u_{1it+1} + g(\pi_{it+1},\mathbf{s}_{it+1},\boldsymbol{\eta}_{it}) \times v_{1it+1}\big) \mid \mathbf{O}_{t-1},\mathbf{O}_t\big\} \\ &= \mathbb{E}\big(\eta_{c,w_1(i,t-1)} \times \Delta u_{1it} \times \eta_{c,w_1(i,t)} \times \Delta u_{1it+1} \mid \mathbf{O}_{t-1},\mathbf{O}_t\big) && \text{(term 1)} \\ &\quad + \mathbb{E}\big(\eta_{c,w_1(i,t-1)} \times \Delta u_{1it} \times g(\pi_{it+1},\mathbf{s}_{it+1},\boldsymbol{\eta}_{it}) \times v_{1it+1} \mid \mathbf{O}_{t-1},\mathbf{O}_t\big) && \text{(term 2)} \\ &\quad + \mathbb{E}\big(g(\pi_{it},\mathbf{s}_{it},\boldsymbol{\eta}_{it-1}) \times v_{1it} \times \eta_{c,w_1(i,t)} \times \Delta u_{1it+1} \mid \mathbf{O}_{t-1},\mathbf{O}_t\big) && \text{(term 3)} \\ &\quad + \mathbb{E}\big(g(\pi_{it},\mathbf{s}_{it},\boldsymbol{\eta}_{it-1}) \times v_{1it} \times g(\pi_{it+1},\mathbf{s}_{it+1},\boldsymbol{\eta}_{it}) \times v_{1it+1} \mid \mathbf{O}_{t-1},\mathbf{O}_t\big) && \text{(term 4)} \\ &= \mathbb{E}\big(\eta_{c,w_1(i,t-1)} \times u_{1it} \times \eta_{c,w_1(i,t)} \times u_{1it+1} \mid \mathbf{O}_{t-1},\mathbf{O}_t\big) && \text{(term 1.1)} \\ &\quad - \mathbb{E}\big(\eta_{c,w_1(i,t-1)} \times u_{1it-1} \times \eta_{c,w_1(i,t)} \times u_{1it+1} \mid \mathbf{O}_{t-1},\mathbf{O}_t\big) && \text{(term 1.2)} \\ &\quad - \mathbb{E}\big(\eta_{c,w_1(i,t-1)} \times u_{1it} \times \eta_{c,w_1(i,t)} \times u_{1it} \mid \mathbf{O}_{t-1},\mathbf{O}_t\big) && \text{(term 1.3)} \\ &\quad + \mathbb{E}\big(\eta_{c,w_1(i,t-1)} \times u_{1it-1} \times \eta_{c,w_1(i,t)} \times u_{1it} \mid \mathbf{O}_{t-1},\mathbf{O}_t\big) && \text{(term 1.4)} \\ &= -\mathbb{E}\big(\eta_{c,w_1(i,t-1)} \times \eta_{c,w_1(i,t)} \mid \mathbf{O}_{t-1},\mathbf{O}_t)\big)\sigma^2_{u_1(t)} \\ &= -\mathbb{E}(\eta^2_{c,w_1(i,t)}|\mathbf{O}_{t-1},\mathbf{O}_t)\sigma^2_{u_1(t)}. \end{aligned}$$

In detail: term 2 drops out because shocks are exogenous (*assumption 1a*), thus past preferences do not vary with future shocks. Moreover, conditional on $\mathbf{O}_{t-1}$, $\eta_{c,w_1(i,t-1)}$ does not vary with $\Delta u_{1it} = u_{1it} - u_{1it-1}$ (*assumption 1b*). Elasticity $\eta_{c,w_1(i,t-1)}$ likely varies with $g(\pi_{it+1},\mathbf{s}_{it+1},\boldsymbol{\eta}_{it})$ through $\boldsymbol{\eta}_{it}$. However, transitory and permanent shocks are independent so the entire term equals zero. Similar arguments prove that terms 3 and 4 are also zero. Term 1 survives these arguments because Δu_{1it} and Δu_{1it+1} are related through u_{1it}.

Expanding term 1, term 1.1 drops out because transitory shocks are exogenous (*assumption 1a*; thus past preferences do not vary with future shocks) and serially uncorrelated. Terms 1.2 and 1.4 drop out because, conditional on the contemporaneous levels of consumption and hours, shocks and elasticities are independent (*assumption 1b*). Term 1.3 survives these arguments.

The last equality is then true because I have assumed that conditional elasticities in immediately adjacent ages are approximately equal, i.e. $\eta_{c,w_j(i,t-1)}|\mathbf{O}_{t-1},\mathbf{O}_t \approx \eta_{c,w_j(i,t)}|\mathbf{O}_{t-1},\mathbf{O}_t$. This assumption simplifies the notation and is not needed for identification. The full expression for $m_{cc(t)}$ in (C.1) obtains by reinstating the female shocks which, for the sake of illustration, I had temporarily shut down.

Expressions for other moments. I derive expressions for all other moments similarly. To ease the notation in this section, I no longer include the conditioning statement $|\mathbf{O}_t$ (or $|\mathbf{O}_{t-1},\mathbf{O}_t$ when applicable) in the elasticities; it is, however, implied that all elasticity moments are conditional on the same consumption and hours levels on which the data moments are also conditioned. Finally, to maintain consistency with BPS, I use earnings y_j in lieu of hours h_j. Growth in log earnings net of observables is given by $\Delta y_{jit} = \Delta w_{jit} + \Delta h_{jit}$. The full list of identifying moments is given by

$$
\begin{aligned}
m_{w_j c(t)} &= \mathbb{E}\big(\Delta w_{jit+1}\Delta c_{it}|\mathbf{O}_{t-1}\big) = -\mathbb{E}(\eta_{c,w_j(i,t)})\sigma^2_{u_j(t)} - \mathbb{E}(\eta_{c,w_{j'}(i,t)})\sigma_{u_1u_2(t)}\\
m_{w_j c^2(t)} &= \mathbb{E}\big(\Delta w_{jit+1}(\Delta c_{it})^2|\mathbf{O}_{t-1}\big)\\
&= -\mathbb{E}(\eta^2_{c,w_j(i,t)})\gamma_{u_j(t)} - \mathbb{E}(\eta^2_{c,w_{j'}(i,t)})\gamma_{u_ju^2_{j'}(t)} - 2\mathbb{E}(\eta_{c,w_1(i,t)}\eta_{c,w_2(i,t)})\gamma_{u^2_ju_{j'}(t)}\\
m_{w_j y_j(t)} &= \mathbb{E}\big(\Delta w_{jit+1}\Delta y_{jit}|\mathbf{O}_{t-1}\big) = -\mathbb{E}(1+\eta_{h_j,w_j(i,t)})\sigma^2_{u_j(t)} - \mathbb{E}(\eta_{h_j,w_{j'}(i,t)})\sigma_{u_1u_2(t)}\\
m_{w_{j'} y_j(t)} &= \mathbb{E}\big(\Delta w_{j'it+1}\Delta y_{jit}|\mathbf{O}_{t-1}\big) = -\mathbb{E}(1+\eta_{h_j,w_j(i,t)})\sigma_{u_1u_2(t)} - \mathbb{E}(\eta_{h_j,w_{j'}(i,t)})\sigma^2_{u_{j'}(t)}\\
m_{y_j y_j(t)} &= \mathbb{E}\big(\Delta y_{jit}\Delta y_{jit+1}|\mathbf{O}_{t-1},\mathbf{O}_t\big)\\
&= -\mathbb{E}((1+\eta_{h_j,w_j(i,t)})^2)\sigma^2_{u_j(t)} - \mathbb{E}(\eta^2_{h_j,w_{j'}(i,t)})\sigma^2_{u_{j'}(t)} - 2\mathbb{E}((1+\eta_{h_j,w_j(i,t)})\eta_{h_j,w_{j'}(i,t)})\sigma_{u_1u_2(t)}\\
m_{w_j y_j^2(t)} &= \mathbb{E}\big(\Delta w_{jit+1}(\Delta y_{jit})^2|\mathbf{O}_{t-1}\big)\\
&= -\mathbb{E}((1+\eta_{h_j,w_j(i,t)})^2)\gamma_{u_j(t)} - \mathbb{E}(\eta^2_{h_j,w_{j'}(i,t)})\gamma_{u_ju^2_{j'}(t)} - 2\mathbb{E}((1+\eta_{h_j,w_j(i,t)})\eta_{h_j,w_{j'}(i,t)})\gamma_{u^2_ju_{j'}(t)}\\
m_{w_{j'} y_j^2(t)} &= \mathbb{E}\big(\Delta w_{j'it+1}(\Delta y_{jit})^2|\mathbf{O}_{t-1}\big)\\
&= -\mathbb{E}((1+\eta_{h_j,w_j(i,t)})^2)\gamma_{u^2_ju_{j'}(t)} - \mathbb{E}(\eta^2_{h_j,w_{j'}(i,t)})\gamma_{u_{j'}(t)} - 2\mathbb{E}((1+\eta_{h_j,w_j(i,t)})\eta_{h_j,w_{j'}(i,t)})\gamma_{u_ju^2_{j'}(t)}\\
m_{y_j c(t)} &= \mathbb{E}\big(\Delta y_{jit+1}\Delta c_{it}|\mathbf{O}_{t-1},\mathbf{O}_t\big)\\
&= -\mathbb{E}(\eta_{c,w_j(i,t)}(1+\eta_{h_j,w_j(i,t)}))\sigma^2_{u_j(t)} - \mathbb{E}(\eta_{c,w_{j'}(i,t)}\eta_{h_j,w_{j'}(i,t)})\sigma^2_{u_{j'}(t)}\\
&\quad - \big(\mathbb{E}(\eta_{c,w_j(i,t)}\eta_{h_j,w_{j'}(i,t)}) + \mathbb{E}(\eta_{c,w_{j'}(i,t)}(1+\eta_{h_j,w_j(i,t)}))\big)\sigma_{u_1u_2(t)}\\
m_{w_j y_j c(t)} &= \mathbb{E}\big(\Delta w_{jit+1}\Delta y_{jit}\Delta c_{it}|\mathbf{O}_{t-1}\big)\\
&= -\mathbb{E}(\eta_{c,w_j(i,t)}(1+\eta_{h_j,w_j(i,t)}))\gamma_{u_j(t)} - \mathbb{E}(\eta_{c,w_{j'}(i,t)}\eta_{h_j,w_{j'}(i,t)})\gamma_{u_ju^2_{j'}(t)}\\
&\quad - \big(\mathbb{E}(\eta_{c,w_j(i,t)}\eta_{h_j,w_{j'}(i,t)}) + \mathbb{E}(\eta_{c,w_{j'}(i,t)}(1+\eta_{h_j,w_j(i,t)}))\big)\gamma_{u^2_ju_{j'}(t)}\\
m_{w_{j'} y_j c(t)} &= \mathbb{E}\big(\Delta w_{j'it+1}\Delta y_{jit}\Delta c_{it}|\mathbf{O}_{t-1}\big)\\
&= -\mathbb{E}(\eta_{c,w_j(i,t)}(1+\eta_{h_j,w_j(i,t)}))\gamma_{u^2_ju_{j'}(t)} - \mathbb{E}(\eta_{c,w_{j'}(i,t)}\eta_{h_j,w_{j'}(i,t)})\gamma_{u_{j'}(t)}\\
&\quad - \big(\mathbb{E}(\eta_{c,w_j(i,t)}\eta_{h_j,w_{j'}(i,t)}) + \mathbb{E}(\eta_{c,w_{j'}(i,t)}(1+\eta_{h_j,w_j(i,t)}))\big)\gamma_{u_ju^2_{j'}(t)}
\end{aligned}
$$

where $j, j' = \{1,2\}$ and $j \neq j'$.

Now I show that functions of these empirical moments identify first and second moments of wage elasticities. Identification proceeds as follows.

The mean wage elasticities, given values for $\mathbf{O}_{t-1}$ and/or $\mathbf{O}_t$, are identified through a combination of wage moments and joint consumption-wage and earnings-wage moments; namely

$$\begin{aligned}
\mathbb{E}(\eta_{c,w_j(i,t)}) &= \left(m_{w_{j'}c(t)}\sigma_{u_1u_2(t)} - m_{w_jc(t)}\sigma^2_{u_{j'}(t)}\right) / \left(\sigma^2_{u_1(t)}\sigma^2_{u_2(t)} - (\sigma_{u_1u_2(t)})^2\right) \\
\mathbb{E}(\eta_{h_j,w_j(i,t)}) &= \left(m_{w_{j'}y_j(t)}\sigma_{u_1u_2(t)} - m_{w_jy_j(t)}\sigma^2_{u_{j'}(t)}\right) / \left(\sigma^2_{u_1(t)}\sigma^2_{u_2(t)} - (\sigma_{u_1u_2(t)})^2\right) - 1 \\
\mathbb{E}(\eta_{h_j,w_{j'}(i,t)}) &= \left(m_{w_jy_j(t)}\sigma_{u_1u_2(t)} - m_{w_{j'}y_j(t)}\sigma^2_{u_j(t)}\right) / \left(\sigma^2_{u_1(t)}\sigma^2_{u_2(t)} - (\sigma_{u_1u_2(t)})^2\right).
\end{aligned}$$

These parameters are heavily over-identified by many additional moments. In addition, symmetry of the matrix of Frisch substitution effects (see appendix B) imposes linear restrictions between reciprocal cross-elasticities. As a result the following relation must hold: $\mathbb{E}(\eta_{h_2,w_1(i,t)}) = \mathbb{E}(\eta_{h_1,w_2(i,t)})\mathbb{E}(Y_{1it}/Y_{2it})$ where Y_{jit} is earnings of spouse j.

The second moments of the consumption-wage elasticities (upper left triangle in table C.1), given values for $\mathbf{O}_{t-1}$ and/or $\mathbf{O}_t$, are identified from wage, consumption, and joint consumption-wage moments; namely

$$\begin{pmatrix}
\sigma^2_{u_1(t)} & \sigma^2_{u_2(t)} & 2\sigma_{u_1u_2(t)} \\
\gamma_{u_1(t)} & \gamma_{u_1u_2^2(t)} & 2\gamma_{u_1^2u_2(t)} \\
\gamma_{u_1^2u_2(t)} & \gamma_{u_2(t)} & 2\gamma_{u_1u_2^2(t)}
\end{pmatrix}
\begin{pmatrix}
\mathbb{E}(\eta^2_{c,w_1(i,t)}) \\
\mathbb{E}(\eta^2_{c,w_2(i,t)}) \\
\mathbb{E}(\eta_{c,w_1(i,t)}\eta_{c,w_2(i,t)})
\end{pmatrix}
= -
\begin{pmatrix}
m_{cc(t)} \\
m_{w_1c^2(t)} \\
m_{w_2c^2(t)}
\end{pmatrix}.$$

The system is linear in the parameters. The matrix of coefficients is nonsingular if the distribution of shocks is asymmetric about the mean, that is, if shocks are skewed. The matrix is nonsingular also if $\sigma_{u_1u_2} = 0$ or $\gamma_{u_1^2u_2} = \gamma_{u_1u_2^2} = 0$. If all cross-moments of shocks are zero, the matrix is singular and the covariance of elasticities is not identified but the variances are.

The second moments of the male and female labor supply elasticities (bottom middle and right triangles in table C.1) are identified similarly from wage, earnings, and joint earnings-wage moments. Given values for $\mathbf{O}_{t-1}$ and/or $\mathbf{O}_t$, the identifying equations are given by

$$\begin{pmatrix}
\sigma^2_{u_j(t)} & \sigma^2_{u_{j'}(t)} & 2\sigma_{u_1u_2(t)} \\
\gamma_{u_j(t)} & \gamma_{u_ju^2_{j'}(t)} & 2\gamma_{u_j^2u_{j'}(t)} \\
\gamma_{u_j^2u_{j'}(t)} & \gamma_{u_{j'}(t)} & 2\gamma_{u_ju^2_{j'}(t)}
\end{pmatrix}
\begin{pmatrix}
\mathbb{E}((1+\eta_{h_j,w_j(i,t)})^2) \\
\mathbb{E}(\eta^2_{h_j,w_{j'}(i,t)}) \\
\mathbb{E}((1+\eta_{h_j,w_j(i,t)})\eta_{h_j,w_{j'}(i,t)})
\end{pmatrix}
= -
\begin{pmatrix}
m_{y_jy_j(t)} \\
m_{w_jy_j^2(t)} \\
m_{w_{j'}y_j^2(t)}
\end{pmatrix}.$$

Frisch symmetry imposes a restriction between $\mathrm{Var}(\eta_{h_1,w_2(i,t)})$ and $\mathrm{Var}(\eta_{h_2,w_1(i,t)})$.

The second cross-moments of consumption and hours elasticities (upper middle and right rectangles in table C.1) are identified as follows. Given values for $\mathbf{O}_{t-1}$ and/or $\mathbf{O}_t$, consider the linear system

$$\begin{pmatrix}
\sigma^2_{u_j(t)} & \sigma^2_{u_{j'}(t)} & \sigma_{u_1u_2(t)} & \sigma_{u_1u_2(t)} \\
\gamma_{u_j(t)} & \gamma_{u_ju^2_{j'}(t)} & \gamma_{u_j^2u_{j'}(t)} & \gamma_{u_j^2u_{j'}(t)} \\
\gamma_{u_j^2u_{j'}(t)} & \gamma_{u_{j'}(t)} & \gamma_{u_ju^2_{j'}(t)} & \gamma_{u_ju^2_{j'}(t)}
\end{pmatrix}
\begin{pmatrix}
\mathbb{E}(\eta_{c,w_j(i,t)}(1+\eta_{h_j,w_j(i,t)})) \\
\mathbb{E}(\eta_{c,w_{j'}(i,t)}\eta_{h_j,w_{j'}(i,t)}) \\
\mathbb{E}(\eta_{c,w_j(i,t)}\eta_{h_j,w_{j'}(i,t)}) \\
\mathbb{E}(\eta_{c,w_{j'}(i,t)}(1+\eta_{h_j,w_j(i,t)}))
\end{pmatrix}
= -
\begin{pmatrix}
m_{y_jc(t)} \\
m_{w_jy_jc(t)} \\
m_{w_{j'}y_jc(t)}
\end{pmatrix}$$

repeated twice for $j = \{1, 2\}$ while $j' = \{1, 2\} \neq j$. This yields 6 equations in 8 parameters. In addition, symmetry of the matrix of Frisch substitution effects provides two linear restrictions $\mathbb{E}(\eta_{c,w_j(i,t)}\eta_{h_2,w_1(i,t)}) = \mathbb{E}(\eta_{c,w_j(i,t)}\eta_{h_1,w_2(i,t)})\mathbb{E}(Y_{1it}/Y_{2it})$, $j = \{1, 2\}$; taken together these 8 equations just identify the parameters of interest. In practice the parameters are over-identified by at least as many additional equations. Finally, the second cross-moments of male and female labor supply elasticities (middle right rectangle in table C.1) are identified in a similar manner.

Higher moments. Identification of higher moments obeys a similar idea: consumption skewness reflects skewness in wage shocks as well as skewness in consumption preferences; earnings kurtosis reflects kurtosis in the distribution of shocks as well as in labor supply preferences, etc. Practically, however, identification is less parsimonious due to the ever-increasing number of parameters involved. As an illustration, the four skewness parameters for the $\eta_{c,w_j(i)}$'s are over-identified by $\mathbb{E}\big((\Delta c_{it})^2\Delta c_{it+1}|\mathbf{O}_{t-1}, \mathbf{O}_t\big)$, $\mathbb{E}\big(\Delta w_{jit-1}(\Delta c_{it})^2\Delta c_{it+1}|\mathbf{O}_{t-1}, \mathbf{O}_t\big)$ and $\mathbb{E}\big((\Delta w_{jit-1})^2(\Delta c_{it})^2\Delta c_{it+1}|\mathbf{O}_{t-1}, \mathbf{O}_t\big)$, $j = \{1, 2\}$. Third and fourth moments alone do not suffice to identify the parameters without restricting co-skewness in the η_{c,w_j}'s. To avoid such restriction, the fifth moment above provides the additional identifying equation that completes identification. All other third moments of wage elasticities are identified in a similar way.

The discussion extends to the n^{th} moment of wage elasticities. This involves an ever-longer intertemporal product of consumption or earnings (for consumption: $\prod_{\tau=0}^{n-3}\Delta c_{it-\tau}\Delta c_{it}\Delta c_{it+1}$, $n \geq 3$) as well as empirical moments of order at least $n+2$. The data requirements quickly become tedious and restrictions on higher cross-moments only partly alleviate such requirements. This is the reason why I focus on the estimation of first and second moments only.

Measurement error. Identification so far assumes measurement error away. If earnings and consumption are contaminated with error, then identification requires moments of the respective earnings and consumption error up to order n. For example, the variance of earnings error enters $m_{y_j y_j(t)}$ additively while the covariance between the error in earnings and the error in wages enters $m_{w_j y_j(t)}$ because wages are constructed as earnings over hours (section 4.2). The variance of consumption error enters $m_{cc(t)}$ also additively. The structure is thus under-identified so one needs external estimates of the error variance or additional restrictions.

The former two moments of the error are available from the validation study of Bound et al. (1994), thus necessitate no additional restrictions. The consumption error variance is not available in the validation study so additional restrictions or an external estimate are needed for identification. Finally, there are no validation studies (at least not for the PSID) with information on higher moments of the earnings and consumption error. This necessitates additional assumptions, e.g. the Gaussian assumption in proposition 1 of section 3.1.

Consumption substitution elasticity. Section 3.3 explains that no moment of the elasticity of consumption with respect to its price is identified without collapsing its distribution to

degenerate. While the lifecycle Marshallian elasticity of consumption κ_{c,v_j} identifies a homogeneous $\eta_{c,p}$ in BPS, here any moment of κ_{c,v_j} depends on *various* moments of $\eta_{c,p}$. One can see this by a Taylor expansion of κ_{c,v_1} around mean preferences. With preference heterogeneity, one cannot separate the first from, say, the second moment of $\eta_{c,p}$ and identification of this parameter fails unless one collapses its distribution to degenerate.

To understand why $\mathbb{E}(\kappa_{c,v_1(i,t)})$ depends on various moments of $\eta_{c,p}$, abstract from female labor supply and consider households who, on average, dislike fluctuations in consumption ($\mathbb{E}(\eta_{c,p(i,t)}) \to 0^-$) and male labor supply ($\mathbb{E}(\eta_{h_1,w_1(i,t)}) \to 0^+$). Furthermore, suppose that households *less* reluctant to intertemporal consumption fluctuations ($\eta_{c,p}$ more negative) also have *less* elastic labor supply (low η_{h_1,w_1}; correlates positively with $\eta_{c,p}$). Because those who barely use labor supply to smooth shocks (smallest η_{h_1,w_1}) are also those who do not resent passing such shocks into consumption (largest absolute $\eta_{c,p}$), average consumption across households is more responsive to permanent shocks (higher Marshallian elasticity) than without the preference correlation.[1] The Marshallian elasticity thus depends not only on $\mathbb{E}(\eta_{c,p(i,t)})$ but also on the covariance with the male labor supply elasticity (and in fact on the covariances with all other elasticities that characterize household preference). Ignoring the correlation results in overestimating $|\mathbb{E}(\eta_{c,p(i)})|$ and mistakenly deeming the average household more willing to trade consumption intertemporally.

D Data and Estimation Details

This appendix provides details on the PSID sample and the estimation of wealth shares s_{jit} and π_{it} . In addition, it reports a number of robustness checks as well as the empirical and fitted values of all moments targeted in the structural estimation.

Sample summary statistics. Table D.1 presents descriptive statistics for the baseline sample (columns 1-3) and for four subsamples of relatively wealthy households (columns W1-W4). In the baseline sample, average earnings of men are 86% higher than average earnings of women; men, however, work on average 524 hours more, almost a third more than women. Women are 71% likely to have had some college education; men are slightly less likely. Household consumption is, on average, a fraction of men's earnings but greater than women's. The largest single component within the consumption basket is housing, followed by vehicles (including gasoline) and food at home. On average, there is one child under 18 in the household.

First stage regressions on past outcome levels. The relationship between growth rates at t and outcome levels at $t-1$ is interesting in its own right, and table D.2 presents the results. Own past levels are negative and highly significant while those of the other variables are not.

[1] Suppose $\mathbb{E}(\eta_{c,p(i,t)}) = -0.05$ and $\mathbb{E}(\eta_{h_j,w_j(i,t)}) = 0.2$. At these values $\mathbb{E}(\kappa_{c,v_1(i,t)})$ increases more than

Table D.1 – Sample Descriptive Statistics

	baseline sample			$A > \overline{C}$	$A > 2\overline{C}$	$A > \overline{C}$ no debt	$A > \overline{C}$ liquid
	(1) mean	(2) median	(3) st.dev	(W1) mean	(W2) mean	(W3) mean	(W4) mean
Male earner							
Earnings	77466	58181	121938	86403	92394	93570	104818
Hours of work	2254	2205	614	2260	2266	2232	2256
Hourly wage	35.4	26.3	72.9	39.6	42.4	41.2	45.7
Age	45.1	45.0	7.8	47.0	47.4	47.4	47.9
Some college %	67.3	100.0	46.9	71.8	75.4	70.9	76.5
Female earner							
Earnings	41663	34612	36166	44807	46442	44607	48333
Hours of work	1730	1880	667	1729	1719	1681	1675
Hourly wage	24.5	19.6	29.6	26.4	27.6	27.1	29.7
Age	43.4	43.0	7.6	45.2	45.7	45.6	46.1
Some college %	70.8	100.0	45.5	73.7	76.1	72.8	76.7
Household consumption							
Total consumption	47307	40850	26373	51246	54186	49618	53324
food at home	7102	6606	3550	7230	7354	6937	7056
food out	3012	2400	2680	3224	3364	3115	3353
vehicles[a]	7136	5298	6653	7400	7579	6668	6841
public transport	347	0	2628	416	473	372	429
childcare	970	0	3228	902	898	793	840
education	3517	0	9538	4371	4878	3848	4402
medical expenses[b]	3657	2547	4266	3799	3925	3543	3825
utilities	4835	4436	2761	4895	4956	4473	4576
housing[c]	16731	12980	13924	19008	20758	19870	22002
Household assets and debt [in thousands]							
Total wealth	408.5	180.7	878.6	539.5	631.1	697.4	842.3
Home equity[d]	131.5	80.8	179.9	171.4	195.8	206.6	234.2
Other debt	12.3	2.7	29.1	9.2	9.0	0.1	0.1
All other assets	289.3	84.3	791.5	377.3	444.4	490.9	608.2
other real estate	46.0	0.0	302.0	59.5	71.2	71.7	84.7
savings accounts	27.2	7.1	71.6	34.6	40.0	51.0	62.7
stocks-shares	46.7	0.0	198.4	62.1	74.2	93.6	119.8
# of children	1.0	1.0	1.1	0.9	0.9	0.9	0.8
Obs. [households × years]		8308		5718	4715	2391	1849

Notes: The table presents summary statistics for the baseline sample (columns 1-3) and for four subsamples of relatively wealthy households (columns W1-W4) over waves 1999-2011 of the PSID. All monetary amounts are in 2010 dollars. Earnings, hours, consumption and wealth/debt are annual. Column W1 is for households with wealth A_t at least as much as average consumption $\overline{C}_t$ in the baseline sample. Column W2 is for households with wealth at least twice as much as average consumption. Column W3 is like column W1 with the additional condition that households hold real debt that does not exceed \$2K. Column W4 is like column W3 but the relevant measure of wealth excludes home equity, thus proxies for liquid assets. [a]including gasoline; [b]including health insurance and prescriptions; [c]including home insurance, rent and rent equivalent for homeowners and people in alternative housing arrangements; [d]the present value of owned house net of outstanding mortgages.

Table D.2 – First Stage Regressions: Past Levels

	baseline sample		
	$\Delta \ln Y_{1it}$	$\Delta \ln Y_{2it}$	$\Delta \ln C_{it}$
H_{1it-1}	-9.30e-05	1.56e-05	3.59e-06
	(-7.79)	(1.16)	(0.59)
H_{2it-1}	1.43e-05	-2.03e-04	-5.29e-06
	(1.29)	(-16.27)	(-0.93)
C_{it-1}	-4.78e-07	7.64e-09	-4.21e-06
	(-1.53)	(0.02)	(-26.31)
observables	yes	yes	yes
Obs. [households $\times\Delta_t$]		6071	

Notes: The table reports the coefficients from first stage regressions of earnings and consumption growth on past levels of hours and consumption. t-stats appear in brackets under the coefficients. Sample sizes are smaller than in summary statistics table D.1 because the variables here are in first differences.

Estimation of s_{it} and π_{it}. Wealth shares $\mathbf{s}_{it} = (s_{1it}, s_{2it})'$ and π_{it} are used in the replication of BPS and the simulation of consumption growth after the moments of wage elasticities are estimated. The simulation of Δc_{it} is used in the estimation of $\eta_{c,p}$ and the discussion of inequality in section 6.1 and partial insurance in section 6.2. From appendix A, $s_{jit} \approx \overline{\overline{Y}}_{jit}/\overline{\overline{Y}}_{it}$ and $\pi_{it} \approx \text{Assets}_{it}/(\text{Assets}_{it} + \overline{\overline{Y}}_{it})$, where $\overline{\overline{Y}}_{jit} = Y_{jit} + \mathbb{E}_t \sum_{\varsigma=1}^{T} \frac{Y_{jit+\varsigma}}{(1+r)^\varsigma}$ is spouse j's *human wealth* at the beginning of t, namely the expected discounted stream of earnings Y_{jit} between t and the end of working life. $\overline{\overline{Y}}_{it} = \sum_j \overline{\overline{Y}}_{jit}$ is the sum of human wealth in the household.

The main difficulty in estimating s_{jit} is that human wealth conforms to expectations through $\mathbb{E}_t Y_{jit+\varsigma}$. I follow BPS and estimate this as follows. I pool earnings across all periods and regress them on a set of predictable characteristics including a cubic polynomial in age, year of birth, race and education dummies, as well as interactions of the polynomial with the race and education dummies. I summarize this regression as $Y_{jit} = \mathbf{Q}'_{jit}\boldsymbol{\delta}_j + \epsilon_{jit}$. I then obtain $\mathbb{E}_t Y_{jit+\varsigma}$ as the appropriate fitted value from this regression, i.e. $\mathbb{E}_t Y_{jit+\varsigma} = \mathbf{Q}'_{jit+\varsigma}\hat{\boldsymbol{\delta}}_j$. I set the discount rate at 2% annually and the end of working life at 65. This allows me to construct s_{jit}, $j = \{1, 2\}$, and π_{it}. Note that assets/wealth are directly observed in the PSID. Table D.3 presents summary statistics. I estimate $\mathbb{E}(s_{1it}) = 0.614$ and $\mathbb{E}(\pi_{it}) = 0.191$. The averages as well as the patterns of $\mathbf{s}_{it}$ and π_{it} by age are similar to BPS.

Targeted moments. The structural estimation targets 80 moments of the joint distribution of residual wages, earnings, and consumption. Tables D.4-D.6 list the targeted conditional moments alongside their empirical values at the sample average of consumption and hours (equivalent to the unconditional moments) and their fitted values in the preferred specification.

1-to-1 with a positive correlation in preferences ($\partial\mathbb{E}(\kappa_{c,v_1(i,t)})/\partial\text{Cov}(\eta_{c,p(i,t)}, \eta_{h_1,w_1(i,t)}) = 1.28$).

Table D.3 – Summary Statistics for Wealth Shares $\mathbf{s}$ and π

s_{1it}					π_{it}				
mean	med.	st.d.	min	max	mean	med.	st.d.	min	max
0.614	0.620	0.094	0.144	0.996	0.191	0.133	0.182	0.000	0.956

Notes: The table presents summary statistics for men's share of human wealth (s_{1it}) and for the partial insurance coefficient (π_{it}) in the baseline sample. Women's share of human wealth is $s_{2it} = 1 - s_{1it}$.

Block bootstrap standard errors for the empirical moments are in parentheses based on 1,000 replications. The t-statistics are for the null hypothesis that the theoretical moment equals the empirical one. More than 90% of targeted moments are associated with $|t\text{-stat}|$ lower than the rule of thumb of 1.96. The magnitude and standard error of most of the 7 moments for which $|t\text{-stat}| > 1.96$ are very small making small and economically unimportant departures from the target easier to generate large t-statistics.

Consumption substitution elasticity. While estimation of the wage elasticities does not require parametric form restrictions on preferences and their distribution, estimation of $\eta_{c,p}$ is not possible without strong distributional assumptions (section 3.3). Such assumptions are not needed when preferences are homogeneous so BPS estimate $\eta_{c,p}$ together with the wage elasticities. This is not possible here unless one restricts the distribution of preferences to a specific class. To avoid subjecting *all* parameters to such restriction, I estimate $\eta_{c,p}$ in a second stage, i.e. after having estimated the wage elasticities *without* distributional restrictions.

I use the variance of consumption growth $\text{Var}(\Delta c_{it})$ at the sample average of consumption and hours (i.e. $\mathbf{O}_t = \mathbb{E}(\mathbf{O}_{it})$) to estimate a homogeneous $\eta_{c,p}$; this variance involves moments of the Marshallian elasticity $\kappa_{c,v_j(i,t)}$ that was shown in section 3.3 to depend on $\eta_{c,p}$. The Marshallian elasticity also depends on the *entire* distribution of wage elasticities thus necessitating assumptions on their joint distribution. A natural benchmark is to restrict that to joint normal and parameterize it at the first and second moments from the preferred specification. Normality does not contradict the previous use of third moments as consumption and hours can still exhibit skewness because wage shocks are skewed. While a full parametric approach would subject all parameters to distributional assumptions, this two-step approach only subjects $\eta_{c,p}$. Estimation of $\eta_{c,p}$ is thus conditional on (rather than joint with) the wage elasticities.

I operationalize this estimation using simulated minimum distance as $\text{Var}(\Delta c_{it})$ depends implicitly and nonlinearly on the parameters. Specifically, I simulate preferences for 10 million households, I calculate the variance of consumption growth across them, and I estimate $\eta_{c,p}$ minimizing the quadratic distance between the simulated variance and its empirical counterpart. This estimation requires information on wealth shares π_{it} and $\mathbf{s}_{it}$ for which I draw random values from their empirical distributions. The distance metric is minimized at $\eta_{c,p} = -0.598$

(simulated and empirical variances matched to the third decimal digit) implying a coefficient of relative risk aversion approximately equal to 1.67.[2]

Table D.4 – Targeted Wage Moments

	data	model	t-stat. diff.		data	model	t-stat. diff.
$\mathbb{E}\big((\Delta w_{1t})^2\big)$	0.129 (0.013)	0.129	0.000	$\mathbb{E}\big((\Delta w_{1t})^2 \Delta w_{2t}\big)$	0.010 (0.005)	0.010	0.000
$\mathbb{E}\big(\Delta w_{1t} \Delta w_{1t^+}\big)$	-0.024 (0.006)	-0.024	-0.001	$\mathbb{E}\big((\Delta w_{1t})^2 \Delta w_{2t^+}\big)$	-0.012 (0.014)	0.000	0.866
$\mathbb{E}\big((\Delta w_{2t})^2\big)$	0.098 (0.008)	0.098	0.000	$\mathbb{E}\big((\Delta w_{1t^+})^2 \Delta w_{2t}\big)$	-0.006 (0.004)	0.000	1.663
$\mathbb{E}\big(\Delta w_{2t} \Delta w_{2t^+}\big)$	-0.012 (0.005)	-0.012	-0.002	$\mathbb{E}\big(\Delta w_{1t} (\Delta w_{2t})^2\big)$	0.001 (0.003)	0.001	0.000
$\mathbb{E}\big(\Delta w_{1t} \Delta w_{2t}\big)$	0.017 (0.003)	0.017	0.000	$\mathbb{E}\big(\Delta w_{1t} (\Delta w_{2t^+})^2\big)$	0.003 (0.003)	0.000	-1.067
$\mathbb{E}\big(\Delta w_{1t} \Delta w_{2t^+}\big)$	-0.003 (0.003)	-0.004	-0.094	$\mathbb{E}\big(\Delta w_{1t^+} (\Delta w_{2t})^2\big)$	0.003 (0.003)	0.000	-1.148
$\mathbb{E}\big(\Delta w_{1t^+} \Delta w_{2t}\big)$	-0.004 (0.003)	-0.004	0.105	$\mathbb{E}\big(\Delta w_{1t} \Delta w_{1t^+} \Delta w_{2t}\big)$	0.003 (0.002)	0.000	-1.443
$\mathbb{E}\big((\Delta w_{1t})^3\big)$	0.044 (0.052)	0.044	0.000	$\mathbb{E}\big(\Delta w_{1t} \Delta w_{1t^+} \Delta w_{2t^+}\big)$	-0.003 (0.002)	0.000	1.116
$\mathbb{E}\big(\Delta w_{1t} (\Delta w_{1t^+})^2\big)$	-0.009 (0.008)	-0.018	-1.112	$\mathbb{E}\big(\Delta w_{1t} \Delta w_{2t} \Delta w_{2t^+}\big)$	-0.001 (0.002)	0.000	0.271
$\mathbb{E}\big(\Delta w_{1t^+} (\Delta w_{1t})^2\big)$	0.027 (0.011)	0.018	-0.852	$\mathbb{E}\big(\Delta w_{1t^+} \Delta w_{2t} \Delta w_{2t^+}\big)$	0.000 (0.002)	0.000	0.344
$\mathbb{E}\big((\Delta w_{2t})^3\big)$	-0.029 (0.011)	-0.029	0.000				
$\mathbb{E}\big(\Delta w_{2t} (\Delta w_{2t^+})^2\big)$	-0.003 (0.006)	-0.008	-0.741				
$\mathbb{E}\big(\Delta w_{2t^+} (\Delta w_{2t})^2\big)$	0.012 (0.006)	0.008	-0.674				

Notes: The notation is as follows: $t^+ \equiv t+1$. The table presents the list of targeted wage moments alongside their empirical and theoretical values. Empirical moments are net of observables and wage measurement error. Block bootstrap standard errors for the empirical moments are in parentheses based on 1,000 bootstrap replications. The reported t-statistic is for the null hypothesis that *theoretical moment* − *empirical moment* = 0.

[2]The coefficient of relative risk aversion is approximately equal to $-\eta_{c,p}^{-1}$ (exactly equal if preferences are separable). Chetty (2006) uses labor supply data and calculates an upper bound on this parameter at 0.97 when consumption and hours are complements. Abstracting from labor supply, Kimball et al. (2009) impute the coefficient of relative risk aversion from hypothetical gamble responses in the PSID and report a range of 1.4-6.7. Guiso and Sodini (2013) calculate household risk aversion based on portfolio risk shares in the US Survey of Consumer Finances. They report a median coefficient at 3.5 with the central 90% of the distribution lying in the range 1.6-30.8 skewed to the left. Cohen and Einav (2007) estimate risk preferences from deductible choices in the auto insurance market and find a median coefficient at 0.37 with the average being much higher.

Table D.5 – Targeted Earnings Moments at Sample Average of Consumption and Hours

	data	model	t-stat. diff.		data	model	t-stat. diff.
$\mathbb{E}\big(\Delta w_{1t}\Delta y_{1t^+}\vert\overline{\mathbf{o}}_t\big)$	-0.036 (0.005)	-0.030	1.068	$\mathbb{E}\big((\Delta w_{1t})^2\Delta y_{2t^+}\vert\overline{\mathbf{o}}_t\big)$	-0.001 (0.005)	0.000	0.223
$\mathbb{E}\big(\Delta w_{1t^+}\Delta y_{1t}\vert\overline{\mathbf{o}}_{t^-}\big)$	-0.035 (0.006)	-0.030	0.835	$\mathbb{E}\big((\Delta w_{1t^+})^2\Delta y_{2t}\vert\overline{\mathbf{o}}_{t^-}\big)$	-0.001 (0.005)	0.000	0.165
$\mathbb{E}\big(\Delta w_{2t}\Delta y_{1t^+}\vert\overline{\mathbf{o}}_t\big)$	-0.003 (0.003)	-0.005	-0.446	$\mathbb{E}\big((\Delta w_{2t})^2\Delta y_{2t^+}\vert\overline{\mathbf{o}}_t\big)$	0.009 (0.006)	0.009	0.010
$\mathbb{E}\big(\Delta w_{2t^+}\Delta y_{1t}\vert\overline{\mathbf{o}}_{t^-}\big)$	-0.002 (0.003)	-0.005	-0.864	$\mathbb{E}\big((\Delta w_{2t^+})^2\Delta y_{2t}\vert\overline{\mathbf{o}}_{t^-}\big)$	-0.001 (0.007)	-0.009	-1.239
$\mathbb{E}\big(\Delta w_{1t}\Delta y_{2t^+}\vert\overline{\mathbf{o}}_t\big)$	-0.004 (0.003)	-0.005	-0.240	$\mathbb{E}\big(\Delta w_{1t}(\Delta y_{1t^+})^2\vert\overline{\mathbf{o}}_t\big)$	-0.021 (0.006)	-0.030	-1.445
$\mathbb{E}\big(\Delta w_{1t^+}\Delta y_{2t}\vert\overline{\mathbf{o}}_{t^-}\big)$	0.002 (0.003)	-0.005	-1.863	$\mathbb{E}\big(\Delta w_{1t^+}(\Delta y_{1t})^2\vert\overline{\mathbf{o}}_{t^-}\big)$	0.026 (0.008)	0.030	0.476
$\mathbb{E}\big(\Delta w_{2t}\Delta y_{2t^+}\vert\overline{\mathbf{o}}_t\big)$	-0.040 (0.005)	-0.015	4.823	$\mathbb{E}\big(\Delta w_{2t}(\Delta y_{1t^+})^2\vert\overline{\mathbf{o}}_t\big)$	-0.005 (0.003)	0.000	1.550
$\mathbb{E}\big(\Delta w_{2t^+}\Delta y_{2t}\vert\overline{\mathbf{o}}_{t^-}\big)$	-0.028 (0.006)	-0.015	2.107	$\mathbb{E}\big(\Delta w_{2t^+}(\Delta y_{1t})^2\vert\overline{\mathbf{o}}_{t^-}\big)$	0.004 (0.003)	0.000	-1.226
$\mathbb{E}\big(\Delta y_{1t}\Delta y_{1t^+}\vert\overline{\mathbf{o}}_{t^-},\overline{\mathbf{o}}_t\big)$	-0.044 (0.006)	-0.039	0.948	$\mathbb{E}\big(\Delta w_{1t}(\Delta y_{2t^+})^2\vert\overline{\mathbf{o}}_t\big)$	0.006 (0.004)	0.001	-1.431
$\mathbb{E}\big(\Delta y_{1t}\Delta y_{2t^+}\vert\overline{\mathbf{o}}_{t^-},\overline{\mathbf{o}}_t\big)$	-0.008 (0.003)	-0.006	0.616	$\mathbb{E}\big(\Delta w_{1t^+}(\Delta y_{2t})^2\vert\overline{\mathbf{o}}_{t^-}\big)$	-0.001 (0.005)	-0.001	0.038
$\mathbb{E}\big(\Delta y_{1t^+}\Delta y_{2t}\vert\overline{\mathbf{o}}_{t^-},\overline{\mathbf{o}}_t\big)$	0.000 (0.004)	-0.006	-1.510	$\mathbb{E}\big(\Delta w_{2t}(\Delta y_{2t^+})^2\vert\overline{\mathbf{o}}_t\big)$	-0.006 (0.006)	-0.012	-0.967
$\mathbb{E}\big(\Delta y_{2t}\Delta y_{2t^+}\vert\overline{\mathbf{o}}_{t^-},\overline{\mathbf{o}}_t\big)$	-0.012 (0.006)	-0.018	-1.117	$\mathbb{E}\big(\Delta w_{2t^+}(\Delta y_{2t})^2\vert\overline{\mathbf{o}}_{t^-}\big)$	0.010 (0.007)	0.012	0.282
$\mathbb{E}\big((\Delta w_{1t})^2\Delta y_{1t^+}\vert\overline{\mathbf{o}}_t\big)$	0.031 (0.014)	0.023	-0.571	$\mathbb{E}\big(\Delta w_{1t}\Delta y_{1t^+}\Delta y_{2t^+}\vert\overline{\mathbf{o}}_t\big)$	-0.005 (0.002)	0.000	2.311
$\mathbb{E}\big((\Delta w_{1t^+})^2\Delta y_{1t}\vert\overline{\mathbf{o}}_{t^-}\big)$	-0.017 (0.008)	-0.023	-0.755	$\mathbb{E}\big(\Delta w_{1t^+}\Delta y_{1t}\Delta y_{2t}\vert\overline{\mathbf{o}}_{t^-}\big)$	-0.001 (0.003)	0.000	0.534
$\mathbb{E}\big((\Delta w_{2t})^2\Delta y_{1t^+}\vert\overline{\mathbf{o}}_t\big)$	0.000 (0.003)	-0.001	-0.107	$\mathbb{E}\big(\Delta w_{2t}\Delta y_{1t^+}\Delta y_{2t^+}\vert\overline{\mathbf{o}}_t\big)$	-0.001 (0.002)	0.001	1.046
$\mathbb{E}\big((\Delta w_{2t^+})^2\Delta y_{1t}\vert\overline{\mathbf{o}}_{t^-}\big)$	0.003 (0.003)	0.001	-0.925	$\mathbb{E}\big(\Delta w_{2t^+}\Delta y_{1t}\Delta y_{2t}\vert\overline{\mathbf{o}}_{t^-}\big)$	0.001 (0.002)	-0.001	-0.993

Notes: The notation is as follows: $t^- \equiv t-1$, $t^+ \equiv t+1$ and $\overline{\mathbf{o}}_{t^-} \equiv (\mathbf{O}_{t-1} = \mathbb{E}(\mathbf{O}_{it-1}))$, $\overline{\mathbf{o}}_t \equiv (\mathbf{O}_t = \mathbb{E}(\mathbf{O}_{it}))$ indicate conditioning on sample averages of consumption and hours. The table presents the list of targeted earnings moments alongside their empirical and theoretical values from the preferred specification. Empirical moments are net of observables and measurement error. Block bootstrap standard errors for the empirical moments are in parentheses based on 1,000 bootstrap replications. The reported t-statistic is for the null hypothesis that *theoretical moment* − *empirical moment* = 0.

Table D.6 – Targeted Consumption Moments at Sample Average of Consumption and Hours

	data	model	t-stat. diff.		data	model	t-stat. diff.
$\mathbb{E}\big(\Delta w_{1t}\Delta c_{t^+}\vert\overline{\mathbf{o}}_t\big)$	0.000 (0.002)	0.001	0.759	$\mathbb{E}\big(\Delta w_{1t}(\Delta c_{t^+})^2\vert\overline{\mathbf{o}}_t\big)$	0.000 (0.001)	-0.002	-3.208
$\mathbb{E}\big(\Delta w_{1t^+}\Delta c_t\vert\overline{\mathbf{o}}_{t^-}\big)$	0.001 (0.002)	0.001	0.213	$\mathbb{E}\big(\Delta w_{1t^+}(\Delta c_t)^2\vert\overline{\mathbf{o}}_{t^-}\big)$	0.000 (0.001)	0.002	2.460
$\mathbb{E}\big(\Delta w_{2t}\Delta c_{t^+}\vert\overline{\mathbf{o}}_t\big)$	0.000 (0.002)	0.001	0.776	$\mathbb{E}\big(\Delta w_{2t}(\Delta c_{t^+})^2\vert\overline{\mathbf{o}}_t\big)$	0.000 (0.001)	-0.002	-3.722
$\mathbb{E}\big(\Delta w_{2t^+}\Delta c_t\vert\overline{\mathbf{o}}_{t^-}\big)$	0.002 (0.002)	0.001	-0.545	$\mathbb{E}\big(\Delta w_{2t^+}(\Delta c_t)^2\vert\overline{\mathbf{o}}_{t^-}\big)$	0.000 (0.001)	0.002	2.884
$\mathbb{E}\big(\Delta y_{1t}\Delta c_{t^+}\vert\overline{\mathbf{o}}_{t^-},\overline{\mathbf{o}}_t\big)$	-0.003 (0.002)	0.000	1.713	$\mathbb{E}\big(\Delta w_{1t}\Delta y_{1t^+}\Delta c_{t^+}\vert\overline{\mathbf{o}}_t\big)$	-0.002 (0.001)	0.000	1.475
$\mathbb{E}\big(\Delta y_{1t^+}\Delta c_t\vert\overline{\mathbf{o}}_{t^-},\overline{\mathbf{o}}_t\big)$	0.002 (0.002)	0.000	-1.064	$\mathbb{E}\big(\Delta w_{1t^+}\Delta y_{1t}\Delta c_t\vert\overline{\mathbf{o}}_{t^-}\big)$	0.000 (0.001)	0.000	0.011
$\mathbb{E}\big(\Delta y_{2t}\Delta c_{t^+}\vert\overline{\mathbf{o}}_{t^-},\overline{\mathbf{o}}_t\big)$	0.002 (0.002)	0.001	-0.496	$\mathbb{E}\big(\Delta w_{2t}\Delta y_{1t^+}\Delta c_{t^+}\vert\overline{\mathbf{o}}_t\big)$	0.001 (0.001)	0.000	-0.996
$\mathbb{E}\big(\Delta y_{2t^+}\Delta c_t\vert\overline{\mathbf{o}}_{t^-},\overline{\mathbf{o}}_t\big)$	0.001 (0.002)	0.001	0.014	$\mathbb{E}\big(\Delta w_{2t^+}\Delta y_{1t}\Delta c_t\vert\overline{\mathbf{o}}_{t^-}\big)$	-0.001 (0.001)	0.000	0.863
$\mathbb{E}\big(\Delta c_t\Delta c_{t^+}\vert\overline{\mathbf{o}}_{t^-},\overline{\mathbf{o}}_t\big)$	-0.008 (0.001)	-0.006	1.764	$\mathbb{E}\big(\Delta w_{1t}\Delta y_{2t^+}\Delta c_{t^+}\vert\overline{\mathbf{o}}_t\big)$	0.001 (0.001)	0.000	-1.485
$\mathbb{E}\big((\Delta w_{1t})^2\Delta c_{t^+}\vert\overline{\mathbf{o}}_t\big)$	0.000 (0.006)	-0.001	-0.028	$\mathbb{E}\big(\Delta w_{1t^+}\Delta y_{2t}\Delta c_t\vert\overline{\mathbf{o}}_{t^-}\big)$	0.002 (0.001)	0.000	-1.680
$\mathbb{E}\big((\Delta w_{1t^+})^2\Delta c_t\vert\overline{\mathbf{o}}_{t^-}\big)$	0.009 (0.004)	0.001	-1.928	$\mathbb{E}\big(\Delta w_{2t}\Delta y_{2t^+}\Delta c_{t^+}\vert\overline{\mathbf{o}}_t\big)$	0.001 (0.001)	0.001	-0.238
$\mathbb{E}\big((\Delta w_{2t})^2\Delta c_{t^+}\vert\overline{\mathbf{o}}_t\big)$	0.001 (0.002)	0.000	-0.911	$\mathbb{E}\big(\Delta w_{2t^+}\Delta y_{2t}\Delta c_t\vert\overline{\mathbf{o}}_{t^-}\big)$	-0.001 (0.001)	-0.001	0.165
$\mathbb{E}\big((\Delta w_{2t^+})^2\Delta c_t\vert\overline{\mathbf{o}}_{t^-}\big)$	0.000 (0.002)	0.000	0.247				

Notes: The notation is as follows: $t^- \equiv t-1$, $t^+ \equiv t+1$ and $\overline{\mathbf{o}}_{t^-} \equiv (\mathbf{O}_{t-1} = \mathbb{E}(\mathbf{O}_{it-1}))$, $\overline{\mathbf{o}}_t \equiv (\mathbf{O}_t = \mathbb{E}(\mathbf{O}_{it}))$ indicate conditioning on sample averages of consumption and hours. The table presents the list of targeted consumption moments alongside their empirical and theoretical values from the preferred specification. Empirical moments are net of observables and measurement error. Block bootstrap standard errors for the empirical moments are in parentheses based on 1,000 bootstrap replications. The reported t-statistic is for the null hypothesis that *theoretical moment* − *empirical moment* = 0.

E Additional Results and Robustness

Alternative 'preferred' specifications. Table E.1 presents alternative 'preferred' specifications, namely results from a number of restrictions that are alternative to the mild homogeneity assumption in the preferred specification. I start from column 7 of tables 4-5 and seek restrictions that improve efficiency of the parameters. Column 1 shuts down all heterogeneity in labor supply elasticities; column 2 shuts down joint heterogeneity in labor supply elasticities; column 3 posits $\eta_{c,w_2(i)} = \alpha_i \times \eta_{c,w_1(i)}$ with $\alpha_i = \alpha \ \forall i$ and estimates α together with all other parameters; column 4 is like column 3 but also equalizes the labor supply elasticities between spouses, i.e. $\eta_{h_1,w_1(i)} = \eta_{h_2,w_2(i)}$; column 5 imposes equal consumption-wage elasticities, i.e. $\eta_{c,w_1(i)} = \eta_{c,w_2(i)}$. The parameters across all columns are estimated at the sample average of consumption and hours. The results are similar to the preferred specification of column 8 in tables 4-5, although efficiency varies with the restrictions imposed. Interestingly, when I equalize the labor supply elasticities between spouses, efficiency of the elasticities improves dramatically (as expected) but the pattern of heterogeneity does not change: these elasticities seem to not exhibit economically meaningful heterogeneity across households.

Extreme observations. Table E.2 presents parameter estimates in the preferred specification after removing extreme observations of wages, earnings, consumption. Extreme observations may matter for the third and other moments so it is meaningful to check the robustness of the results to removing those. Column 1 shows the baseline results from tables 4-5. Column 2 trims the bottom and top 0.5% of the distribution of wages. This drops 3.2% of the baseline sample of table D.1 because the condition applies separately to male and female wages and drops additionally households that now appear in the sample only once. Column 3 trims the bottom and top 2% of the distribution of wages (drops 11.8% of the baseline sample) while column 4 trims the bottom and top 0.5% of the distributions of wages, earnings and consumption (drops 5.1% of the baseline sample). The main conclusions remain unchanged. Consumption preference heterogeneity remains substantial and by an order of magnitude greater than heterogeneity in the labor supply elasticities. The largest change from the baseline appears in column 3 where the magnitudes of $\text{Var}(\eta_{c,w_j(i)})$ and $\mathbb{E}(\eta_{h_2,w_2(i)})$ increase considerably.

Additional first-stage controls: chores and children's age. Tables E.3-E.4 replicate the main results, this time controlling for the age of the youngest child and each spouse's past levels of chores in the first stage regressions. Blundell et al. (2018) show that the household response to wage shocks depends on the substitutability of parental time in home production, while Boerma and Karabarbounis (2019) show that heterogeneity in home production may be mistakenly classified as heterogeneity in preferences. The data do not allow me to control for childcare but I can control for the age of the youngest child, as well as for time spent on chores. Accounting for these variables enables me to check the extent to which preference

heterogeneity masks heterogeneity in home production, assuming that the latter is either due to differences in children's age or captured by heterogeneity in chores. Unsurprisingly, the results are unchanged. The baseline results already control for parental age *and* the number of children in the household, both of which have large predictive power for the age of the youngest child. The baseline also controls for a long list of observables, thus apparently exhaustingly capturing heterogeneity in home production.

Diagonally weighted GMM. While equally weighted GMM weighs all target moments equally and thus favors numerically large moments, diagonally weighted GMM favors moments that are more precise. It uses the diagonal of the inverse covariance matrix of moments as weighting matrix, thus emphasizing moments whose variance in the data is lowest. Unless the model is misspecified, the two weighting schemes should deliver unbiased estimates of the parameters. In practice, however, possible misspecification or small-sample issues may produce materially different results so it is important to check for this possibility.

Tables E.5-E.6 replicate the main set of results using diagonally weighted GMM.[3] Five observations emerge. First, in replicating BPS in column 2, the average female labor supply elasticity turns negative but insignificant. A negative value contradicts most evidence in the literature (Keane, 2011), suggesting some form of possible misspecification in the moments used by BPS. Second, in targeting moments of transitory shocks in column 3, this elasticity turns again positive and all parameters become remarkably similar to the baseline. Third, adding third moments in column 4 reduces the size of the elasticities exactly as in the baseline; the reduction is in the magnitude of 25%, versus 35% in the baseline, reflecting the *relative* imprecision of third moments. Fourth, introducing marginal preference heterogeneity in column 5 produces conceptually similar results to the baseline: consumption elasticities exhibit substantial heterogeneity (although slightly less pronounced than in the baseline), while labor supply elasticities do not. Fifth, introducing joint heterogeneity (column 6), shutting down the labor supply cross-elasticities (column 7), and imposing a mild homogeneity assumption among the η_{c,w_j}'s results in: average labor supply elasticities drop further, consumption preference heterogeneity remains substantial and significant at the 10% level (column 8), and labor supply heterogeneity rises to become comparable, albeit statistically insignificant, to consumption heterogeneity. This last result is not observed in the baseline.

While consumption preference heterogeneity is consistently large across all specifications, heterogeneity in labor supply preferences fluctuates between zero and amounts comparable to consumption heterogeneity. Labor supply heterogeneity is never statistically significant while consumption heterogeneity is; however, this may be an artifact of the mild homogeneity assumption I impose on the η_{c,w_j}'s but not on the labor supply elasticities. Could a similar restriction on the labor supply elasticities result in statistically significant labor supply hetero-

[3]The set of target moments appears in appendix tables D.4-D.6. I estimate the covariance matrix of moments via block bootstrap based on 1,000 replications.

geneity comparable to consumption heterogeneity? The answer is a firm no. Table E.7 presents results from a number of restrictions alternative to those in the preferred specification, mimicking table E.1 for the baseline results. Columns 4 therein attempts to improve efficiency of labor supply preferences by imposing $\eta_{h_1,w_1(i)} = a_i \times \eta_{h_2,w_2(i)}$ for $a_i = 1, \forall i$. As soon as this is done, $\text{Var}(\eta_{h_1,w_1(i)})$ and $\text{Var}(\eta_{h_2,w_2(i)})$ both drop to a statistically significant 0.001 while consumption preference heterogeneity remains at least an order of magnitude larger.[4] I therefore conclude that the results from diagonally weighted GMM are qualitatively and in most cases quantitatively similar to the baseline. There is substantial heterogeneity in consumption preferences but not in preferences over labor supply; the average labor supply elasticities drop as soon as the model targets third moments of consumption and earnings in the data. At face value, consumption preference heterogeneity in the preferred specification (column 8 of tables E.5-E.6) implies that one st.d. of η_{c,w_1} about its mean falls approximately in the range $(-0.21; 0.17)$ while one st.d. of η_{c,w_2} in $(-0.39; 0.33)$.

Consumption measurement error. The variance of consumption measurement error is identified in certain specifications only after imposing additional restrictions (section 3.2). To avoid building in inconsistencies across specifications (namely impose restrictions in some specifications, e.g. when allowing for preference heterogeneity, but not others, e.g. in replicating BPS), I opt to fix this at 15% of the variance of consumption growth. While this number is higher than error in wages (13%) or earnings (4%) in Bound et al. (1994), it is ultimately arbitrary so I check here how the results change with a different amount of consumption error.

Figure E.1 plots the variances of consumption and labor supply elasticities against the variance of consumption error. Consumption preference heterogeneity remains substantial for amounts of consumption error up to about 40-45% of the variance of consumption growth; heterogeneity in labor supply elasticities remains always negligible. Most other parameters, including $\mathbb{E}(\eta_{c,w_1(i)})$ and $\mathbb{E}(\eta_{c,w_2(i)})$, do not change materially from the baseline. An exception is $\eta_{c,p}$ and figure E.2 illustrates this.

Naturally, a bigger amount of consumption error reduces the scope of preferences in the model especially as the amounts of earnings & wage error do not move in parallel. A larger consumption error reduces the 'true' variance of consumption; the model then gradually attributes a larger share of the consumption variation to wage variation, which is constant throughout the counterfactual of figure E.1. To see this, consider expression (9) for consumption inequality and focus for now on the first part of it: $\text{Var}(\Delta c_{it}) \approx \sum_{j=1}^{2} \mathbb{E}(\eta^2_{c,w_j(i,t-1)}) \times \left(\sigma^2_{u_j(t)} + \sigma^2_{u_j(t-1)}\right)$. As the left hand side become smaller with a larger amount of consumption error but variation in wages (i.e. $\sigma^2_{u_j}$) remains unchanged, the model pushes consumption preference heterogeneity (i.e. $\mathbb{E}(\eta^2_{c,w_j(i)})$) gradually towards zero. This is, however, not true if the amount of wage error

[4] Neither $\text{Var}(\eta_{c,w_1(i)})$ nor $\text{Var}(\eta_{c,w_2(i)})$ is statistically significant in column 4 of table E.1 as the proportionality α_i of the underlying elasticities is not fixed in this specification. As soon as I fix α_i, consumption preference heterogeneity becomes statistically significant exactly as in the preferred and other specifications.

increases proportionally to the amount of consumption error, thus reducing $\sigma^2_{u_j}$ in parallel to $\text{Var}(\Delta c_{it})$. In such case, consumption preference heterogeneity retains its relative importance; moreover, for most values of consumption, wage, and earnings error, heterogeneity in labor supply preferences remains negligible (related figures not shown for brevity). For completeness, table E.8 presents the decomposition of consumption inequality and figure E.5 visualizes the distributions of pass-through rates of shocks for different amounts of consumption error.

Progressive joint taxation. With progressive joint taxation in the family, the dynamics of consumption and hours are different from baseline expressions (5)-(7). Each equation is augmented by an additional term that is a function of *all* shocks and reflects the disincentives joint taxation induces on family labor supply. Without taxation, a transitory shock shifts own labor supply reflecting the substitution between hours and leisure, i.e. the Frisch elasticity of labor supply. With joint taxation, the labor supply response is mitigated because part of the shock is taxed or compensated. This depends *nonlinearly* on the tax system progressivity, the partner's hours response to the tax (earnings are taxed jointly so the tax disincentivizes *family* labor supply), and the relative shares of spouses' earnings. Consequently, the response of labor supply (or of consumption) to the transitory shock no longer picks up a single Frisch elasticity but, instead, a plethora of elasticities and tax parameters. BPS derive analytical expressions under joint taxation and preference homogeneity, and I refer to them for the details. The extension of their derivations to heterogeneous preferences is straightforward.

With joint taxation, the intertemporal moments of consumption, earnings, and wages that have so far identified preference heterogeneity are no longer *linear* functions of moments of the elasticities. The reason is that the response to transitory shocks, which the said moments reflect, is a nonlinear function of elasticities and tax parameters as explained above. For example, the transmission parameter of Δu_{1it} into Δc_{it} ($\eta_{c,w_1(i,t-1)}$ in the baseline) now becomes $(\eta_{c,w_1(i,t-1)} - \nu_{it} s_{1it} \sum_j \eta_{c,w_j(i,t-1)})/(1 + \nu_{it} s_{1it} \sum_j \eta_{h_1,w_j(i,t-1)} + \nu_{it} s_{2it} \sum_j \eta_{h_2,w_j(i,t-1)})$ where ν_{it} determines the progressivity of the tax system. The denominator reflects the labor supply disincentives of joint taxation while the extra term in the numerator reflects the feedback on consumption due to non-separability with labor supply. Consequently, identification of heterogeneity can no longer be shown analytically, while estimation requires parametric restrictions on the distribution of preferences. Given that I do not want to a priori restrict preferences to a specific distribution, my baseline model so far has been one without joint taxation.

To understand the implications of joint taxation for preference heterogeneity, I draw preferences for 10 million households from the multivariate normal distribution $\mathcal{N}(\boldsymbol{\mu}, \boldsymbol{\Sigma})$ and I construct all second and third moments that I fit in the baseline. I fix $\nu_{it} = 0.185$ as in Heathcote et al. (2014) and I draw human wealth shares from the empirical distribution of $\mathbf{s}_{it}$; the proportionality parameter χ_{it} drops out because of the nature of the approximation. I match these moments to their empirical counterparts keeping all estimation details as in the baseline; now $\boldsymbol{\mu}$ and $\boldsymbol{\Sigma}$ are the parameters of interest. Results from the preferred specification

(column 1, table E.9) show that joint taxation makes the *average* labor supply elasticities a bit larger, exactly as in BPS, but does not change the baseline pattern of preference heterogeneity. Results for the unrestricted model specifications produce similar conclusions.

Three remarks are due here. First, the results keep ν_{it} fixed; a more detailed treatment should have this vary across households. However, any such variation is justified on the basis of varying demographics and earnings/hours levels, both of which I control for empirically. Second, any neglected heterogeneity in ν_{it} would also be picked up by $\text{Var}(\eta_{h_j,w_j(i)})$ which serves as an upper bound to $\text{Var}(\nu_{it})$; see Theloudis (2017). As $\text{Var}(\eta_{h_j,w_j(i)})$ is close to zero, conditional heterogeneity in ν is practically small. Third, joint taxation may produce different results from the baseline *also* due to the normality assumption. I reestimate the baseline model (i.e. without taxation) imposing joint normality and I find that the results are not very different from the baseline.[5] Joint normality of preferences seems not too strong an assumption *ex post*.

Liquidity constraints and adjustment costs of work. To understand the implications of consumption equation (10), it helps to focus on the transmission of women's transitory shock u_2 and abstract from male wages as if $q_{2it-1} = 1$.

- The average loading factor of u_2 into consumption, captured by $\mathbb{E}(\Delta w_{2it}\Delta c_{it+1}|\mathbf{O}_t)$, identifies $\mathbb{E}(\eta_{c,w_2(i,t)})$ in the baseline but now reflects the degree of liquidity tightness among constrained households. Pooling both types of households together, the average transmission parameter identifies $\varrho_t\mathbb{E}(\eta_{c,w_2(i,t)}) + (1-\varrho_t)\mathbb{E}(\theta_{2it})$, thus biases $\mathbb{E}(\eta_{c,w_2(i,t)})$ upwards if consumption and hours are Frisch substitutes, as in BPS, and the measure of tightness positive (in principle $\theta_j \in [0,1]$ when labor supply is fixed).

- The second moment of this loading factor, captured by $\mathbb{E}(\Delta c_{it}\Delta c_{it+1}|\mathbf{O}_{t-1},\mathbf{O}_t)$, identifies $\mathbb{E}(\eta^2_{c,w_2(i,t)})$ in the baseline but $\mathbb{E}(\theta^2_{2it})$ among the constrained. Pooling the two together, and assuming households do not switch status from $t-1$ to $t+1$, this moment identifies $\varrho_t\mathbb{E}(\eta^2_{c,w_2(i,t)})+(1-\varrho_t)\mathbb{E}(\theta^2_{2it})$ and picks up heterogeneity in η_{c,w_2} and variability in liquidity tightness. This biases $\text{Var}(\eta_{c,w_2(i,t)})$ upwards overstating true preference heterogeneity.[6]

Similar expressions can be obtained for all other moments and transmission parameters (though not all offer testable conditions). For example, $\mathbb{E}(\Delta w_{2it}\Delta y_{2it+1}|\mathbf{O}_t)$identifies $\varrho_t\mathbb{E}(\eta_{h_2,w_2(i,t)})$ and understates the true labor supply elasticity. This last point is an implication of fixed labor supply and does not hold if labor supply is flexible.

These implications are testable among *unconstrained* households. Assuming household membership in each group is fixed over time: (1.) average consumption elasticities are smaller (more negative) than in the pool of constrained and unconstrained; (2.) the variance of the consumption elasticities is lower; (3.) the average labor supply elasticities are larger. These

[5] These results, and the results with taxation for all model specifications, are available upon request.

[6] This holds if heterogeneity in θ_j is larger than preference heterogeneity.

implications should hold also if household membership changes over the span of the sample. The following discussion is only an approximation to true behavior (the model does not allow me to formally characterize the consumption dynamics when households switch between constrained and unconstrained) but it highlights the main issues at play.

Suppose a household is unconstrained at $t-1$, constrained at t (which matters for how c_t changes to c_{t+1} once shocks hit at the start of $t+1$), but then again unconstrained at $t+1$. Moments involving one outcome (earnings, consumption) only, such as $\mathbb{E}(\Delta w_{2it}\Delta c_{it+1}|\mathbf{O}_t)$, are unaffected. All that matters for them is the snapshot classification as constrained/unconstrained at t as this is what determines the change Δc_{it+1}. So if ϱ_t households are unconstrained at t and $1-\varrho_t$ constrained, then $\mathbb{E}(\Delta w_{2it}\Delta c_{it+1}|\mathbf{O}_t)$ still identifies $\varrho_t\mathbb{E}(\eta_{c,w_2(i,t)}) + (1-\varrho_t)\mathbb{E}(\theta_{2it})$. Moments involving two outcomes (or the same outcome twice) are affected. In the case of $\mathbb{E}(\Delta c_{it}\Delta c_{it+1}|\mathbf{O}_{t-1},\mathbf{O}_t)$, Δc_{it} is given by (5) (the hypothetical household is unconstrained at $t-1$) and Δc_{it+1} by (10) (they are constrained at t). The covariance identifies the product $\mathbb{E}(\eta_{c,w_2(i,t-1)}\theta_{2it})$ among those who switch. This is negative (assuming consumption and hours are Frisch substitutes as in BPS), mitigating the upward bias from those continuously constrained. The mitigation depends on the fraction of households who switch at t.

I take wealthy households as the empirical counterpart of the theoretically *unconstrained*. Table D.1 presents descriptive statistics for four subsamples of gradually more stringently defined wealthy households (see also table 2). Column W1 describes households whose annual wealth A_t is at least as much as average annual consumption $\overline{C}_t$ in the baseline sample. These are households who can fund at least a year's consumption without working. Column W2 is for households whose annual wealth is at least twice as much as average annual consumption. Column W3 is like W1 with the additional condition that households hold real debt lower than \$2K in annual terms. Finally, column W4 is like W3 but wealth now excludes home equity (house value net of mortgages), therefore better proxies for liquid assets. Nearly 80% of the baseline sample is excluded (which clearly has implications for statistical power).

Table E.9 (columns W1-W4) estimates the preferred specification on the wealthy. Three observations emerge. First, the average consumption elasticities remain unchanged upon departure from the baseline, thus contradicting the first testable implication. Second, the variances of the consumption elasticities still reveal substantial consumption preference heterogeneity across households. These parameters are mostly smaller than the baseline so this pattern seems consistent with the second testable implication: consumption preference heterogeneity is partly eaten away as one moves towards households who are likelier to be less constrained. This is, however, expected to a certain extent as the most stringent samples are also more homogeneous. Third, most average labor supply elasticities get smaller the more stringent wealth is, thus invalidating the third testable implication. However, these households are richer so shocks likely induce strong income effects on their labor supply. Overall, the evidence does not provide clear support for liquidity constraints or adjustment costs of work.

Table E.1 – Robustness: Alternative Restrictions for Preferred Specification

	2^{nd} & 3^{rd} moments; labor supply cross-elasticities set to 0				
	(1)	(2)	(3)	(4)	(5)
restrictions:	fix α, no variation in η_{h_j,w_j}	fix α, no joint variation in η_{h_j,w_j}	estimate α	estimate α & $\eta_{h_1,w_1} = \eta_{h_2,w_2}$	$\eta_{c,w_1} = \eta_{c,w_2}$
$\mathbb{E}(\eta_{c,w_1(i)})$	-0.023	-0.023	-0.033	-0.055	-0.043
	(0.030)	(0.030)	(0.040)	(0.072)	(0.042)
$\mathbb{E}(\eta_{c,w_2(i)})$	-0.036	-0.036	-0.053	-0.080	-0.043
	(0.048)	(0.047)	(0.047)	(0.057)	(0.042)
$\mathbb{E}(\eta_{h_1,w_1(i)})$	0.281	0.281	0.276	0.275	0.274
	(0.123)	(0.122)	(0.119)	(0.106)	(0.121)
$\mathbb{E}(\eta_{h_2,w_2(i)})$	0.248	0.248	0.247	0.275	0.247
	(0.195)	(0.195)	(0.196)	(0.106)	(0.196)
$\text{Var}(\eta_{c,w_1(i)})^{\#}$	0.088	0.088	0.091	0.094	0.129
	[0.016]	[0.016]	[0.091]	[0.105]	[0.011]
$\text{Var}(\eta_{c,w_2(i)})^{\#}$	0.225	0.226	0.233	0.201	0.129
	[0.016]	[0.016]	[0.073]	[0.097]	[0.011]
$\text{Var}(\eta_{h_1,w_1(i)})^{\#}$	0	0.002	0.018	0.001	0.022
		[0.149]	[0.212]	[0.092]	[0.201]
$\text{Var}(\eta_{h_2,w_2(i)})^{\#}$	0	0.001	0.003	0.001	0.003
		[0.060]	[0.156]	[0.092]	[0.156]
$\text{Cov}(\eta_{c,w_1(i)}, \eta_{c,w_2(i)})$	0.141	0.141	0.146	0.138	0.129
	(0.050)	(0.050)	(0.056)	(0.077)	(0.043)
$\text{Cov}(\eta_{c,w_1(i)}, \eta_{h_1,w_1(i)})$	0	0	0.036	0.065	0.049
			(0.028)	(0.087)	(0.028)
$\text{Cov}(\eta_{c,w_1(i)}, \eta_{h_2,w_2(i)})$	0	0	-0.008	0.065	-0.010
			(0.019)	(0.087)	(0.020)
$\text{Cov}(\eta_{c,w_2(i)}, \eta_{h_1,w_1(i)})$	0	0	0.058	0.094	0.049
			(0.040)	(0.066)	(0.028)
$\text{Cov}(\eta_{c,w_2(i)}, \eta_{h_2,w_2(i)})$	0	0	-0.013	0.094	-0.010
			(0.023)	(0.066)	(0.020)
$\text{Cov}(\eta_{h_1,w_1(i)}, \eta_{h_2,w_2(i)})$	0	0	-0.003	0.001	-0.004
			(0.019)	(0.001)	(0.018)
Obs. [households $\times\Delta_t$]	6071	6071	6071	6071	6071

Notes: The table presents GMM estimates of first and second moments of wage elasticities under a number of alternative restrictions on preferences. The restrictions serve the purpose to improve efficiency of estimates in column 7 of tables 4-5 and can be seen as alternatives to the preferred specification in column 8 therein. All columns posit $\eta_{c,w_2(i)} = \alpha_i \times \eta_{c,w_1(i)}$. Column 1 fixes $\alpha_i = 1.6\ \forall i$ and shuts down heterogeneity in labor supply elasticities; column 2 fixes $\alpha_i = 1.6\ \forall i$ and shuts down joint heterogeneity in labor supply elasticities; column 3 estimates $\alpha_i = \alpha\ \forall i$ together with all other parameters; column 4 is like column 3 but also restricts the own labor supply elasticities to equal between spouses, i.e. $\eta_{h_1,w_1(i)} = \eta_{h_2,w_2(i)}$; column 5 imposes equal consumption-wage elasticities, i.e. $\alpha_i = 1\ \forall i$. Across all columns, the labor supply cross-elasticities are set to zero. All moments are estimated at the sample average of consumption and hours, i.e. $\mathbf{O}_t = \mathbb{E}(\mathbf{O}_{it})$. $^{\#}p$-value in square brackets for the one-sided test that the respective parameter equals zero; standard errors appear in parentheses for all other parameters.

Table E.2 – Robustness: Remove Extreme Observations

	preferred specification			
	(1)	(2)	(3)	(4)
	baseline	distribution of wages central 99%	distribution of wages central 96%	distribution of W_j, Y_j, C central 99%
$\mathbb{E}(\eta_{c,w_1(i)})$	-0.033	-0.006	-0.012	-0.011
	(0.032)	(0.021)	(0.019)	(0.020)
$\mathbb{E}(\eta_{c,w_2(i)})$	-0.053	-0.010	-0.019	-0.017
	(0.052)	(0.033)	(0.030)	(0.033)
$\mathbb{E}(\eta_{h_1,w_1(i)})$	0.276	0.219	0.266	0.200
	(0.120)	(0.174)	(0.171)	(0.151)
$\mathbb{E}(\eta_{h_2,w_2(i)})$	0.247	0.194	0.542	0.271
	(0.196)	(0.109)	(0.101)	(0.109)
$\text{Var}(\eta_{c,w_1(i)})^{\#}$	0.091	0.082	0.151	0.080
	[0.014]	[0.000]	[0.000]	[0.000]
$\text{Var}(\eta_{c,w_2(i)})^{\#}$	0.233	0.209	0.387	0.206
	[0.014]	[0.000]	[0.000]	[0.000]
$\text{Var}(\eta_{h_1,w_1(i)})^{\#}$	0.018	0.014	0.008	0.018
	[0.209]	[0.461]	[0.491]	[0.405]
$\text{Var}(\eta_{h_2,w_2(i)})^{\#}$	0.003	0.003	0.005	0.014
	[0.152]	[0.426]	[0.378]	[0.443]
$\text{Cov}(\eta_{c,w_1(i)}, \eta_{c,w_2(i)})$	0.146	0.131	0.242	0.129
	(0.050)	(0.016)	(0.016)	(0.015)
$\text{Cov}(\eta_{c,w_1(i)}, \eta_{h_1,w_1(i)})$	0.036	0.009	0.006	0.019
	(0.024)	(0.024)	(0.026)	(0.019)
$\text{Cov}(\eta_{c,w_1(i)}, \eta_{h_2,w_2(i)})$	-0.008	0.000	-0.009	-0.018
	(0.017)	(0.018)	(0.013)	(0.020)
$\text{Cov}(\eta_{c,w_2(i)}, \eta_{h_1,w_1(i)})$	0.058	0.014	0.010	0.030
	(0.038)	(0.039)	(0.041)	(0.030)
$\text{Cov}(\eta_{c,w_2(i)}, \eta_{h_2,w_2(i)})$	-0.013	0.000	-0.015	-0.028
	(0.027)	(0.028)	(0.021)	(0.033)
$\text{Cov}(\eta_{h_1,w_1(i)}, \eta_{h_2,w_2(i)})$	-0.003	-0.002	-0.001	-0.012
	(0.019)	(0.110)	(0.078)	(0.112)
Obs. [households $\times\Delta_t$]	6071	5876	5357	5764

Notes: The table presents GMM estimates of first and second moments of wage elasticities in the preferred specification. Column 1 shows the baseline results of tables 4-5. Column 2 removes extreme observations of male and female wages trimming the bottom 0.5% and top 0.5% of the respective distributions. Column 3 extends this by trimming the bottom 2% and top 2% of the wage distributions. Column 4 removes extreme observations of wages, earnings, and consumption trimming the bottom 0.5% and top 0.5% of the respective distributions. All moments are estimated at the sample average of consumption and hours, i.e. $\mathbf{O}_t = \mathbb{E}(\mathbf{O}_{it})$. $^{\#}p$-value in square brackets for the one-sided test that the respective parameter equals zero; standard errors appear in parentheses for all other parameters.

Table E.3 – Robustness: Estimates of Preferences net of Age of Youngest Child & Chores, Means and Variances

specification/moments:	(1)* BPS	(2) BPS-repl.	(3) 2^{nd}	(4) 2^{nd} & 3^{rd}	(5) 2^{nd} & 3^{rd}	(6) 2^{nd} & 3^{rd}	(7) 2^{nd} & 3^{rd}	(8) 2^{nd} & 3^{rd}
heterogeneity:	no	no	no	no	marginal	joint	joint-restr.	preferred
change from column on the left:		2011 data, past levels	only transitory	third moments	marg. het-erogeneity	joint het-erogeneity	$\eta_{h_j,w_{j'}} = 0$	mild homo-geneity
$\mathbb{E}(\eta_{c,w_1(i)})$		-0.236	0.034	-0.018	-0.018	-0.040	-0.042	-0.033
		(0.058)	(0.064)	(0.060)	(0.055)	(0.062)	(0.063)	(0.033)
$\mathbb{E}(\eta_{c,w_2(i)})$		0.051	-0.117	-0.055	-0.045	-0.030	-0.030	-0.052
		(0.050)	(0.113)	(0.085)	(0.071)	(0.075)	(0.075)	(0.052)
$\mathbb{E}(\eta_{h_1,w_1(i)})$		0.591	0.419	0.281	0.281	0.274	0.271	0.273
		(0.176)	(0.152)	(0.128)	(0.127)	(0.129)	(0.122)	(0.123)
$\mathbb{E}(\eta_{h_1,w_2(i)})$		0.087	-0.056	-0.015	-0.015	-0.014		
		(0.054)	(0.061)	(0.048)	(0.047)	(0.047)		
$\mathbb{E}(\eta_{h_2,w_1(i)})$		0.180	-0.117	-0.031	-0.031	-0.030		
		(0.112)	(0.125)	(0.100)	(0.096)	(0.100)		
$\mathbb{E}(\eta_{h_2,w_2(i)})$		0.753	0.446	0.270	0.269	0.268	0.257	0.258
		(0.149)	(0.294)	(0.215)	(0.222)	(0.226)	(0.196)	(0.194)
$\mathrm{Var}(\eta_{c,w_1(i)})^{\#}$					0.074	0.093	0.086	0.091
					[0.155]	[0.107]	[0.120]	[0.012]
$\mathrm{Var}(\eta_{c,w_2(i)})^{\#}$					0.283	0.269	0.255	0.233
					[0.127]	[0.119]	[0.114]	[0.012]
$\mathrm{Var}(\eta_{h_1,w_1(i)})^{\#}$					0.002	0.022	0.024	0.020
					[0.129]	[0.215]	[0.221]	[0.213]
$\mathrm{Var}(\eta_{h_1,w_2(i)})^{\#}$					0.000	0.000		
					[0.190]	[0.243]		
$\mathrm{Var}(\eta_{h_2,w_1(i)})^{\#}$					0.002	0.003		
					[0.201]	[0.244]		
$\mathrm{Var}(\eta_{h_2,w_2(i)})^{\#}$					0.001	0.004	0.004	0.003
					[0.056]	[0.164]	[0.180]	[0.165]

Notes: See notes for tables 4-5 in the paper. Observations: 6057 (households $\times\Delta_t$); these are slightly fewer than the baseline because of some missing data on chores. *BPS do not report similar results. $^{\#}p$-value in square brackets for the one-sided test that the respective parameter equals zero. All moments are estimated at the sample average of consumption and hours, i.e. $\mathbf{O}_t = \mathbb{E}(\mathbf{O}_{it})$.

Table E.4 – Robustness *(continues from previous table)*: Estimates of Preferences net of Age of Youngest Child & Chores, Covariances

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\text{Cov}(\eta_{c,w_1(i)}, \eta_{c,w_2(i)})$						0.001	0.127	0.146
						(0.010)	(0.129)	(0.048)
$\text{Cov}(\eta_{c,w_1(i)}, \eta_{h_1,w_1(i)})$						0.041	0.042	0.039
						(0.035)	(0.036)	(0.024)
$\text{Cov}(\eta_{c,w_1(i)}, \eta_{h_1,w_2(i)})$						-0.001		
						(0.005)		
$\text{Cov}(\eta_{c,w_1(i)}, \eta_{h_2,w_1(i)})$						-0.002		
						(0.009)		
$\text{Cov}(\eta_{c,w_1(i)}, \eta_{h_2,w_2(i)})$						-0.002	-0.010	-0.009
						(0.013)	(0.022)	(0.018)
$\text{Cov}(\eta_{c,w_2(i)}, \eta_{h_1,w_1(i)})$						0.017	0.061	0.063
						(0.026)	(0.050)	(0.039)
$\text{Cov}(\eta_{c,w_2(i)}, \eta_{h_1,w_2(i)})$						0.001		
						(0.005)		
$\text{Cov}(\eta_{c,w_2(i)}, \eta_{h_2,w_1(i)})$						0.003		
						(0.011)		
$\text{Cov}(\eta_{c,w_2(i)}, \eta_{h_2,w_2(i)})$						-0.021	-0.021	-0.014
						(0.029)	(0.035)	(0.028)
$\text{Cov}(\eta_{h_1,w_1(i)}, \eta_{h_1,w_2(i)})$						0.000		
						(0.003)		
$\text{Cov}(\eta_{h_1,w_1(i)}, \eta_{h_2,w_1(i)})$						0.000		
						(0.007)		
$\text{Cov}(\eta_{h_1,w_1(i)}, \eta_{h_2,w_2(i)})$						-0.003	-0.005	-0.004
						(0.019)	(0.030)	(0.023)
$\text{Cov}(\eta_{h_1,w_2(i)}, \eta_{h_2,w_1(i)})$					0.000	0.000		
					(0.002)	(0.001)		
$\text{Cov}(\eta_{h_1,w_2(i)}, \eta_{h_2,w_2(i)})$						0.000		
						(0.001)		
$\text{Cov}(\eta_{h_2,w_1(i)}, \eta_{h_2,w_2(i)})$						0.000		
						(0.003)		

Notes: See notes for tables 4-5 in the paper. Observations: 6057 (households $\times\Delta_t$); these are slightly fewer than the baseline because of some missing data on chores. All moments are estimated at the sample average of consumption and hours, i.e. $\mathbf{O}_t = \mathbb{E}(\mathbf{O}_{it})$.

Table E.5 – Estimates of Preferences: Means and Variances, Diagonally Weighted GMM

specification/moments:	(1)* BPS	(2) BPS-repl.	(3) 2^{nd}	(4) 2^{nd} & 3^{rd}	(5) 2^{nd} & 3^{rd}	(6) 2^{nd} & 3^{rd}	(7) 2^{nd} & 3^{rd}	(8) 2^{nd} & 3^{rd}
heterogeneity:	no	no	no	no	marginal	joint	joint-restr.	preferred
change from column on the left:		2011 data, past levels	only transitory	third moments	marg. het-erogeneity	joint het-erogeneity	$\eta_{h_j,w_{j'}} = 0$	mild homo-geneity
$\mathbb{E}(\eta_{c,w_1(i)})$		-0.402	0.047	0.018	0.013	-0.017	-0.027	-0.017
		(0.103)	(0.115)	(0.049)	(0.038)	(0.051)	(0.048)	(0.026)
$\mathbb{E}(\eta_{c,w_2(i)})$		-0.198	-0.178	-0.081	-0.059	-0.023	-0.011	-0.032
		(0.078)	(0.309)	(0.088)	(0.058)	(0.066)	(0.064)	(0.049)
$\mathbb{E}(\eta_{h_1,w_1(i)})$		0.273	0.401	0.324	0.323	0.307	0.260	0.287
		(0.107)	(0.139)	(0.104)	(0.112)	(0.109)	(0.110)	(0.109)
$\mathbb{E}(\eta_{h_1,w_2(i)})$		-0.054	-0.048	-0.037	-0.037	-0.033		
		(0.037)	(0.058)	(0.040)	(0.040)	(0.041)		
$\mathbb{E}(\eta_{h_2,w_1(i)})$		-0.113	-0.100	-0.077	-0.077	-0.068		
		(0.077)	(0.123)	(0.084)	(0.084)	(0.086)		
$\mathbb{E}(\eta_{h_2,w_2(i)})$		-0.262	0.437	0.298	0.301	0.286	0.213	0.210
		(0.213)	(0.282)	(0.208)	(0.217)	(0.215)	(0.177)	(0.178)
$\mathrm{Var}(\eta_{c,w_1(i)})^{\#}$					0.061	0.057	0.038	0.036
					[0.179]	[0.182]	[0.250]	[0.086]
$\mathrm{Var}(\eta_{c,w_2(i)})^{\#}$					0.115	0.127	0.137	0.130
					[0.237]	[0.221]	[0.221]	[0.086]
$\mathrm{Var}(\eta_{h_1,w_1(i)})^{\#}$					0.001	0.057	0.159	0.068
					[0.251]	[0.286]	[0.205]	[0.289]
$\mathrm{Var}(\eta_{h_1,w_2(i)})^{\#}$					0.000	0.002		
					[0.095]	[0.270]		
$\mathrm{Var}(\eta_{h_2,w_1(i)})^{\#}$					0.003	0.013		
					[0.143]	[0.258]		
$\mathrm{Var}(\eta_{h_2,w_2(i)})^{\#}$					0.000	0.037	0.064	0.037
					[0.074]	[0.228]	[0.243]	[0.263]

Notes: See notes for tables 4-5 in the paper. Observations: 6071 (households $\times\Delta_t$). *BPS do not report results from diagonally weighted GMM. $^{\#}p$-value in square brackets for the one-sided test that the respective parameter equals zero.

Table E.6 – Estimates of Preferences *(continues from previous table)*: Covariances, Diagonally Weighted GMM

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\text{Cov}(\eta_{c,w_1(i)}, \eta_{c,w_2(i)})$						0.004	0.052	0.068
						(0.017)	(0.093)	(0.042)
$\text{Cov}(\eta_{c,w_1(i)}, \eta_{h_1,w_1(i)})$						0.034	0.032	0.039
						(0.040)	(0.046)	(0.030)
$\text{Cov}(\eta_{c,w_1(i)}, \eta_{h_1,w_2(i)})$						0.002		
						(0.007)		
$\text{Cov}(\eta_{c,w_1(i)}, \eta_{h_2,w_1(i)})$						0.005		
						(0.015)		
$\text{Cov}(\eta_{c,w_1(i)}, \eta_{h_2,w_2(i)})$						-0.002	-0.020	-0.033
						(0.024)	(0.048)	(0.027)
$\text{Cov}(\eta_{c,w_2(i)}, \eta_{h_1,w_1(i)})$						0.070	0.136	0.074
						(0.091)	(0.091)	(0.057)
$\text{Cov}(\eta_{c,w_2(i)}, \eta_{h_1,w_2(i)})$						-0.014		
						(0.012)		
$\text{Cov}(\eta_{c,w_2(i)}, \eta_{h_2,w_1(i)})$						-0.029		
						(0.026)		
$\text{Cov}(\eta_{c,w_2(i)}, \eta_{h_2,w_2(i)})$						-0.068	-0.086	-0.062
						(0.063)	(0.063)	(0.052)
$\text{Cov}(\eta_{h_1,w_1(i)}, \eta_{h_1,w_2(i)})$						-0.006		
						(0.018)		
$\text{Cov}(\eta_{h_1,w_1(i)}, \eta_{h_2,w_1(i)})$						-0.013		
						(0.037)		
$\text{Cov}(\eta_{h_1,w_1(i)}, \eta_{h_2,w_2(i)})$						-0.038	-0.100	-0.048
						(0.130)	(0.166)	(0.155)
$\text{Cov}(\eta_{h_1,w_2(i)}, \eta_{h_2,w_1(i)})$					0.000	0.003		
					(0.000)	(0.011)		
$\text{Cov}(\eta_{h_1,w_2(i)}, \eta_{h_2,w_2(i)})$						0.007		
						(0.012)		
$\text{Cov}(\eta_{h_2,w_1(i)}, \eta_{h_2,w_2(i)})$						0.016		
						(0.025)		

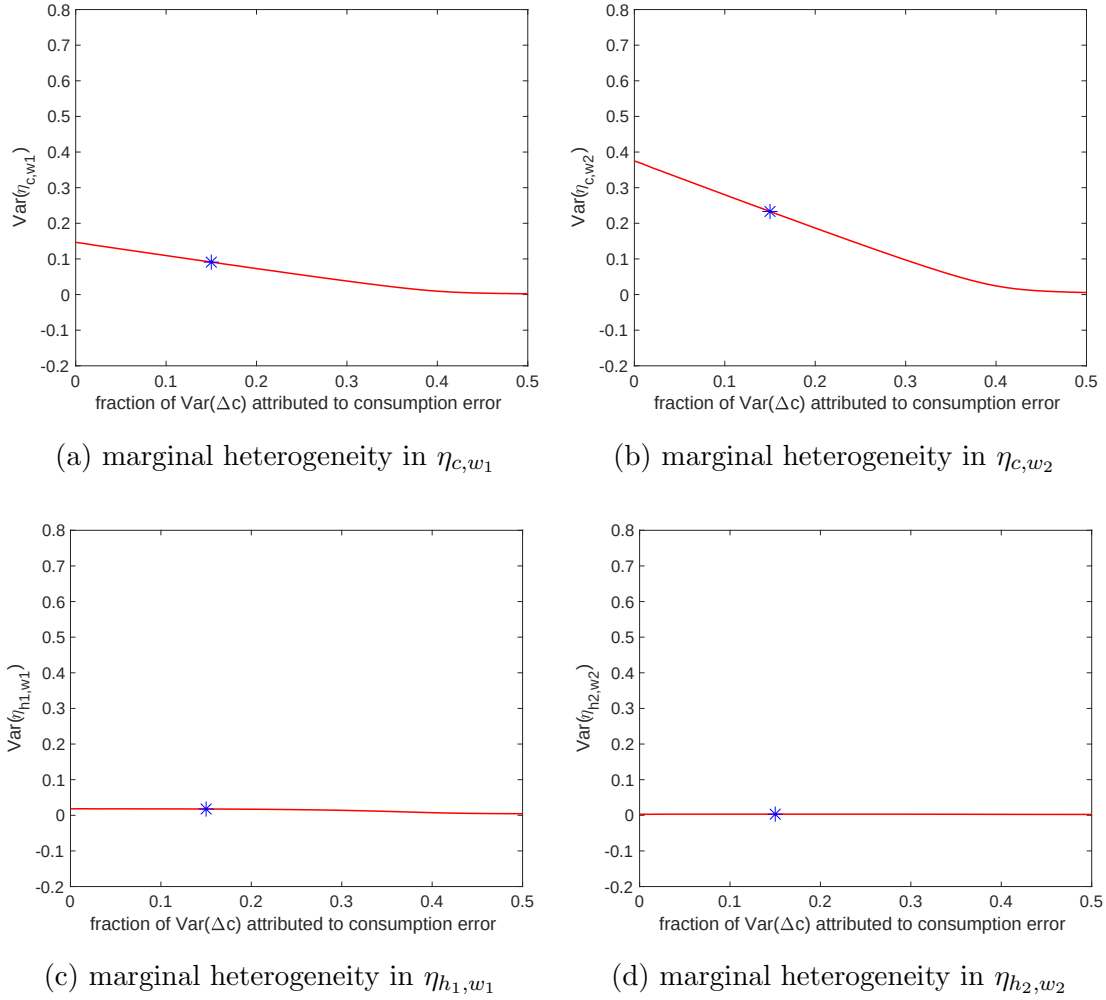
Notes: See notes for tables 4-5 in the paper. Observations: 6071 (households $\times \Delta_t$).

Table E.7 – Robustness: Alternative Restrictions, Diagonally Weighted GMM

	2^{nd} & 3^{rd} moments; labor supply cross-elasticities set to 0				
	(1)	(2)	(3)	(4)	(5)
restrictions:	fix α, no variation in η_{h_j,w_j}	fix α, no joint variation in η_{h_j,w_j}	estimate α	estimate α & $\eta_{h_1,w_1} = \eta_{h_2,w_2}$	$\eta_{c,w_1} = \eta_{c,w_2}$
$\mathbb{E}(\eta_{c,w_1(i)})$	-0.012	-0.012	-0.016	-0.013	-0.027
	(0.020)	(0.021)	(0.032)	(0.036)	(0.035)
$\mathbb{E}(\eta_{c,w_2(i)})$	-0.022	-0.022	-0.032	-0.027	-0.027
	(0.039)	(0.040)	(0.038)	(0.042)	(0.035)
$\mathbb{E}(\eta_{h_1,w_1(i)})$	0.304	0.302	0.286	0.282	0.287
	(0.102)	(0.114)	(0.109)	(0.094)	(0.110)
$\mathbb{E}(\eta_{h_2,w_2(i)})$	0.215	0.216	0.210	0.282	0.208
	(0.181)	(0.185)	(0.179)	(0.094)	(0.178)
$\text{Var}(\eta_{c,w_1(i)})^{\#}$	0.036	0.036	0.033	0.031	0.062
	[0.086]	[0.086]	[0.200]	[0.208]	[0.075]
$\text{Var}(\eta_{c,w_2(i)})^{\#}$	0.130	0.130	0.137	0.140	0.062
	[0.086]	[0.086]	[0.143]	[0.141]	[0.075]
$\text{Var}(\eta_{h_1,w_1(i)})^{\#}$		0.005	0.070	0.001	0.068
		[0.310]	[0.280]	[0.047]	[0.279]
$\text{Var}(\eta_{h_2,w_2(i)})^{\#}$		0.000	0.037	0.001	0.049
		[0.150]	[0.266]	[0.047]	[0.255]
$\text{Cov}(\eta_{c,w_1(i)}, \eta_{c,w_2(i)})$	0.069	0.069	0.067	0.066	0.062
	(0.042)	(0.042)	(0.049)	(0.052)	(0.035)
$\text{Cov}(\eta_{c,w_1(i)}, \eta_{h_1,w_1(i)})$			0.037	0.002	0.052
			(0.036)	(0.042)	(0.039)
$\text{Cov}(\eta_{c,w_1(i)}, \eta_{h_2,w_2(i)})$			-0.031	0.002	-0.051
			(0.039)	(0.042)	(0.041)
$\text{Cov}(\eta_{c,w_2(i)}, \eta_{h_1,w_1(i)})$			0.076	0.004	0.052
			(0.055)	(0.045)	(0.039)
$\text{Cov}(\eta_{c,w_2(i)}, \eta_{h_2,w_2(i)})$			-0.063	0.004	-0.051
			(0.050)	(0.045)	(0.041)
$\text{Cov}(\eta_{h_1,w_1(i)}, \eta_{h_2,w_2(i)})$			-0.049	0.001	-0.055
			(0.149)	(0.000)	(0.154)
Obs. [households $\times\Delta_t$]	6071	6071	6071	6071	6071

Notes: See notes for table E.1 on appendix page 26. The table presents diagonally weighted GMM estimates of first and second moments of wage elasticities under a number of alternative restrictions on preferences. All moments are estimated at the sample average of consumption and hours, i.e. $\mathbf{O}_t = \mathbb{E}(\mathbf{O}_{it})$. $^{\#}p$-value in square brackets for the one-sided test that the respective parameter equals zero; standard errors appear in parentheses for all other parameters.

Figure E.1 – Preference Heterogeneity against Consumption Measurement Error

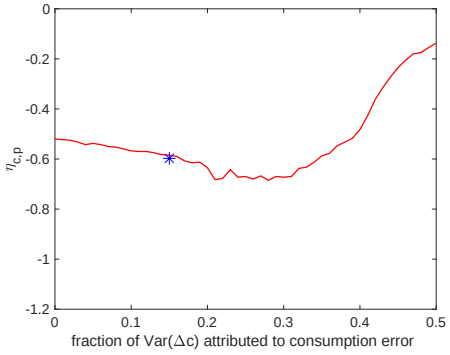


(a) marginal heterogeneity in η_{c,w_1} (b) marginal heterogeneity in η_{c,w_2}

(c) marginal heterogeneity in η_{h_1,w_1} (d) marginal heterogeneity in η_{h_2,w_2}

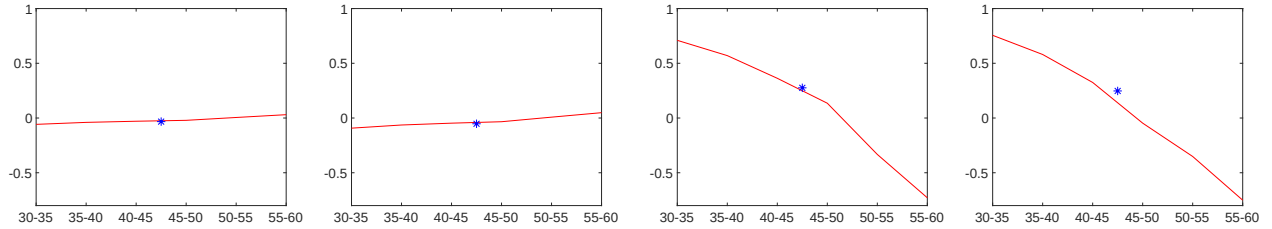
Notes: The figures present the evolution of the variances of consumption and labor supply elasticities in the preferred specification against values for the variance of consumption measurement error between zero and $50\% \times \text{Var}(\Delta c_{it})$. Measurement error in wages and earnings remains fixed at the baseline values of 13% of the variance of wages and 4% of the variance of earnings respectively. The blue asterisk marks the baseline parameter estimate when consumption measurement error is fixed at $15\% \times \text{Var}(\Delta c_{it})$. All parameters are estimated at the sample average of consumption and hours, i.e. $\mathbf{O}_t = \mathbb{E}(\mathbf{O}_{it})$.

Figure E.2 – Consumption Substitution Elasticity against Consumption Measurement Error

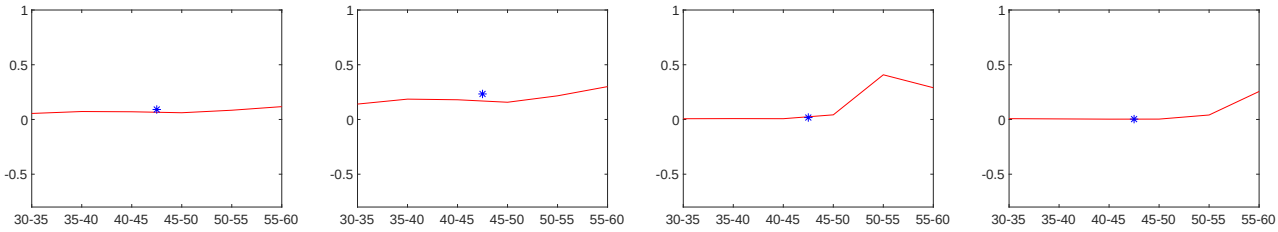


Notes: The figure presents the evolution of the consumption substitution elasticity against values for the variance of consumption measurement error between zero and $50\% \times \text{Var}(\Delta c_{it})$. Measurement error in wages and earnings remains fixed at the baseline values of 13% of the variance of wages and 4% of the variance of earnings respectively. The blue asterisk marks the baseline parameter estimate when consumption measurement error is fixed at $15\% \times \text{Var}(\Delta c_{it})$. The elasticity is estimated at the sample average of consumption and hours, i.e. $\mathbf{O}_t = \mathbb{E}(\mathbf{O}_{it})$, using simulated minimum distance and assuming that all other parameters are jointly normally distributed, parameterized at the consumption error specific preference estimates underlying figure E.1.

Figure E.3 – Parameter Estimates over Age Brackets



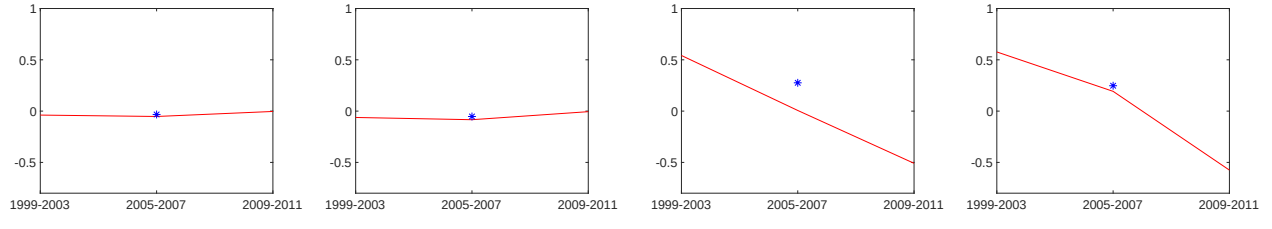
(a) $\mathbb{E}(\eta_{c,w_1(i)})$ (b) $\mathbb{E}(\eta_{c,w_2(i)})$ (c) $\mathbb{E}(\eta_{h_1,w_1(i)})$ (d) $\mathbb{E}(\eta_{h_2,w_2(i)})$



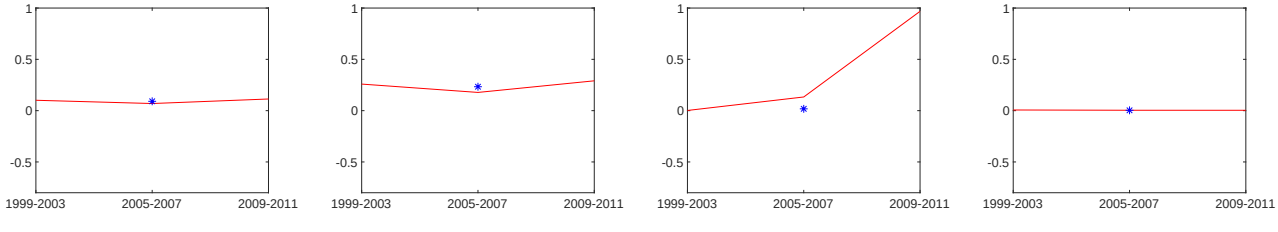
(e) $\mathrm{Var}(\eta_{c,w_1(i)})$ (f) $\mathrm{Var}(\eta_{c,w_2(i)})$ (g) $\mathrm{Var}(\eta_{h_1,w_1(i)})$ (h) $\mathrm{Var}(\eta_{h_2,w_2(i)})$

Notes: This figure plots selected parameter estimates in the preferred specification, over six brackets for the age of the male spouse: 30-35, 35-40, 40-45, 45-50, 50-55, 55-60. I condition on the sample average of consumption and hours within each age bracket. The blue asterisk marks the parameter estimate in the baseline of tables 4-5 in the paper.

Figure E.4 – Parameter Estimates over Calendar Years



(a) $\mathbb{E}(\eta_{c,w_1(i)})$ (b) $\mathbb{E}(\eta_{c,w_2(i)})$ (c) $\mathbb{E}(\eta_{h_1,w_1(i)})$ (d) $\mathbb{E}(\eta_{h_2,w_2(i)})$



(e) $\mathrm{Var}(\eta_{c,w_1(i)})$ (f) $\mathrm{Var}(\eta_{c,w_2(i)})$ (g) $\mathrm{Var}(\eta_{h_1,w_1(i)})$ (h) $\mathrm{Var}(\eta_{h_2,w_2(i)})$

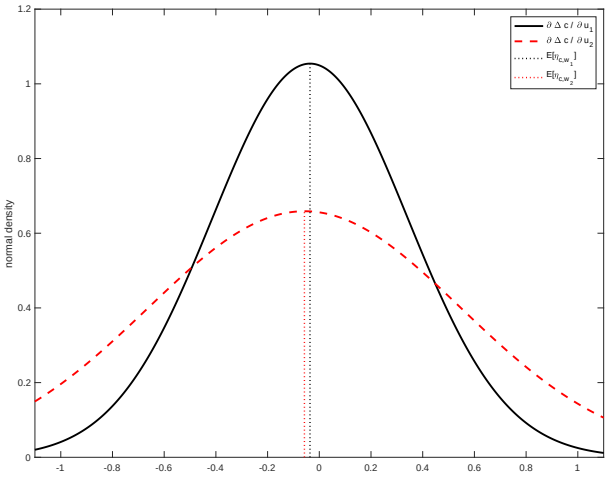
Notes: This figure plots selected parameter estimates in the preferred specification, over different calendar periods: 1999-2003 (3 waves of PSID data), 2005-2007 (two waves), 2009-2011 (two waves). I condition on the sample average of consumption and hours within each calendar period. The blue asterisk marks the parameter estimate in the baseline of tables 4-5 in the paper.

Table E.8 – Accounting Decomposition of Consumption Inequality for varying Consumption Measurement Error

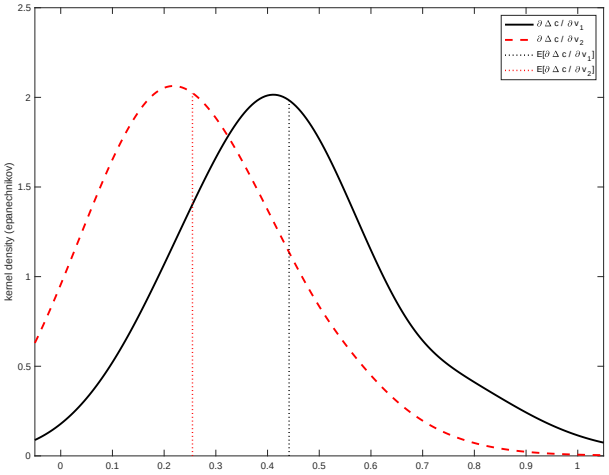
		% of cons. inequality	% of cons. instability	% of perm. inequality
	A. no consumption error			
$\text{Var}(\Delta c_{it})$	0.065	100%		
consumption instability	0.019	29.1%	100%	
without pref. heterogeneity	0.000		0.9%	
pref. heterogeneity induced	0.019		99.1%	
permanent inequality	0.046	70.9%		100%
without heterogeneity	0.024			51.4%
heterogen. in preferences only	0.034			73.2%
heterogen. in preferences, π_{it}, $\mathbf{s}_{it}$	0.046			100%
	B. consumption error at 40% $\times$ Var(Δc_{it})			
$\text{Var}(\Delta c_{it})$	0.040	100%		
consumption instability	0.002	3.9%	100%	
without pref. heterogeneity	0.000		5.1%	
pref. heterogeneity induced	0.001		94.9%	
permanent inequality	0.038	96.3%		100%
without heterogeneity	0.024			63.2%
heterogen. in preferences only	0.029			76.1%
heterogen. in preferences, π_{it}, $\mathbf{s}_{it}$	0.038			100%

Notes: The table presents the decomposition of consumption inequality into consumption instability and permanent inequality for two different amounts of consumption measurement error: no error in panel A, and consumption error at 40% of the variance of consumption growth in panel B. $\text{Var}(\Delta c_{it})$ is estimated at the sample average of consumption and hours (i.e. $\mathbf{O}_t = \mathbb{E}(\mathbf{O}_{it})$). Simulations of permanent inequality assume preferences are jointly normal, parameterized at the consumption error specific preference estimates underlying figure E.1. The consumption substitution elasticity $\eta_{c,p}$ is also consumption error specific, reflecting figure E.2. Wealth shares π_{it} and $\mathbf{s}_{it}$ are drawn from their empirical distributions. The sum of consumption instability and permanent inequality slightly overshoots the empirical amount of inequality in panel B reflecting that the model is unable to perfectly match its empirical target in this case. The decomposition suggests that preference heterogeneity accounts for up to 44% of consumption inequality when consumption error is absent (99.1% of consumption instability and 21.8% of permanent inequality in panel A) and as little as 16% of consumption inequality when consumption error is prevalent (94.9% of consumption instability and 12.9% of permanent inequality in panel B).

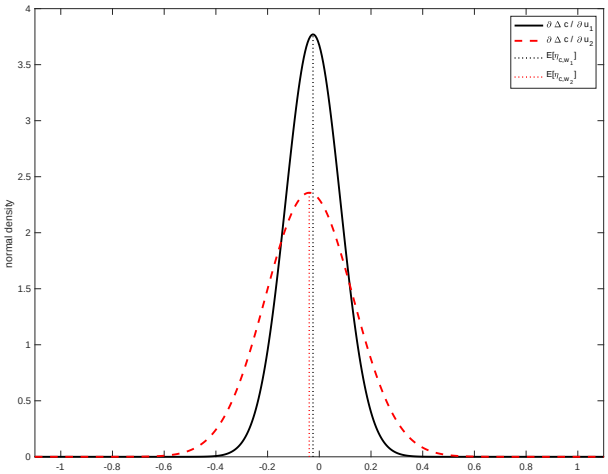
Figure E.5 – Distributions of Pass-Through Rates of Shocks into Consumption for varying Consumption Measurement Error



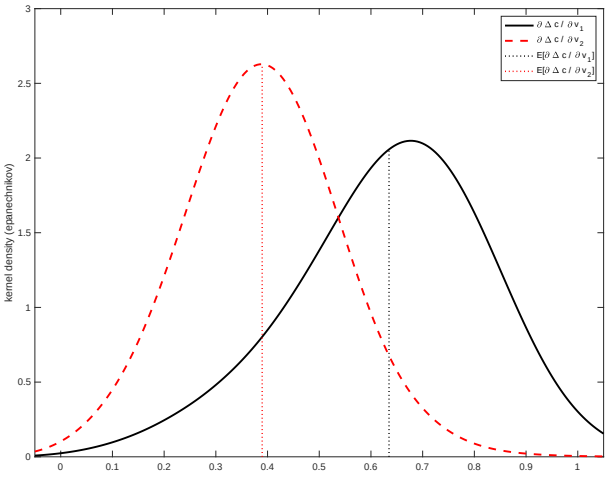
(a) transitory shocks, no consumption error



(b) permanent shocks, no consumption error



(c) transitory shocks, consumption error at $40\% \times \text{Var}(\Delta c_{it})$



(d) permanent shocks, consumption error at $40\% \times \text{Var}(\Delta c_{it})$

Notes: The figures visualize the distributions of pass-through rates of shocks for two different amounts of consumption measurement error: no error in graphs (a) and (b), and consumption error at 40% of the variance of consumption growth in graphs (c) and (d). The distributions are across 10 million households whose preferences are drawn from the joint normal, parameterized at the consumption error specific preference estimates underlying figure E.1. The consumption substitution elasticity $\eta_{c,p}$ is also consumption error specific (figure E.2), while π_{it} and $\mathbf{s}_{it}$ are drawn from their empirical distributions. The mass placed over specific pass-through rates is arbitrary following the normality assumption. Consumption measurement error reduces the scope of preference heterogeneity in the model and this is best reflected in graph (c) vis-à-vis (a). However, a limited preference heterogeneity when consumption error is at $40\% \times \text{Var}(\Delta c_{it})$ can still produce substantial heterogeneity in the consumption response to permanent shocks in graph (d). This is because the limited preference heterogeneity interacts with the underlying heterogeneity in wealth shares π_{it} and $\mathbf{s}_{it}$. The implied *average* pass-through of permanent shocks is as large as 0.6 in this case; given that the evidence in Blundell et al. (2008) and BPS suggests a lower empirical pass-through of permanent shocks, an amount of consumption error as large as $40\% \times \text{Var}(\Delta c_{it})$ is likely counterfactual given this model.

Table E.9 – Robustness: Joint Taxation and Wealthy Households

	preferred specification				
	(1)	(W1)	(W2)	(W3)	(W4)
taxation:	joint	no joint taxation			
sample:	baseline	$A > \overline{C}$	$A > 2\overline{C}$	$A > \overline{C}$ no debt	$A > \overline{C}$ liquid
$\mathbb{E}(\eta_{c,w_1(i)})$	-0.037	-0.035	-0.028	0.028	0.083
	(0.021)	(0.025)	(0.026)	(0.038)	(0.036)
$\mathbb{E}(\eta_{c,w_2(i)})$	-0.058	-0.055	-0.044	0.044	0.133
	(0.034)	(0.040)	(0.041)	(0.061)	(0.057)
$\mathbb{E}(\eta_{h_1,w_1(i)})$	0.326	0.184	0.171	0.398	0.214
	(0.103)	(0.203)	(0.219)	(0.439)	(0.443)
$\mathbb{E}(\eta_{h_2,w_2(i)})$	0.277	0.138	0.059	-0.055	-0.431
	(0.350)	(0.133)	(0.146)	(0.168)	(0.174)
$\mathrm{Var}(\eta_{c,w_1(i)})^{\#}$	0.124	0.071	0.051	0.087	0.022
	[0.000]	[0.000]	[0.000]	[0.000]	[0.034]
$\mathrm{Var}(\eta_{c,w_2(i)})^{\#}$	0.318	0.181	0.129	0.223	0.057
	[0.000]	[0.000]	[0.000]	[0.000]	[0.034]
$\mathrm{Var}(\eta_{h_1,w_1(i)})^{\#}$	0.028	0.005	0.004	0.009	0.047
	[0.233]	[0.435]	[0.464]	[0.390]	[0.323]
$\mathrm{Var}(\eta_{h_2,w_2(i)})^{\#}$	0.005	0.003	0.002	0.045	0.035
	[0.122]	[0.424]	[0.429]	[0.147]	[0.097]
$\mathrm{Cov}(\eta_{c,w_1(i)}, \eta_{c,w_2(i)})$	0.199	0.113	0.081	0.139	0.036
	(0.001)	(0.015)	(0.016)	(0.022)	(0.019)
$\mathrm{Cov}(\eta_{c,w_1(i)}, \eta_{h_1,w_1(i)})$	0.053	0.016	0.010	0.013	0.019
	(0.051)	(0.025)	(0.027)	(0.039)	(0.036)
$\mathrm{Cov}(\eta_{c,w_1(i)}, \eta_{h_2,w_2(i)})$	-0.013	0.001	0.001	0.057	0.014
	(0.014)	(0.019)	(0.020)	(0.015)	(0.009)
$\mathrm{Cov}(\eta_{c,w_2(i)}, \eta_{h_1,w_1(i)})$	0.085	0.025	0.016	0.021	0.031
	(0.082)	(0.040)	(0.043)	(0.062)	(0.057)
$\mathrm{Cov}(\eta_{c,w_2(i)}, \eta_{h_2,w_2(i)})$	-0.021	0.001	0.001	0.091	0.023
	(0.023)	(0.030)	(0.033)	(0.024)	(0.014)
$\mathrm{Cov}(\eta_{h_1,w_1(i)}, \eta_{h_2,w_2(i)})$	-0.006	0.000	0.000	0.006	-0.011
	(0.012)	(0.137)	(0.141)	(0.062)	(0.042)
Obs. [households $\times\Delta_t$]	6071	4614	3789	1806	1374

Notes: The table presents GMM estimates of first and second moments of wage elasticities in the preferred specification. Column 1 uses the baseline sample and estimates a model with progressive joint taxation. The remaining columns estimate the baseline model, i.e. without taxation. Column W1 is for households with wealth A_t at least as much as average consumption $\overline{C}_t$ in the baseline sample. Column W2 is for households with wealth at least twice as much as average annual consumption. Column W3 is like column W1 with the additional condition that households hold real debt that does not exceed \$2K. Column W4 is like column W3 but the relevant measure of wealth excludes home equity (the value of one's home net of outstanding mortgages), therefore it proxies for liquid assets. All parameters are estimated at the average of consumption and hours within each sample, i.e. $\mathbf{O}_t = \mathbb{E}(\mathbf{O}_{it})$. $^{\#}p$-value in square brackets for the one-sided test that the respective parameter equals zero; standard errors appear in parentheses for all other parameters.

F Consumption, Earnings, and Hours Inequality

To simplify the illustration of the derivation of consumption inequality, I write consumption growth as $\Delta c_{it} \approx \eta_{c,w_1(i,t-1)}\Delta u_{1it} + \eta_{c,w_2(i,t-1)}\Delta u_{2it} + \phi_{1it}v_{1it} + \phi_{2it}v_{2it}$. This mimics expression (5) in the main text with $\phi_{jit} = \eta_{c,w_j(i,t-1)} + \bar{\eta}_{c(i,t-1)}\varepsilon_j(\pi_{it}, \mathbf{s}_{it}; \boldsymbol{\eta}_{it-1})$. I also define $t^- \equiv t-1$. From the properties of the variance operator it follows that

$$\begin{aligned}
\text{Var}(\Delta c_{it}) \approx\ & \text{Var}(\eta_{c,w_1(i,t^-)}\Delta u_{1it}) + \text{Var}(\eta_{c,w_2(i,t^-)}\Delta u_{2it}) + \text{Var}(\phi_{1it}v_{1it}) + \text{Var}(\phi_{2it}v_{2it}) \\
&+ 2\text{Cov}(\eta_{c,w_1(i,t^-)}\Delta u_{1it}, \eta_{c,w_2(i,t^-)}\Delta u_{2it}) + 2\text{Cov}(\eta_{c,w_1(i,t^-)}\Delta u_{1it}, \phi_{1it}v_{1it}) \\
&+ 2\text{Cov}(\eta_{c,w_1(i,t^-)}\Delta u_{1it}, \phi_{2it}v_{2it}) + 2\text{Cov}(\eta_{c,w_2(i,t^-)}\Delta u_{2it}, \phi_{1it}v_{1it}) \\
&+ 2\text{Cov}(\eta_{c,w_2(i,t^-)}\Delta u_{2it}, \phi_{2it}v_{2it}) + 2\text{Cov}(\phi_{1it}v_{1it}, \phi_{2it}v_{2it}).
\end{aligned}$$

Given assumption 1 and results from Goodman (1960), $\text{Var}(\eta_{c,w_1(i,t^-)}\Delta u_{1it})$ becomes equal to $\mathbb{E}(\eta^2_{c,w_1(i,t^-)})\text{Var}(\Delta u_{1it})$. Results for the other variances are similar. From Bohrnstedt and Goldberger (1969) one can show that most covariances are zero except those involving exclusively transitory shocks or exclusively permanent shocks. Most covariances are zero because of assumption 1, shocks have zero mean, and the assumption that permanent and transitory shocks are independent. The non-zero covariances are $\text{Cov}(\eta_{c,w_1(i,t^-)}\Delta u_{1it}, \eta_{c,w_2(i,t^-)}\Delta u_{2it}) = \mathbb{E}(\eta_{c,w_1(i,t^-)}\eta_{c,w_2(i,t^-)})\text{Cov}(\Delta u_{1it}, \Delta u_{2it})$ and $\text{Cov}(\phi_{1it}v_{1it}, \phi_{2it}v_{2it})$.

By similar arguments, the analytical expression for hours inequality is given by

$$\begin{aligned}
\text{Var}(\Delta h_{jit}) \approx\ & \sum_{j'=1}^{2} \mathbb{E}(\eta^2_{h_j,w_{j'}(i,t^-)}) \times \left(\sigma^2_{u_{j'}(t)} + \sigma^2_{u_{j'}(t^-)}\right) \\
&+ 2\mathbb{E}(\eta_{h_j,w_1(i,t^-)}\eta_{h_j,w_2(i,t^-)}) \times \left(\sigma_{u_1u_2(t)} + \sigma_{u_1u_2(t^-)}\right) \\
&+ \sum_{j'=1}^{2} \mathbb{E}\left(\left(\eta_{h_j,w_{j'}(i,t^-)} + \bar{\eta}_{h_j(i,t^-)}\varepsilon_{j'}(\cdot; \boldsymbol{\eta}_{it^-})\right)^2\right) \times \sigma^2_{v_{j'}(t)} \\
&+ 2\mathbb{E}\left(\left(\eta_{h_j,w_1(i,t^-)} + \bar{\eta}_{h_j(i,t^-)}\varepsilon_1(\cdot; \boldsymbol{\eta}_{it^-})\right)\left(\eta_{h_j,w_2(i,t^-)} + \bar{\eta}_{h_j(i,t^-)}\varepsilon_2(\cdot; \boldsymbol{\eta}_{it^-})\right)\right) \times \sigma_{v_1v_2(t)}.
\end{aligned}$$

The expression for $\text{Var}\left(\Delta y_{jit}\right)$ follows from the identity $\Delta y_{jit} = \Delta h_{jit} + \Delta w_{jit}$.

Two remarks are due. First, as consumption (or hours/earning) inequality increases with preference heterogeneity, neglecting such heterogeneity results in understating inequality or biasing mean preferences upwards. Second, positive assortative matching between spousal wages, captured by a positive correlation between shocks, may not always increase inequality. Consider the loading factor of the *covariance* of transitory shocks into consumption inequality, given by $\mathbb{E}(\eta_{c,w_1(i,t^-)}\eta_{c,w_2(i,t^-)}) = \mathbb{E}(\eta_{c,w_1(i,t^-)})\mathbb{E}(\eta_{c,w_2(i,t^-)}) + \text{Cov}(\eta_{c,w_1(i,t^-)}, \eta_{c,w_2(i,t^-)})$. What (also) matters for loading such covariance is the correlation between consumption-wage elasticities. If $\mathbb{E}(\eta_{c,w_1(i,t^-)}\eta_{c,w_2(i,t^-)})$ is negative due to a strong negative correlation between elasticities, positive assortative matching on wages actually decreases inequality.

G Time Aggregation in the PSID

This appendix highlights the implications of time aggregation using a stylized setting in which wages are paid on a monthly basis but are observed on a yearly basis as the sum over the previous twelve months. Therefore, *model* time now refers to months rather than years. I discuss extensions to this stylized setting in the end. Like Working (1960) but unlike Crawley (2020), I maintain that time is discrete; otherwise I follow these two papers closely.

Following the baseline notation, let residual log wage of spouse $j = \{1, 2\}$ in year t and month m be $w_{jit,m} \equiv \ln W_{jit,m} - \mathbf{X}'_{jit,m}\boldsymbol{\alpha}_{W_j}$. In what follows, I drop the cross-sectional subscript i in order to ease the notation. The monthly wage process is given by

$$\begin{aligned} w_{jt,m} &= w^p_{jt,m} + u_{jt,m} \\ w^p_{jt,m} &= w^p_{jt,m-1} + v_{jt,m}, \end{aligned} \tag{G.1}$$

where $w^p_{jit,m} \equiv \ln W^p_{jit,m}$ is the permanent component. All properties of shocks remain as in the baseline so, among other things, shocks $v_{jt,m}$ and $u_{jt,m}$ are serially uncorrelated.

We do not observe $w_{jt,m}$ but we do observe the sum of wages over $M = 12$ calendar months in the year,[7] namely

$$w^{\text{year}}_{jt} = \sum_{m=1}^{M} w_{jt,m} = \sum_{m=1}^{M} w^p_{jt,m} + \sum_{m=1}^{M} u_{jt,m}. \tag{G.2}$$

Following Working (1960), I use (G.1) to express the first sum in (G.2) in terms of $w^p_{jt,1}$ (the permanent wage in January of year t) and the permanent shocks since then; this is given by $\sum_{m=1}^{M} w^p_{jt,m} = M \times w^p_{jt,1} + \sum_{m=1}^{M-1}(M-m)v_{jt,1+m}$. In a similar way, I express the sum of permanent wages in year $t-1$ in terms of $w^p_{jt,1}$ and the permanent shocks until then; namely $\sum_{m=1}^{M} w^p_{jt-1,m} = M \times w^p_{jt,1} - M \times v_{jt,1} - \sum_{m=1}^{M-1}(M-m)v_{jt-1,M+1-m}$. One can then obtain the expression for yearly wage growth $\Delta^{\text{year}} w^{\text{year}}_{jt} = w^{\text{year}}_{jt} - w^{\text{year}}_{jt-1}$.

The PSID is biennial after 1997 so observed wage growth is a first difference over *two years*, namely $\Delta^{\text{psid}} w^{\text{year}}_{jt} = w^{\text{year}}_{jt} - w^{\text{year}}_{jt-2}$. This is equivalent to the sum of two consecutive yearly growth rates, i.e. $\Delta^{\text{psid}} w^{\text{year}}_{jt} = \Delta^{\text{year}} w^{\text{year}}_{jt} + \Delta^{\text{year}} w^{\text{year}}_{jt-1}$, given by

$$\Delta^{\text{psid}} w^{\text{year}}_{jt} = \sum_{m=0}^{M-1}(M-m)v_{jt,1+m} + M\sum_{m=1}^{M} v_{jt-1,m} + \sum_{m=1}^{M-1}(M-m)v_{jt-2,M+1-m} + \sum_{m=1}^{M}\Delta^{\text{psid}} u_{jt,m}$$

where $\Delta^{\text{psid}} u_{jt,m} = u_{jt,m} - u_{jt-2,m}$. The expressions for $\Delta^{\text{psid}} w^{\text{year}}_{jt-2}$ etc. are analogous.

The baseline model remains effectively unchanged, except that households make consumption and hours decisions on a month-by-month basis rather than yearly. All the approximations

[7] We observe the annual *level* of wages, not the *logarithm*, and the logarithm of the sum is not the same as the sum of the logarithms. I refer to Crawley (2020) for a discussion of this point. Another problem arises from the fact that wages in the PSID are earnings over hours, and the denominator itself is subject to time aggregation. I do not attempt to address this point here but it certainly deserves attention in future work.

and derivations still hold, but they are now recast on a monthly basis. The system of consumption and hours equations, analogous to (5)-(7), is now given by

$$\begin{aligned}
\Delta c_{t,m} &\approx \eta_{c,w_1(t,m-1)}\Delta u_{1t,m} + \eta_{c,w_2(t,m-1)}\Delta u_{2t,m} + \kappa_{cv_1(t,m-1)}v_{1t,m} + \kappa_{cv_2(t,m-1)}v_{2t,m} \\
\Delta h_{1t,m} &\approx \eta_{h_1,w_1(t,m-1)}\Delta u_{1t,m} + \eta_{h_1,w_2(t,m-1)}\Delta u_{2t,m} + \kappa_{h_1v_1(t,m-1)}v_{1t,m} + \kappa_{h_1v_2(t,m-1)}v_{2t,m} \\
\Delta h_{2t,m} &\approx \eta_{h_2,w_1(t,m-1)}\Delta u_{1t,m} + \eta_{h_2,w_2(t,m-1)}\Delta u_{2t,m} + \kappa_{h_2v_1(t,m-1)}v_{1t,m} + \kappa_{h_2v_2(t,m-1)}v_{2t,m},
\end{aligned}$$

where the lifecycle Marshallian elasticities are given by

$$\begin{aligned}
\kappa_{cv_j(t,m-1)} &= \eta_{c,w_j(t,m-1)} + \bar{\eta}_{c(t,m-1)}\varepsilon_j(\pi_{t,m}, \mathbf{s}_{t,m}; \boldsymbol{\eta}_{t,m-1}) \\
\kappa_{h_1v_j(t,m-1)} &= \eta_{h_1,w_j(t,m-1)} + \bar{\eta}_{h_1(t,m-1)}\varepsilon_j(\pi_{t,m}, \mathbf{s}_{t,m}; \boldsymbol{\eta}_{t,m-1}) \\
\kappa_{h_2v_j(t,m-1)} &= \eta_{h_2,w_j(t,m-1)} + \bar{\eta}_{h_2(t,m-1)}\varepsilon_j(\pi_{t,m}, \mathbf{s}_{t,m}; \boldsymbol{\eta}_{t,m-1}),
\end{aligned}$$

and growth here refers to months (model time). As in the case of wages, we do not observe $c_{t,m}$ and $h_{jt,m}$; instead we observe $c_t^{\text{year}} = \sum_{m=1}^{M} c_{t,m}$ and $h_{jt}^{\text{year}} = \sum_{m=1}^{M} h_{jt,m}$ for $j = \{1, 2\}$.[8]

Following Working (1960), I use the expression for $\Delta c_{t,m}$ to obtain yearly consumption $c_t^{\text{year}} \approx M \times c_{t,1} + \sum_j \sum_{m=1}^{M-1}(M-m)\eta_{c,w_j(t,m)}\Delta u_{jt,1+m} + \sum_j \sum_{m=1}^{M-1}(M-m)\kappa_{cv_j(t,m)}v_{jt,1+m}$. In a similar way, one can show that $c_{t-1}^{\text{year}} \approx M \times c_{t,1} - M\sum_j \eta_{c,w_j(t-1,M)}\Delta u_{jt,1} - M\sum_j \kappa_{cv_j(t-1,M)}v_{jt,1} - \sum_j \sum_{m=1}^{M-1}(M-m)\eta_{c,w_j(t-1,M-m)}\Delta u_{jt-1,M+1-m} - \sum_j \sum_{m=1}^{M-1}(M-m)\kappa_{cv_j(t-1,M-m)}v_{jt-1,M+1-m}$. One can then obtain the expression for yearly consumption growth $\Delta^{\text{year}} c_t^{\text{year}} = c_t^{\text{year}} - c_{t-1}^{\text{year}}$. Observed consumption growth is, however, a first difference over *two years*, namely $\Delta^{\text{psid}} c_t^{\text{year}} = c_t^{\text{year}} - c_{t-2}^{\text{year}} = \Delta^{\text{year}} c_t^{\text{year}} + \Delta^{\text{year}} c_{t-1}^{\text{year}}$, given by

$$\begin{aligned}
\Delta^{\text{psid}} c_t^{\text{year}} \approx & \sum_j \sum_{m=0}^{M-1}(M-m)\kappa_{cv_j(t,m)}v_{jt,1+m} + M\sum_j \sum_{m=1}^{M}\kappa_{cv_j(t-1,m-1)}v_{jt-1,m} \\
& + \sum_j \sum_{m=1}^{M-1}(M-m)\kappa_{cv_j(t-2,M-m)}v_{jt-2,M+1-m} \\
& + \sum_j \sum_{m=1}^{M}\left(\eta_{c,w_j(t,m-1)}u_{jt,m} - \eta_{c,w_j(t-2,m-1)}u_{jt-2,m}\right).
\end{aligned}$$

To obtain the last expression, I assume for simplicity that $\eta_{c,w_j(t,m)} \approx \eta_{c,w_j(t,m-1)}$ and similarly for $t-1$ etc. Then multiple terms involving transitory shocks cancel out due to mean reversion. One can obtain analogous expressions for $\Delta^{\text{psid}} h_{jt}^{\text{year}}$ in a similar way. Detailed steps for all these derivations (admittedly presented here only at a high level) are available upon request.

[8] This is not strictly true for consumption. Certain consumption items are observed as a snapshot in a given calendar month (food) while most items are observed on a varying basis, such as weekly, biweekly, half-yearly, or yearly. The overall timing of consumption is often ambiguous and subject to alternative interpretations. As my focus here is on the implications of neglected time aggregation in wages, I maintain simplicity by treating consumption in a comparable way to wages and hours. I assume that the snapshot of consumption that agents report is a monthly equivalent of their underlying purchases. In the data, I convert consumption to annual amounts; thus consumption is the sum of monthly snapshots over $M = 12$ calendar months. This allows me to address lost time aggregation without confounding it with the timing of consumption in the PSID.

Wage moments. Here I show the main wage moments I target, adjusted for time aggregation.

$$\begin{aligned}
\mathbb{E}\left((\Delta^{\text{psid}} w_{jt}^{\text{year}})^2\right) &= \frac{1}{6}(2M^3+3M^2+M)\sigma^2_{v_j(t)} + M^3\sigma^2_{v_j(t-1)} \\
&\quad + \frac{1}{6}(2M^3-3M^2+M)\sigma^2_{v_j(t-2)} + M(\sigma^2_{u_j(t)} + \sigma^2_{u_j(t-2)}) \\
\mathbb{E}\left(\Delta^{\text{psid}} w_{jt}^{\text{year}} \times \Delta^{\text{psid}} w_{jt-2}^{\text{year}}\right) &= \frac{1}{6}(M^3-M)\sigma^2_{v_j(t-2)} - M\sigma^2_{u_j(t-2)} \\
\mathbb{E}\left((\Delta^{\text{psid}} w_{jt}^{\text{year}})^3\right) &= \frac{1}{4}M^2(M+1)^2\gamma_{v_j(t)} + M^4\gamma_{v_j(t-1)} + \frac{1}{4}M^2(M-1)^2\gamma_{v_j(t-2)} \\
&\quad + M\gamma_{u_j(t)} - M\gamma_{u_j(t-2)} \\
\mathbb{E}\left(\Delta^{\text{psid}} w_{jt}^{\text{year}} \times (\Delta^{\text{psid}} w_{jt+2}^{\text{year}})^2\right) &= \frac{1}{12}(M^4-M^2)\gamma_{v_j(t)} + M\gamma_{u_j(t)}.
\end{aligned}$$

I use Faulhaber's formula to express the sum of integers. To obtain these expressions, recall that shock increments are serially uncorrelated. It is easy to see how time aggregation causes serial correlation even in the absence of mean-reverting transitory shocks. The covariance between consecutive wage growths reflects the variance of transitory shocks *and* that of permanent shocks. The expressions for all other own- and cross-moments of wages are analogous.

Consumption and earnings moments. Here I show the main earnings and consumption moments, adjusted for time aggregation. To ease the notation, I do not include the conditioning statement $|\mathbf{O}_t$ (or $|\mathbf{O}_{t-2}, \mathbf{O}_t$ when applicable) in the Frisch or Marshallian elasticities; it is implied that all elasticity moments are conditional on the same consumption and hours levels on which the data moments are also conditioned.

$$\begin{aligned}
\mathbb{E}(\Delta^{\text{psid}} w_{1t}^{\text{year}} \times \Delta^{\text{psid}} c_{t+2}^{\text{year}} \mid \mathbf{O}_t) &= \frac{1}{6}(M^3-M)\sigma^2_{v_1(t)}\mathbb{E}(\kappa_{cv_1(t)}) + \frac{1}{6}(M^3-M)\sigma_{v_1v_2(t)}\mathbb{E}(\kappa_{cv_2(t)}) \\
&\quad - M\sigma^2_{u_1(t)}\mathbb{E}(\eta_{c,w_1(t)}) - M\sigma_{u_1u_2(t)}\mathbb{E}(\eta_{c,w_2(t)}) \\
\mathbb{E}(\Delta^{\text{psid}} w_{2t}^{\text{year}} \times \Delta^{\text{psid}} c_{t+2}^{\text{year}} \mid \mathbf{O}_t) &= \frac{1}{6}(M^3-M)\sigma_{v_1v_2(t)}\mathbb{E}(\kappa_{cv_1(t)}) + \frac{1}{6}(M^3-M)\sigma^2_{v_2(t)}\mathbb{E}(\kappa_{cv_2(t)}) \\
&\quad - M\sigma_{u_1u_2(t)}\mathbb{E}(\eta_{c,w_1(t)}) - M\sigma^2_{u_2(t)}\mathbb{E}(\eta_{c,w_2(t)}) \\
\mathbb{E}(\Delta^{\text{psid}} w_{1t}^{\text{year}} \times \Delta^{\text{psid}} y_{jt+2}^{\text{year}} \mid \mathbf{O}_t) &= \frac{1}{6}(M^3-M)\sigma^2_{v_1(t)}\mathbb{E}(\kappa_{y_jv_1(t)}) + \frac{1}{6}(M^3-M)\sigma_{v_1v_2(t)}\mathbb{E}(\kappa_{y_jv_2(t)}) \\
&\quad - M\sigma^2_{u_1(t)}\mathbb{E}(\kappa_{y_ju_1(t)}) - M\sigma_{u_1u_2(t)}\mathbb{E}(\kappa_{y_ju_2(t)}) \\
\mathbb{E}(\Delta^{\text{psid}} w_{2t}^{\text{year}} \times \Delta^{\text{psid}} y_{jt+2}^{\text{year}} \mid \mathbf{O}_t) &= \frac{1}{6}(M^3-M)\sigma_{v_1v_2(t)}\mathbb{E}(\kappa_{y_jv_1(t)}) + \frac{1}{6}(M^3-M)\sigma^2_{v_2(t)}\mathbb{E}(\kappa_{y_jv_2(t)}) \\
&\quad - M\sigma_{u_1u_2(t)}\mathbb{E}(\kappa_{y_ju_1(t)}) - M\sigma^2_{u_2(t)}\mathbb{E}(\kappa_{y_ju_2(t)}) \\
\mathbb{E}(\Delta^{\text{psid}} c_{t}^{\text{year}} \times \Delta^{\text{psid}} c_{t+2}^{\text{year}} \mid \mathbf{O}_{t-2}, \mathbf{O}_t) &= \frac{1}{6}(M^3-M)\sigma^2_{v_1(t)}\mathbb{E}(\kappa^2_{cv_1(t)}) + \frac{1}{6}(M^3-M)\sigma^2_{v_2(t)}\mathbb{E}(\kappa^2_{cv_2(t)}) \\
&\quad + \frac{1}{3}(M^3-M)\sigma_{v_1v_2(t)}\mathbb{E}(\kappa_{cv_1(t)}\kappa_{cv_2(t)}) \\
&\quad - M\sigma^2_{u_1(t)}\mathbb{E}(\eta^2_{c,w_1(t)}) - M\sigma^2_{u_2(t)}\mathbb{E}(\eta^2_{c,w_2(t)}) \\
&\quad - 2M\sigma_{u_1u_2(t)}\mathbb{E}(\eta_{c,w_1(t)}\eta_{c,w_2(t)})
\end{aligned}$$

$$
\begin{aligned}
\mathbb{E}\left(\Delta^{\text{psid}} w_{1t}^{\text{obs}} \times (\Delta^{\text{psid}} c_{t+2}^{\text{obs}})^2 \mid \mathbf{O}_t\right) &= \frac{1}{12}(M^4 - M^2)\gamma_{v_1(t)}\mathbb{E}(\kappa_{cv_1(t)}^2) + \frac{1}{12}(M^4 - M^2)\gamma_{v_1 v_2^2(t)}\mathbb{E}(\kappa_{cv_2(t)}^2) \\
&+ \frac{1}{6}(M^4 - M^2)\gamma_{v_1^2 v_2(t)}\mathbb{E}(\kappa_{cv_1(t)}\kappa_{cv_2(t)}) \\
&+ M\gamma_{u_1(t)}\mathbb{E}(\eta_{c,w_1(t)}^2) + M\gamma_{u_1 u_2^2(t)}\mathbb{E}(\eta_{c,w_2(t)}^2) \\
&+ 2M\gamma_{u_1^2 u_2(t)}\mathbb{E}(\eta_{c,w_1(t)}\eta_{c,w_2(t)}) \\
\mathbb{E}\left(\Delta^{\text{psid}} w_{2t}^{\text{obs}} \times (\Delta^{\text{psid}} c_{t+2}^{\text{obs}})^2 \mid \mathbf{O}_t\right) &= \frac{1}{12}(M^4 - M^2)\gamma_{v_1^2 v_2(t)}\mathbb{E}(\kappa_{cv_1(t)}^2) + \frac{1}{12}(M^4 - M^2)\gamma_{v_2(t)}\mathbb{E}(\kappa_{cv_2(t)}^2) \\
&+ \frac{1}{6}(M^4 - M^2)\gamma_{v_1 v_2^2(t)}\mathbb{E}(\kappa_{cv_1(t)}\kappa_{cv_2(t)}) \\
&+ M\gamma_{u_1^2 u_2(t)}\mathbb{E}(\eta_{c,w_1(t)}^2) + M\gamma_{u_2(t)}\mathbb{E}(\eta_{c,w_2(t)}^2) \\
&+ 2M\gamma_{u_1 u_2^2(t)}\mathbb{E}(\eta_{c,w_1(t)}\eta_{c,w_2(t)}) \\
\mathbb{E}\left(\Delta^{\text{psid}} w_{1t}^{\text{obs}} \times (\Delta^{\text{psid}} y_{jt+2}^{\text{obs}})^2 \mid \mathbf{O}_t\right) &= \frac{1}{12}(M^4 - M^2)\gamma_{v_1(t)}\mathbb{E}(\kappa_{y_j v_1(t)}^2) + \frac{1}{12}(M^4 - M^2)\gamma_{v_1 v_2^2(t)}\mathbb{E}(\kappa_{y_j v_2(t)}^2) \\
&+ \frac{1}{6}(M^4 - M^2)\gamma_{v_1^2 v_2(t)}\mathbb{E}(\kappa_{y_j v_1(t)}\kappa_{y_j v_2(t)}) \\
&+ M\gamma_{u_1(t)}\mathbb{E}(\kappa_{y_j u_1(t)}^2) + M\gamma_{u_1 u_2^2(t)}\mathbb{E}(\kappa_{y_j u_2(t)}^2) \\
&+ 2M\gamma_{u_1^2 u_2(t)}\mathbb{E}(\kappa_{y_j u_1(t)}\kappa_{y_j u_2(t)}) \\
\mathbb{E}\left(\Delta^{\text{psid}} w_{2t}^{\text{obs}} \times (\Delta^{\text{psid}} y_{jt+2}^{\text{obs}})^2 \mid \mathbf{O}_t\right) &= \frac{1}{12}(M^4 - M^2)\gamma_{v_1^2 v_2(t)}\mathbb{E}(\kappa_{y_j v_1(t)}^2) + \frac{1}{12}(M^4 - M^2)\gamma_{v_2(t)}\mathbb{E}(\kappa_{y_j v_2(t)}^2) \\
&+ \frac{1}{6}(M^4 - M^2)\gamma_{v_1 v_2^2(t)}\mathbb{E}(\kappa_{y_j v_1(t)}\kappa_{y_j v_2(t)}) \\
&+ M\gamma_{u_1^2 u_2(t)}\mathbb{E}(\kappa_{y_j u_1(t)}^2) + M\gamma_{u_2(t)}\mathbb{E}(\kappa_{y_j u_2(t)}^2) \\
&+ 2M\gamma_{u_1 u_2^2(t)}\mathbb{E}(\kappa_{y_j u_1(t)}\kappa_{y_j u_2(t)}),
\end{aligned}
$$

where the Marshallian elasticities of earnings (the $\kappa_{y_j v_j}$'s) are linear transformations of the Marshallian elasticities of hours given that $\Delta y_{jt} = \Delta w_{jt} + \Delta h_{jt}$; in addition $\kappa_{y_j u_j(t)} = 1 + \eta_{h_j, w_j(t)}$ and $\kappa_{y_j u_{-j}(t)} = \eta_{h_j, w_{-j}(t)}$. All other joint moments are analogous.

Identification. Identification of the wage parameters is similar to the baseline: the covariance between current wage growth and the sum of three consecutive growth rates identifies the variance of permanent shocks. Given this, the covariance between consecutive wage growths identifies the variance of transitory shocks (see Crawley, 2020, for a similar income process).

Identification of preferences is different from the baseline because the targeted earnings and consumption moments now also depend on moments of the transmission parameters of *permanent* shocks (i.e. the lifecycle Marshallian elasticities) that the baseline does not depend on. One can see this from $\mathbb{E}(\Delta^{\text{psid}} c_t^{\text{year}} \times \Delta^{\text{psid}} c_{t+2}^{\text{year}} \mid \mathbf{O}_{t-2}, \mathbf{O}_t)$ or other moments. While this identifies second moments of the consumption Frisch elasticities in the baseline (the η_{c,w_j}'s), here this depends also on moments of the Marshallian elasticities (the κ_{cv_j}'s). Of course, moments of the Marshallian elasticities are identified from concurrent wage, earnings, and consumption moments. However, such moments are not useful for identification of the underlying preferences under heterogeneity (sections 3.3 and 4.2), so the baseline does not target them.

There are two ways in which identification can proceed here. One is to also target *concurrent* wage, earnings, and consumption moments, obtain moments of the Marshallian elasticities,[9] and then identify moments of Frisch elasticities from *consecutive* wage, earnings, and consumption growth rates. The downside is that the empirical target of this estimation is markedly different from the baseline, so differences between the parameter estimates here and the baseline cannot be attributed exclusively to time aggregation. An alternative is to fix the Marshallian elasticities at some reasonable value, and identify the moments of Frisch elasticities from consecutive wage and outcome growth rates. The empirical target of the latter estimation remains as in the baseline.

Estimation and results. I follow the second approach above and fix the Marshallian elasticities. The value at which one fixes the κ's likely matters for the results so one must check the robustness of the results to alternative values.

Estimation proceeds in two steps. In the first step, I estimate the parameters of the wage process; these are independent of the Marshallian elasticities. In the second step, and conditional on the wage parameters, I estimate the moments of Frisch elasticities over a *grid* of alternative values for the κ's. There are six lifecycle Marshallian elasticities; these are κ_{cv1}, κ_{cv2}, κ_{y1v1}, κ_{y1v2}, κ_{y2v1}, and κ_{y2v2}. All first and second moments of these elasticities appear in the estimation amounting to 6 first moments, 6 variances, and 15 covariances. This is a total of 27 parameters for which I need to loop over possible values. Even with a conservative grid of, say, 5 values for each parameter, the curse of dimensionality is insurmountable.

To overcome this, I fix several covariances to zero and thus mostly loop over values for the averages and variances only. Specifically, I loop over four different values for each *average* Marshallian elasticity; in each case the grid contains equidistant points over an interval around the corresponding elasticity from BPS. For example, BPS find that $\kappa_{cv1} = 0.34$ homogeneously; my grid contains the values 0.05, 0.22, 0.38, 0.55. Neither the density of the grid, nor small deviations from the endpoints matter. There are no external estimates that can inform the grid for the *variance* of the Marshallian elasticities, so in this case I use arbitrary values mostly between zero and 0.4. The upper bound is higher than the variance of any Frisch elasticity in the baseline. Finally, I loop over certain covariances, namely $\mathbb{E}(\kappa_{cv_1}\kappa_{cv_2})$ and $\mathbb{E}(\kappa_{y_jv_1}\kappa_{y_jv_2})$; these are most likely positive because of the underlying structure of the problem (the Marshallian in each pair is a function of the same underlying Frisch elasticities).

Each instance of this large nested loop has values for the moments of the Marshallian elasticities that appear in the model. Given said values, I estimate the preferred specification of the model in order to obtain estimates for the Frisch elasticities. It is computationally very expensive to bootstrap each instance of the loop, so I do not calculate standard errors; however, all other estimation details are exactly as in the baseline.

[9] One can obtain moments of the Marshallian elasticities in a way analogous to the identification of moments of permanent shocks; see Crawley (2020) for the first moment.

Table G.1 – Robustness: Addressing Time Aggregation

	preferred specification				
parameter:	at lowest $fval$	average over loops	st. dev. over loops	25^{th} percentile	75^{th} percentile
$\mathbb{E}(\eta_{c,w_1(i)})$	-0.020	0.008	0.017	-0.007	0.022
$\mathbb{E}(\eta_{c,w_2(i)})$	-0.032	0.013	0.027	-0.011	0.035
$\mathbb{E}(\eta_{h_1,w_1(i)})$	0.228	0.238	0.015	0.225	0.250
$\mathbb{E}(\eta_{h_2,w_2(i)})$	0.260	0.305	0.036	0.279	0.328
$\text{Var}(\eta_{c,w_1(i)})$	0.086	0.120	0.019	0.104	0.133
$\text{Var}(\eta_{c,w_2(i)})$	0.220	0.306	0.049	0.267	0.341
$\text{Var}(\eta_{h_1,w_1(i)})$	0.021	0.020	0.008	0.014	0.025
$\text{Var}(\eta_{h_2,w_2(i)})$	0.003	0.009	0.007	0.004	0.012
$\text{Cov}(\eta_{c,w_1(i)}, \eta_{c,w_2(i)})$	0.137	0.191	0.031	0.167	0.213
$\text{Cov}(\eta_{c,w_1(i)}, \eta_{h_1,w_1(i)})$	0.037	0.037	0.012	0.028	0.045
$\text{Cov}(\eta_{c,w_1(i)}, \eta_{h_2,w_2(i)})$	-0.007	-0.023	0.016	-0.034	-0.010
$\text{Cov}(\eta_{c,w_2(i)}, \eta_{h_1,w_1(i)})$	0.058	0.059	0.019	0.045	0.071
$\text{Cov}(\eta_{c,w_2(i)}, \eta_{h_2,w_2(i)})$	-0.012	-0.037	0.026	-0.054	-0.017
$\text{Cov}(\eta_{h_1,w_1(i)}, \eta_{h_2,w_2(i)})$	-0.004	-0.010	0.007	-0.013	-0.004

Notes: Observations: 6071 (households $\times\Delta_t$). The table presents summary statistics of estimates from the preferred specification over various values for the moments of Marshallian elasticities. All parameters are conditional on $\mathbf{O}_t = \mathbb{E}(\mathbf{O}_{it})$.

Given the loop, I obtain a large number of estimates for the Frisch elasticities. Here I report only a summary of the results. Specifically, I report the estimates associated with the lowest value of the GMM distance metric, the average and standard deviation of estimates over all loops, and the 25^{th} and 75^{th} percentile of estimates across the loops.

The results are in table G.1. Despite time aggregation changing the target moments substantially, the baseline conclusions remain unchanged. The average consumption elasticities are near zero, the average labor supply elasticities are close to the baseline (around 0.25-0.30), consumption preference heterogeneity remains substantial, heterogeneity in the labor supply elasticities is about an order of magnitude lower. The standard deviation of the estimates for $\text{Var}(\eta_{h_j,w_j(i)})$ is low, suggesting that this pattern of heterogeneity is present across different values for the moments of the Marshallian elasticities. Overall, the results are in line with those obtained from the non-aggregated wage process in the baseline.

Discussion. Time aggregation here is subject to certain limitations. The underlying wage shocks are assumed to hit the household only in 12 instances in a year; while this seems more realistic than one that assumes wage shocks appear on January 1^{st} only, it is ultimately ad hoc. Moreover, transitory shocks are assumed to last for only one month, while they most certainly

last longer. Crawley (2020) reports that the time aggregated results in his setting are not very sensitive to this assumption. A more serious issue may be the exact timing of consumption in the PSID. Of course, lack of additional information restricts what one can ultimately do and there is a point where one must make choices balancing generality and tractability.

H Simulation of Quantitative Model

The model in WK is a parametric version of the lifecycle model for consumption and family labor supply that I developed in section 2. Their baseline parametrization imposes separability between consumption and family labor supply. Given heterogeneity in the consumption-wage elasticities η_{c,w_j} in my baseline, I work directly with the non-separable parametrization that WK present as an extension. The utility function is given by

$$U_t(C_{it}, H_{1it}, H_{2it}) = \beta^t(1-\sigma)^{-1}\left(\{\alpha C_{it}^{\gamma} + (1-\alpha)[\xi H_{1it}^{\theta} + (1-\xi)H_{2it}^{\theta}]^{-\frac{\gamma}{\theta}}\}^{\frac{1-\sigma}{\gamma}} - 1\right) \quad \text{(H.1)}$$

where β is the discount factor, σ governs the intertemporal substitution of consumption, γ governs the substitution between consumption and labor supply, and θ governs the substitution between spousal hours. This utility function allows for flexible substitution between consumption, male hours, and female hours, although it is *not* flexible enough to generate independent variation in all 9 underlying Frisch elasticities of consumption and hours.

A first difference between my model and WK is that the specification above abstracts from preference heterogeneity. All utility parameters are common across households. However, one can accommodate heterogeneity indirectly, namely by solving the model for different sets of parameters, simulating random households for each set, and pooling all households together to form one large population that exhibits preference heterogeneity.

A second difference is that WK restrict shocks to joint normal. Therefore, $\gamma_{v_j(t)} = 0$ and $\gamma_{u_j(t)} = 0$, and similarly for all other third moments. In my baseline estimation, I have found substantial left skewness in wage shocks. Abstracting from such skewness, the model in WK is unable to generate skewness in earnings and consumption (thus contradicting the data – table 2 in the paper). Estimation of the variances and covariances of Frisch elasticities relies on the third moments of outcomes conveying information about preferences. With those moments restricted to zero, I cannot use WK's setting to estimate the second moments of preferences.

Allowing for skewness in wage shocks is not simply a matter of replacing the model's normal distribution by, say, the skew normal or a mixture of normals. Several complications arise. First, one needs the statistical tools to calculate multivariate skewed distribution functions (cdf and pdf). In the absence of analytical expressions for them, one must resort to numerical integration which, given the state space, may become prohibitively expensive. Second, a long tail in income requires sufficient support in the state space for the model to be able to 'visit' such extreme events. Replacing WK's joint normal with the bivariate skew normal (Azzalini and Valle, 1996) failed to generate *any* skewness in earnings or consumption without

Table H.1 – Quantitative Model: Heterogeneity in β and $\eta_{c,p}$

	true	transitory		true	transitory
$\mathbb{E}(\eta_{c,w_1(i)})$	-0.151	-0.146	$\mathbb{E}(\eta_{h_1,w_2(i)})$	0.145	0.125
$\mathbb{E}(\eta_{c,w_2(i)})$	-0.065	-0.060	$\mathbb{E}(\eta_{h_2,w_1(i)})$	0.318	0.301
$\mathbb{E}(\eta_{h_1,w_1(i)})$	0.818	0.806	$\mathbb{E}(\eta_{h_2,w_2(i)})$	0.646	0.649

Notes: The table presents GMM estimates of first moments of wage elasticities based on simulated data for four sub-populations of households from the parametric model of WK. In addition to heterogeneity in the parameters governing the estimable Frisch elasticities, households are heterogeneous in the discount factor β and the consumption substitution elasticity $\eta_{c,p}$.

substantially modifying the support of the state space. Third, the solution algorithm must be made proof to realizations in the tails of the state space, often associated with numerical instability. In practice, and despite increasing evidence for skewness in earnings dynamics, few only papers have deviated from normality to date (for a discussion see De Nardi et al., 2019). I do not attempt this extension here so I can only use the simulated data to estimate *average* elasticities under heterogeneity (but not second moments). I can also check if the implications of heterogeneity for inequality or partial insurance are broadly in line with my baseline.

Unless explicitly said otherwise, I keep the calibration of the non-separable model precisely as in the original paper. WK's budget constraint allows for joint taxation; my baseline abstracts from this so I set all tax parameters to zero. Except cols. 4 & 5 in table 9, I simulate four sub-populations of 50000 households each, and I pool them together to form a larger population of households. In cols. 4 & 5, I draw a sample of 1508 observations from each sub-population to create a dataset of 6032 household $\times\Delta t$ observations as in the baseline sample.

The four sub-populations differ in parameters γ and θ that control the substitution between consumption, male hours, and female hours, thus contributing to heterogeneity in the consumption-wage and labor supply elasticities. The first sub-population in all cases has $\gamma = -3$ and $\theta = 3$ (the choice in WK), the second has $\gamma = -2$ and $\theta = 4$, the third $\gamma = -3.5$ and $\theta = 2.3$, and the fourth has $\gamma = -3.9$ and $\theta = 3.5$. While these choices are ultimately arbitrary, note that it has not been possible to try parameter values that are too far away from WK's calibration without running into numerical instability.

In addition to this heterogeneity, the sub-populations for columns 1 & 2 in table 10 differ over $\beta = \{0.99; 0.98; 0.97; 0.95\}$. Those in columns 3 & 4 differ over $\sigma = \{2.24; 3; 2.1; 2.8\}$. Heterogeneity in σ induces heterogeneity in all Frisch elasticities. Finally, table H.1 has $(\beta, \sigma) = \{(0.99, 2.24); (0.99, 3), (0.98, 2.24), (0.98, 3)\}$. All choices are again arbitrary, subject to being 'close enough' to WK's default calibration at $(0.99, 2.24)$ in order to avoid numerical instability.

Welfare loss from idiosyncratic wage risk. I calculate this as the root CEV of the equation $W((1 + CEV)\boldsymbol{C}^0, \boldsymbol{H}_1^0, \boldsymbol{H}_2^0) = W(\boldsymbol{C}^1, \boldsymbol{H}_1^1, \boldsymbol{H}_2^1)$ where $(\boldsymbol{C}^0, \boldsymbol{H}_1^0, \boldsymbol{H}_2^0)$ is the allocation of outcomes without wage risk and $(\boldsymbol{C}^1, \boldsymbol{H}_1^1, \boldsymbol{H}_2^1)$ is the allocation with risk. CEV measures

Table H.2 – Welfare Loss from Idiosyncratic Wage Risk

specification:	preferred	BPS
Total welfare change	-16.6%	-14.6%
A. Consumption (level, distribution)	-15.4% (2.1%, -17.1%)	-12.5% (4.1%, -15.9%)
B. Male hours (level, distribution)	-0.6% (0.8%, -1.4%)	0.0% (2.6%, -2.5%)
C. Female hours (level, distribution)	-0.8% (0.5%, -1.3%)	-2.4% (0.2%, -2.6%)

Notes: The table presents welfare losses from idiosyncratic wage risk in the average household (one with average preferences) and a decomposition to consumption and hours. See appendix B in WK and text for details on these calculation.

the % of lifetime consumption that households are willing to give up in order to maintain the same expected lifetime utility in a world without male and female wage risk.

With preference heterogeneity, the welfare function W and aggregation across households matter. The best treatment would be to solve and simulate the model for an underlying distribution of households that reflects my baseline parameter estimates, namely the preferences at which I want to calculate the welfare losses from wage risk. That would enable me to obtain the *distribution* of welfare losses across households. This is, however, hard to do for two reasons: (1.) solving the model for a realistic distribution of preferences is computationally tedious; (2.) unlike the previous part in which preference heterogeneity was ad hoc, the distribution of preferences here should reflect my baseline estimates. This requires *estimation* of the non-separable model allowing for preference heterogeneity.

To avoid these complications, I follow WK and simply calculate the welfare loss for the *average* household, i.e. the household with average preferences from the preferred specification in column 8 of table 4 in the paper. I also compare the losses with those for a household that has preferences as in BPS (column 2, table 4). Given that average preferences in these two cases are separable, the Frisch elasticities become deep parameters. I can thus directly plug in the parameters from table 4 without estimating the quantitative model.[10]

The results are in the first row of table H.2. Households are willing to give up about 17% of their lifetime consumption in order to avoid wage risk. This is 2 percentage points larger than the cost in BPS, simply because households here are more exposed to risk given the limited insurance role of family labor supply. It is also closer by 20% to welfare losses with exogenous labor supply (the latter are about 25% of lifetime consumption - table 6 in WK). The welfare losses stem predominantly from consumption as wage risk translates into consumption risk; this is stronger in the preferred specification where the role of labor supply is limited. Details of this decomposition are in appendix B of WK.

[10]Given that average preferences are separable, I use WK's separable specification for utility, namely $U_t = \beta^t\big((1-\sigma)^{-1}C_{it}^{1-\sigma} - \psi_1(1-1/\eta_1)^{-1}H_{1it}^{1-1/\eta_1} - \psi_2(1-1/\eta_2)^{-1}H_{2it}^{1-1/\eta_2}\big)$, instead of specification (H.1). I allow for taxes precisely as in WK's welfare calculations.

References

Azzalini, A. and A. D. Valle (1996). The multivariate skew-normal distribution. *Biometrika 83*(4), 715–726.

Blundell, R., H. Low, and I. Preston (2013). Decomposing changes in income risk using consumption data. *Quantitative Economics 4*(1), 1–37.

Blundell, R., L. Pistaferri, and I. Preston (2008). Consumption inequality and partial insurance. *American Economic Review 98*(5), 1887–1921.

Blundell, R., L. Pistaferri, and I. Saporta-Eksten (2016). Consumption inequality and family labor supply. *American Economic Review 106*(2), 387–435.

Blundell, R., L. Pistaferri, and I. Saporta-Eksten (2018). Children, time allocation, and consumption insurance. *Journal of Political Economy 126*(S1), S73–S115.

Boerma, J. and L. Karabarbounis (2019). Inferring inequality with home production. NBER Working Paper 24166, NBER.

Bohrnstedt, G. and A. Goldberger (1969). On the exact covariance of products of random variables. *Journal of the American Statistical Association 64*(328), 1439–1442.

Bound, J., C. Brown, G. J. Duncan, and W. L. Rodgers (1994). Evidence on the validity of cross-sectional and longitudinal labor market data. *Journal of Labor Economics 12*(3), pp. 345–368.

Campbell, J. Y. (1993). Intertemporal asset pricing without consumption data. *American Economic Review 83*(3), pp. 487–512.

Chetty, R. (2006). A new method of estimating risk aversion. *American Economic Review 96*(5), 1821–1834.

Cohen, A. and L. Einav (2007). Estimating risk preferences from deductible choice. *American Economic Review 97*(3), 745–788.

Crawley, E. (2020). In search of lost time aggregation. *Economics Letters 189*.

De Nardi, M., G. Fella, and G. Paz-Pardo (2019). Nonlinear Household Earnings Dynamics, Self-Insurance, and Welfare. *Journal of the European Economic Association 18*(2), 890–926.

Goodman, L. (1960). On the exact variance of products. *Journal of the American Statistical Association 55*(292), 708–713.

Guiso, L. and P. Sodini (2013). *Household Finance: An Emerging Field*, Volume 2 of *Handbook of the Economics of Finance*, pp. 1397–1532. Elsevier.

Heathcote, J., K. Storesletten, and G. L. Violante (2014). Consumption and labor supply with partial insurance: An analytical framework. *American Economic Review 104*(7), 2075–2126.

Keane, M. P. (2011). Labor supply and taxes: A survey. *Journal of Economic Literature 49*(4), 961–1075.

Kimball, M. S., C. R. Sahm, and M. D. Shapiro (2009). Risk preferences in the PSID: Individual imputations and family covariation. *American Economic Review 99*(2), 363–368.

Meghir, C. and L. Pistaferri (2011). Earnings, consumption and life cycle choices. Volume 4 of *Handbook of Labor Economics*, pp. 773–854. Elsevier.

Phlips, L. (1974). *Applied Consumption Analysis*. Advanced textbooks in economics. North-Holland.

Theloudis, A. (2017). Consumption inequality across heterogeneous families. LISER Working Paper Series 2017-18, LISER.

Working, H. (1960). Note on the correlation of first differences of averages in a random chain. *Econometrica 28*(4), 916–918.