



# Department of Economics Discussion Paper Series

## Consumption and Income Inequality across Generations

Giovanni Gallipoli, Hamish Low, Aruni Mitra

Number 985  
July, 2022

# Consumption and Income Inequality across Generations<sup>\*</sup>

Giovanni Gallipoli<sup>†</sup>

Hamish Low<sup>‡</sup>

Aruni Mitra<sup>§</sup>

July 2, 2022

## Abstract

We characterize the joint evolution of cross-sectional inequality in earnings, other sources of income and consumption across generations in the U.S. To account for cross-sectional dispersion, we estimate a model of intergenerational persistence and separately identify the influences of parental factors and of idiosyncratic life-cycle components. We find evidence of family persistence in earnings, consumption and saving behaviours, and marital sorting patterns. However, the quantitative contribution of idiosyncratic heterogeneity to cross-sectional inequality is significantly larger than parental effects. Our estimates imply that intergenerational persistence is not high enough to induce further large increases in inequality over time and across generations.

**Keywords:** income, consumption, intergenerational persistence, inequality

**JEL codes:** D15, D64, E21

---

<sup>\*</sup>We are grateful for comments from Tom Crossley, Michael Devereux, Lorenzo Garlappi, David Green, Maria Prados, Victor Rios-Rull, and seminar participants at the Society for Economic Dynamics, NBER Summer Institute, Econometric Society World Congress, Barcelona Summer Workshop, Bonn Human Capital Conference, the Bundesbank, the Rimini Centre, Bank of Canada, Bristol, Cambridge, Chicago, Manchester, Naples, UBC and College of William & Mary. Financial support from the SSHRC of Canada is gratefully acknowledged. We alone are responsible for all errors and interpretations.

<sup>†</sup>University of British Columbia, CEPR and HCEO. E-mail: gallipol@mail.ubc.ca

<sup>‡</sup>University of Oxford and IFS. E-mail: hamish.low@economics.ox.ac.uk

<sup>§</sup>University of Manchester. E-mail: aruni.mitra@manchester.ac.uk

# 1 Introduction

Parents influence their children’s life-cycle outcomes in many ways: through choices about education, through transmission of ability and preferences, by providing income-enhancing opportunities, as well as through inter-vivos and bequest transfers affecting wealth and consumption.<sup>1</sup> Economists often quantify these influences using measures of intergenerational persistence along dimensions of heterogeneity such as earnings, wealth, or consumption. The various channels of family influence are inter-related, for example, these mechanisms may be substitutes: investing in a child’s education to increase their earnings potential may imply less transfers of wealth. Several studies have looked at either income or consumption in isolation, mostly focusing on the estimation of intergenerational pass-through parameters. In this paper we pursue a different approach and develop a parsimonious model of the *joint* persistence of expenditures, earnings and other income. Rather than focusing on persistence alone, our focus is on understanding the importance of different aspects of family heterogeneity, compared to idiosyncratic life-cycle events, for the evolution of income and consumption inequality across generations. Our work has two main objectives: first, to estimate the diverse ways parental influences shape children’s economic outcomes in a unified framework; second, to quantify how much of the inequality observed in a particular generation can be attributed to parental factors.

To assess the importance of parental heterogeneity, we model intergenerationally linked households that choose their optimal consumption given their income processes. In our baseline model, the income process is assumed to be sum of an individual fixed effect component that is intergenerationally linked and idiosyncratic life-cycle shocks. Specifically, we allow parents to influence outcomes of children through three channels: through earned income of the male household head, through other sources of income such as public and private transfers and earnings of the head’s wife, and through consumption. The extent to which inequality among parents is passed through to inequality among children depends on (i) the strength of the intergenerational pass-through captured by the intergenerational elasticity parameters, (ii) the magnitude of initial heterogeneity in the parents’ generation, and (iii) the magnitude of family-independent idiosyncratic variation in the children’s generation. Hence, a decomposition of observed inequality into parental and idiosyncratic factors requires estimates of all these three channels. To this purpose we use theoretical restrictions in the variances of the income and consumption processes of parents and their adult children and their covariances both within and between generations. These moments jointly identify the parameters dictating intergenerational linkages as well as the life-cycle shocks to income and

---

<sup>1</sup>Research linking family outcomes across generations focuses on income and earnings persistence (for a survey, see [Aaronsen and Mazumder, 2008](#)). Related work documents the persistence of wealth (e.g., [Charles and Hurst, 2003](#)), consumption (e.g. [Waldkirch, Ng and Cox, 2004](#); [Charles et al., 2014](#)), skill (e.g. [Lochner and Park, 2021](#)) and occupations ([Corak and Piraino, 2010](#); [Bello and Morchio, 2016](#)). [Boar \(2021\)](#) documents parental precautionary motives geared to insure children. For the role of transfers, [Abbott et al. \(2019\)](#). [Restuccia and Urrutia \(2004\)](#), [Cunha, Heckman and Schennach \(2010\)](#), [Carneiro et al. \(2021\)](#), [Lee and Seshadri \(2019\)](#) and [Caucutt and Lochner \(2019\)](#) examine parental investments and credit constraints at different stages of the life-cycle.

consumption. We use a generalized method of moments (GMM) approach to jointly estimate the parameters determining each of these elements. We can then quantify the contribution of observed parental factors in children’s outcomes and to overall cross-sectional inequality.

For estimation we employ data from the Panel Study of Income Dynamics (PSID) on household income, expenditures and other family characteristics, linked across generations in a long panel format, covering birth-cohorts of individuals born between the early 1950s and the late 1970s. To avoid the selection issues associated with women’s labour force participation, we focus on a sample of father-son pairs to characterize earnings persistence; however, we include women’s labour earnings within our measure of other income. The availability of expenditure data varies across survey waves.<sup>2</sup> For this reason, we can either use food expenditure for the full sample period (Waldkirch, Ng and Cox, 2004) or restrict attention to the period since 1997 for which extensive consumption records are available (Charles et al., 2014). Our baseline estimation uses food consumption going back to the late 1960s but we document the robustness of our findings by replicating the analysis for sample periods that have detailed expenditure records for most categories and also by using imputed measures of total household outlays in the full-length sample (Attanasio and Pistaferri, 2014).

We find that intergenerational persistence is highest for earnings, with an elasticity of 0.23. We also estimate a significant pass-through in consumption expenditures from parent to child, albeit slightly below the elasticity of earnings. Of course, consumption persistence operates also indirectly through other channels. The intra-family elasticity for other income is only 0.10 and mostly reflects similarities in spousal earnings across generations. This spousal selection emphasizes an important trait of family influences, as men tend to marry women who have similar economic outcomes as their mothers (Fernandez, Fogli and Olivetti, 2004). In addition, better parental earnings are associated with higher unearned income among kids, with a cross-elasticity of 0.21. This suggests that higher parental earnings is associated with higher spousal earnings among children. We show that ignoring this cross-elasticity leads to substantial under-estimates of the parental influences on consumption inequality. Taken together, our estimates of the intergenerational pass-through are consistent with the view that persistence is driven largely by associations in the lifetime earnings of both spouses as well as by family preferences for consumption, with persistence in observable characteristics like educational attainment playing a crucial role.<sup>3</sup>

The central question that we address in the debate on the role of family background for life-cycle outcomes is whether observed within-generation inequality would be much different if heterogeneity

---

<sup>2</sup>The PSID initially recorded only housing and food-related expenditures. After 1999 more consumption categories were added; since 2005, the PSID covers all the categories in the Consumption Expenditure Survey (CEX). The CEX started providing detailed data about multiple consumption categories in the 1980s but followed individuals for a maximum of four quarters only.

<sup>3</sup>See Landersø and Heckman (2017) and Gayle, Golan and Soytaş (2018) for evidence on the importance of education and human capital for intergenerational persistence.

due to parents were removed. The model delivers a transparent setting to perform such an inequality accounting exercise and quantify the contribution of parental factors: these exercises under various model specifications and sample selection criteria consistently indicate that idiosyncratic heterogeneity, rather than family background, accounts for the bulk of cross-sectional dispersion in income and expenditures. The largest impact of parental factors is on consumption inequality, with our baseline estimates attributing about a third of within-generation consumption inequality to family characteristics. This is followed by the size of parental influence in determining child earnings heterogeneity, about a tenth, and finally in other sources of income, for which the influence is a meagre 4%. Note that these results do not imply that life-cycle shocks matter more than initial conditions for an individual, rather that parental factors are dwarfed by idiosyncratic factors in determining heterogeneity in individual fixed effects.

One key implication of our finding is that cross-generational insurance motives within the family increases cross-sectional inequality. For instance, if richer parents are better able to insure their own children through different types of transfer, then this insurance will exacerbate ex-post inequality (see also [Koeniger and Zanella, 2022](#)). This occurs because similar ability children without access to parental transfers would be in a very different situation from those that do. This inter-generational insurance stands in contrast to intra-generational insurance, e.g., through government taxes and transfers, that reduces cross-sectional inequality in economic outcomes. Thus, the intensity of within-family insurance as opposed to other mechanisms that equalize consumption in the cross-section are central to establish the determinants of cross-sectional inequality. Our analysis captures both channels of insurance and finds that while intra-family insurance does increase the cross-sectional variance in consumption by about 30%, the intra-generational insurance channel is effective in reducing aggregate consumption inequality to roughly half that of earnings.

Our results can help reconcile the somewhat puzzling observation that intergenerational persistence is fairly stable ([Hertz, 2007](#); [Lee and Solon, 2009](#)) in the face of growing inequality over the past few decades ([Heathcote, Perri and Violante, 2010](#); [Attanasio and Pistaferri, 2016](#)). Mechanically, a negative association between economic inequality and mobility arises in the model with stronger intergenerational pass-through channels, which in turn induce greater dispersion in the children’s generation. Such an association would be consistent with the empirical observation that more unequal societies exhibit lower economic mobility across generations, a relationship often dubbed the ‘Great Gatsby’ curve (see [Krueger, 2012](#); [Corak, 2013](#); [Rauh, 2017](#)). However, our estimates also indicate that rising idiosyncratic heterogeneity has had a prominent role for the growing dispersion in the younger generation, more than offsetting family factors. Moreover, as we discuss later, current estimates of intergenerational persistence suggest that family linkages are not large enough to trigger substantially greater inequality in subsequent generations.

The rest of the paper is organized as follows. In [Section 2](#) we introduce the benchmark model

with intergenerational linkages through various income sources and consumption. Section 3 discusses parameter identification and the estimation approach. Results are presented in Section 4 along with the implications of our estimates for the evolution of cross-sectional inequality and consumption insurance across generations. We delve deeper into the underlying mechanisms behind our baseline results in Section 5, and show the robustness of our baseline findings in Section 6. Section 7 summarizes our key conclusions.

## 2 Framework of Intergenerational Linkages

We develop an estimable model of heterogeneous and intergenerationally linked households, who make optimal consumption choices subject to a budget constraint comprising of various income sources. The building blocks of our analysis are the time-series processes for earnings and other income of parents and children, along with a mechanism mapping them into distributions of family outcomes through multiple parent-child linkages.

In the baseline model, earnings and other income are expressed as the sum of a fixed effect, which we allow to be linked across generations, an AR(1) persistent shock and a transitory innovation independent over time. To account for alternative forms of cross-generational persistence, we later consider in Section 6.2, an extension with intergenerationally correlated contemporaneous permanent shocks to earnings and other income.

To provide context, and further motivate the baseline model, in Appendix A we report reduced-form estimates of the intergenerational pass-through of earnings, family income and consumption over several decades. We find little evidence of changes in the intergenerational elasticity of income over time, with similar patterns holding for expenditures. The stationarity of cross-generational pass-through is consistent with evidence in Lee and Solon (2009), whose methodology we adopt for the analysis, and in Chetty et al. (2014), who examine large administrative U.S. earnings records and conclude that measures of “...intergenerational mobility have remained extremely stable for the 1971-1993 birth cohorts”. Therefore, we maintain the assumption of stationarity in our analysis.

**Problem of the Household.** Every household maximizes a discounted flow of expected utility by choosing its total expenditure level, subject to a budget constraint that is determined by stochastic income processes. When a household makes consumption decisions, it has knowledge of its own permanent income but does not know the value of future income shocks. The dynamic life-cycle problem of the family  $f$  at time  $t$  is given by:

$$\begin{aligned}
& \max_{\{\mathcal{X}_{f,s}\}_{s=t}^T} \mathbb{E}_t \sum_{j=0}^{T-t} \beta^j \mathcal{U}(\mathcal{X}_{f,t+j}) \\
& \text{s.t.} \\
& A_{f,t+1} = (1+r)(A_{f,t} + E_{f,t} + N_{f,t} - X_{f,t}).
\end{aligned} \tag{1}$$

The expenditure vector  $\mathcal{X}_{f,t}$  includes own consumption and transfers to the offspring, while  $X_{f,t}$  in the budget equation is total expenditure from adding the components of  $\mathcal{X}_{f,t}$ .  $\mathcal{U}(\cdot)$  is the utility from the expenditure vector;  $A_{f,t}$  is assets at the start of the period;  $E_{f,t}$  is the male household head's labour earnings;  $N_{f,t}$  is other household income defined as a sum of spousal earnings and total transfer income received by the husband and wife;  $\beta$  is the discount factor and  $r$  is the real interest rate.

Transfers to the offspring can be either in the form of education and other human capital investments when the young offspring is living with the parents, or in the form of inter-vivos and bequest transfers when the adult offspring is the head of a separate household. Due to the lack of consistent records of transfers made to offspring in our data, in the baseline specification we measure  $\mathcal{X}_{f,t}$  as the household consumption expenditures  $C_{f,t}$ ; that is,  $\mathcal{U}(\mathcal{X}_{f,t}) = U(C_{f,t})$  and  $X_{f,t} = C_{f,t}$ . As we discuss below, given the availability of expenditure measures for both parents and children, the unobserved transfers made to the offspring are subsumed in estimates of consumption-shifters that vary across families.

Our baseline specification does not impose an explicit motive for parental transfers to children. We also study an extended model where the utility of the household depends on both own consumption  $C_{f,t}$  and transfers made to the offspring  $\mathcal{T}_{f,t}$ ; that is,  $\mathcal{U}(\mathcal{X}_{f,t}) = U(C_{f,t}, \mathcal{T}_{f,t})$  and  $X_{f,t} = C_{f,t} + \mathcal{T}_{f,t}$ , so that parents derive a warm-glow from making transfers to their offspring. We derive an empirical counterpart for this specification in Section 5.3 and show that inference about intergenerational linkages and inequality in the extended model does not change qualitatively relative to the baseline.

**Earnings and Other Income.** We assume the following time-series processes for the income flows of the household. In year  $t$  the parent in family  $f$  has pre-tax log-earnings  $e_{f,t}^p$  consisting of an individual fixed effect  $\bar{e}_f^p$ , a persistent AR(1) innovation,  $\mathcal{E}_{f,t}^p = \alpha_e^p \mathcal{E}_{f,t-1}^p + \epsilon_{f,t}^p$ , and a transitory shock,  $\epsilon_{f,t}^p$ . Similarly, the process for the log of other income,  $n_{f,t}^p$  comprises a fixed effect  $\bar{n}_f^p$ , an AR(1) innovation  $\Theta_{f,t}^p = \alpha_n^p \Theta_{f,t-1}^p + \theta_{f,t}^p$ , and a transitory shock,  $\vartheta_{f,t}^p$ :

$$e_{f,t}^p = \bar{e}_f^p + \mathcal{E}_{f,t}^p + \epsilon_{f,t}^p \tag{2}$$

$$n_{f,t}^p = \bar{n}_f^p + \Theta_{f,t}^p + \vartheta_{f,t}^p \tag{3}$$

The innovations to the AR(1) shocks ( $\varepsilon_{f,t}^p$  and  $\theta_{f,t}^p$ ) and the transitory shocks ( $\varepsilon_{f,t}^p$  and  $\vartheta_{f,t}^p$ ) are mean zero white noise processes with variances  $\sigma_{\varepsilon^p}^2$ ,  $\sigma_{\theta^p}^2$ ,  $\sigma_{\varepsilon^p}^2$  and  $\sigma_{\vartheta^p}^2$ , respectively.

The processes for adult children of the same family  $f$  have similar structure; however, the child fixed effects,  $\bar{e}_f^k$  and  $\bar{n}_f^k$ , depend on parental fixed effects,  $\bar{e}_f^p$  and  $\bar{n}_f^p$ , as well as on idiosyncratic components independent of parents,  $\check{e}_f^k$  and  $\check{n}_f^k$ . Thus, for the children of family  $f$  this structure results in the following income components:

$$e_{f,t}^k = \underbrace{\gamma \bar{e}_f^p + \rho_e \bar{n}_f^p}_{\text{Parental Channel}} + \underbrace{\check{e}_f^k + \mathcal{E}_{f,t}^k + \varepsilon_{f,t}^k}_{\text{Child Idiosyncratic Channel}} \quad (4)$$

$$n_{f,t}^k = \underbrace{\rho \bar{n}_f^p + \gamma_n \bar{e}_f^p}_{\text{Parental Channel}} + \underbrace{\check{n}_f^k + \Theta_{f,t}^k + \vartheta_{f,t}^k}_{\text{Child Idiosyncratic Channel}} \quad (5)$$

We allow for the most general structure of dependence among income processes across generations: alongside a direct channel from parental earnings to child earnings (through  $\gamma$ ) and a direct channel from other income of parents to other income of children (through  $\rho$ ), the specification features cross-effects so that parental earnings can influence other income of children (through  $\gamma_n$ ), and other income of parents can affect earnings of children (through  $\rho_e$ ). The per-period perturbations to the child's income processes are governed by a different set of parameters; namely,  $\alpha_e^k$  and  $\alpha_n^k$  denote the persistence of the child AR(1) components,  $\sigma_{\varepsilon^k}^2$  and  $\sigma_{\theta^k}^2$  are the variances of the innovations to the AR(1) processes, and  $\sigma_{\varepsilon^k}^2$  and  $\sigma_{\vartheta^k}^2$  are the variances of the transitory shocks to child earnings and other income, respectively.

**Consumption.** The optimization problem in (1) yields a simple representation of consumption  $C_{f,t}$  as the annuity value of total lifetime resources. The latter can be derived under the assumption of quadratic utility or from a Taylor approximation of the Euler equation under general concave utility functions like CRRA (see Appendix A for the analytical solution of the optimal consumption path). As the time horizon  $(T - t)$  becomes larger, the approximate log-consumption process for a household of any generation can be represented as,

$$c_{f,t} \approx q_{f,t} + \bar{e}_f + \bar{n}_f + \left( \frac{r}{1 + r - \alpha_e} \right) \mathcal{E}_{f,t} + \left( \frac{r}{1 + r - \alpha_n} \right) \Theta_{f,t} + \left( \frac{r}{1 + r} \right) (\varepsilon_{f,t} + \vartheta_{f,t}).$$

The variable  $q_{f,t}$  is a consumption-shifter subsuming the annuitized value of non-earned resources, e.g., rental income from savings and housing, non-labour part of business income, etc. Like the income processes, we assume  $q_{f,t}^g$  consists of a fixed effect as well as of persistent shock  $\Phi_{f,t}^g$  and transitory shock  $\varphi_{f,t}^g$ . Then  $q_{f,t}^g = \bar{q}_f^g + \Phi_{f,t}^g + \varphi_{f,t}^g$  for any generation  $g \in \{p, k\}$ . The persistent AR(1) component is  $\Phi_{f,t}^g = \alpha_q^g \Phi_{f,t-1}^g + \phi_{f,t}^g$  with the innovation  $\phi_{f,t}^g \stackrel{i.i.d.}{\sim} WN(0, \sigma_{\phi^g}^2)$ ; the transitory shock  $\varphi_{f,t}^g \stackrel{i.i.d.}{\sim} WN(0, \sigma_{\varphi^g}^2)$  for each generation  $g \in \{p, k\}$ .

The term  $q_{f,t}$  also accounts for higher-order preference terms due to precautionary saving motives, if present, that are not reflected in the linear approximation of the Euler equation. Perhaps more importantly, the  $q_{f,t}$  component contains any unobserved outflows like transfers made to children or others, and income and wealth taxes, when pre-tax income measures are used. The omitted components that are subsumed in  $q_{f,t}$  are correlated with the income of the household: for example, transfers to children must be correlated with parental earnings. In estimation we acknowledge this possible co-movement by allowing for the individual fixed effect  $\bar{q}_f$  to be correlated with the fixed effects in both earnings ( $\bar{e}_f$ ) and other income of the household ( $\bar{n}_f$ ).

Combining these processes, the log-consumption of a parent can be written as:

$$\begin{aligned} c_{f,t}^p &= \bar{q}_f^p + \bar{e}_f^p + \bar{n}_f^p \\ &+ \Phi_{f,t}^p + \left[ \frac{r}{1+r-\alpha_e^p} \right] \mathcal{E}_{f,t}^p + \left[ \frac{r}{1+r-\alpha_n^p} \right] \Theta_{f,t}^p + \varphi_{f,t}^p + \frac{r}{1+r} (\varepsilon_{f,t}^p + \vartheta_{f,t}^p) \end{aligned} \quad (6)$$

Apart from the family persistence in earnings and other income, we allow for the possibility of a direct channel of parental influence through the consumption-shifter. The individual fixed effect of the child generation comprises an inherited component and a child-specific component,  $\bar{q}_f^k = \lambda \bar{q}_f^p + \check{q}_f^k$ . There are, therefore, three ways in which parents can affect the consumption process of their children: (i) the earnings channel; (ii) the channel operating through other household income; and (iii) inherited consumption shifters. Substituting these intra-family transmission mechanisms into the log-consumption process for children, we obtain:

$$\begin{aligned} c_{f,t}^k &= \underbrace{\lambda \bar{q}_f^p + (\gamma + \gamma_n) \bar{e}_f^p + (\rho + \rho_e) \bar{n}_f^p}_{\text{Parental Channel}} + \underbrace{\check{q}_f^k + \check{e}_f^k + \check{n}_f^k}_{\text{Child Idiosyncratic Permanent Components}} \\ &+ \underbrace{\Phi_{f,t}^k + \left[ \frac{r}{1+r-\alpha_e^k} \right] \mathcal{E}_{f,t}^k + \left[ \frac{r}{1+r-\alpha_n^k} \right] \Theta_{f,t}^k}_{\text{Child Idiosyncratic Persistent Shocks}} + \underbrace{\varphi_{f,t}^k + \frac{r}{1+r} (\varepsilon_{f,t}^k + \vartheta_{f,t}^k)}_{\text{Child Idiosyncratic Transitory Shocks}} \end{aligned} \quad (7)$$

A set of six equations, (2) through (7), describing the earnings, other income and consumption processes for the parent and child generations, summarizes the baseline model of intergenerational dependency. Next, we consider the variances and covariances of these six outcome variables and derive the moment restrictions used to estimate the parameters dictating intergenerational persistence, cross-sectional inequality and the volatilities and persistence of the per-period shocks.<sup>4</sup>

---

<sup>4</sup>We use the following convention for denoting the intergenerational elasticity parameters — the ones without any subscript are the pass-through of the same variable across generations, viz.,  $\gamma$  for head earnings,  $\rho$  for other income and  $\lambda$  for consumption-shifters; while the ones with the subscripts are the cross-elasticities with the subscripts denoting the effect on the corresponding child variable, e.g.,  $\gamma_n$  is the pass-through of parental head earnings to child other income, and so on.

### 3 Identification and Estimation

To mitigate concerns about measurement error, and take full advantage of the cross-sectional variation across parent-child pairs, in the baseline implementation of our model we define the unit of observation as the time-average of each outcome variable at the household level. This implies that all mean-zero shocks, whether persistent or transitory, are averaged out. In Section 6.1 we study an unrestricted specification with full panel variation and use it to gauge the robustness of baseline estimates. In what follows we overview identification results and estimation procedures for the case with time-averaged variables. Details for the richer specification featuring transitory and persistent shock processes are presented in Appendix E.1.

#### 3.1 Identification

Identification proceeds in three steps. First, we use cross-sectional moments for parents to identify variances and covariances among their sources of income and consumption. Second, given these estimates and cross-generational covariances, we recover intergenerational elasticity parameters. Lastly, we employ information from the previous two steps alongside second moments from the cross-section of children outcomes to identify the components of earnings, other income and consumption inequality that are idiosyncratic to the child generation. A graphical illustration of the main identification argument is presented in Appendix B.

**(a) Cross-sectional variation among parents.** Equations (2), (3) and (6) describe parental earnings, other income and consumption. The time-average of those processes can be mapped into the following cross-sectional variances:

$$\text{Var}(\bar{e}_f^p) = \sigma_{\bar{e}^p}^2 \quad (8)$$

$$\text{Var}(\bar{n}_f^p) = \sigma_{\bar{n}^p}^2 \quad (9)$$

$$\text{Var}(\bar{c}_f^p) = \sigma_{\bar{q}^p}^2 + \sigma_{\bar{e}^p}^2 + \sigma_{\bar{n}^p}^2 + 2(\sigma_{\bar{e}^p, \bar{q}^p} + \sigma_{\bar{n}^p, \bar{q}^p} + \sigma_{\bar{e}^p, \bar{n}^p}) \quad (10)$$

Equation (10) highlights how consumption inequality among parents depends not only on the inequality in earnings, other income and consumption-shifters, but also on their covariances. Accounting for the co-dependence between consumption propensities and income turns out to be quantitatively important (see Alan, Browning and Ejrnæs, 2018). To the extent that intra-generational insurance implies that these covariances are negative in aggregate, consumption inequality will be lower than income inequality. To account for co-movement among different income sources and consumption-shifters in the parents' generation, we consider the following relationships:

$$\text{Cov}(\bar{e}_f^p, \bar{n}_f^p) = \sigma_{\bar{e}^p, \bar{n}^p} \quad (11)$$

$$\text{Cov}(\bar{e}_f^p, \bar{c}_f^p) = \sigma_{\bar{e}^p}^2 + \sigma_{\bar{e}^p, \bar{q}^p} + \sigma_{\bar{e}^p, \bar{n}^p} \quad (12)$$

$$\text{Cov}(\bar{n}_f^p, \bar{c}_f^p) = \sigma_{\bar{n}^p}^2 + \sigma_{\bar{n}^p, \bar{q}^p} + \sigma_{\bar{e}^p, \bar{n}^p} \quad (13)$$

Equations (8), (9) and (11) deliver  $\sigma_{\bar{e}^p}^2$ ,  $\sigma_{\bar{n}^p}^2$  and  $\sigma_{\bar{e}^p, \bar{n}^p}$ . Then, the covariances  $\sigma_{\bar{e}^p, \bar{q}^p}$  and  $\sigma_{\bar{n}^p, \bar{q}^p}$  are identified from equations (12) and (13), leaving the dispersion of consumption-shifters,  $\sigma_{\bar{q}^p}^2$ , to be recovered from equation (10).

**(b) Intergenerational persistence.** The intergenerational elasticity parameters  $(\gamma, \rho, \gamma_n, \rho_e, \lambda)$  are identified using within-family covariation. Since parental parameters  $\sigma_{\bar{e}^p}^2$ ,  $\sigma_{\bar{n}^p}^2$  and  $\sigma_{\bar{e}^p, \bar{n}^p}$  have already been recovered using the cross-sectional variation among parents, we use equations (14) and (15) below to jointly identify the intergenerational earnings pass-through parameters  $\gamma$  and  $\rho_e$ .

$$\text{Cov}(\bar{e}_f^p, \bar{e}_f^k) = \gamma \sigma_{\bar{e}^p}^2 + \rho_e \sigma_{\bar{e}^p, \bar{n}^p} \quad (14)$$

$$\text{Cov}(\bar{n}_f^p, \bar{e}_f^k) = \gamma \sigma_{\bar{e}^p, \bar{n}^p} + \rho_e \sigma_{\bar{n}^p}^2 \quad (15)$$

Similarly, the pass-through parameters from parental other income to child other income and earnings,  $\rho$  and  $\gamma_n$  respectively, are identified from equations (16) and (17).

$$\text{Cov}(\bar{n}_f^p, \bar{n}_f^k) = \rho \sigma_{\bar{n}^p}^2 + \gamma_n \sigma_{\bar{e}^p, \bar{n}^p} \quad (16)$$

$$\text{Cov}(\bar{e}_f^p, \bar{n}_f^k) = \rho \sigma_{\bar{e}^p, \bar{n}^p} + \gamma_n \sigma_{\bar{e}^p}^2. \quad (17)$$

Finally, the intra-family persistence of consumption-shifters,  $\lambda$ , is identified from equation (18).

$$\begin{aligned} \text{Cov}(\bar{c}_f^p, \bar{c}_f^k) &= \lambda (\sigma_{\bar{q}^p}^2 + \sigma_{\bar{e}^p, \bar{q}^p} + \sigma_{\bar{n}^p, \bar{q}^p}) + (\gamma + \gamma_n) (\sigma_{\bar{e}^p}^2 + \sigma_{\bar{e}^p, \bar{q}^p} + \sigma_{\bar{e}^p, \bar{n}^p}) \\ &\quad + (\rho + \rho_e) (\sigma_{\bar{n}^p}^2 + \sigma_{\bar{n}^p, \bar{q}^p} + \sigma_{\bar{e}^p, \bar{n}^p}) \end{aligned} \quad (18)$$

Additional cross-generational moments can be used as over-identifying restrictions in the estimation exercise. We present these moments in Appendix B.

**(c) Cross-sectional variation among children.** Identification of the variances and covariances of the idiosyncratic permanent components of offspring follows similar logic as in the parental case. Equations (4), (5) and (7) describe the key income and expenditure processes for children, and can be mapped into the following cross-sectional variances:

$$\text{Var}(\bar{e}_f^k) = \gamma^2 \sigma_{\bar{e}^p}^2 + \rho_e^2 \sigma_{\bar{n}^p}^2 + 2\gamma\rho_e \sigma_{\bar{e}^p, \bar{n}^p} + \sigma_{\bar{e}^k}^2 \quad (19)$$

$$\text{Var}(\bar{n}_f^k) = \rho^2 \sigma_{\bar{n}^p}^2 + \gamma_n^2 \sigma_{\bar{e}^p}^2 + 2\rho\gamma_n \sigma_{\bar{e}^p, \bar{n}^p} + \sigma_{\bar{n}^k}^2 \quad (20)$$

$$\begin{aligned} \text{Var}(\bar{c}_f^k) &= \lambda^2 \sigma_{\bar{q}^p}^2 + (\gamma + \gamma_n)^2 \sigma_{\bar{e}^p}^2 + (\rho + \rho_e)^2 \sigma_{\bar{n}^p}^2 \\ &\quad + 2[(\gamma + \gamma_n) \lambda \sigma_{\bar{e}^p, \bar{q}^p} + (\rho + \rho_e) \lambda \sigma_{\bar{n}^p, \bar{q}^p} + (\rho + \rho_e)(\gamma + \gamma_n) \sigma_{\bar{e}^p, \bar{n}^p}] \\ &\quad + \sigma_{\bar{e}^k}^2 + \sigma_{\bar{n}^k}^2 + \sigma_{\bar{q}^k}^2 + 2[\sigma_{\bar{e}^k, \bar{n}^k} + \sigma_{\bar{e}^k, \bar{q}^k} + \sigma_{\bar{n}^k, \bar{q}^k}] \end{aligned} \quad (21)$$

To account for covariation among the two income channels and consumption-shifters, we consider the following moment conditions in the children's generation:

$$\text{Cov}(\bar{e}_f^k, \bar{n}_f^k) = (\rho\gamma + \rho_e\gamma_n) \sigma_{\bar{e}^p, \bar{n}^p} + \gamma\gamma_n \sigma_{\bar{e}^p}^2 + \rho\rho_e \sigma_{\bar{n}^p}^2 + \sigma_{\bar{e}^k, \bar{n}^k} \quad (22)$$

$$\begin{aligned} \text{Cov}(\bar{e}_f^k, \bar{c}_f^k) &= \gamma(\gamma + \gamma_n) \sigma_{\bar{e}^p}^2 + \rho_e(\rho_e + \rho) \sigma_{\bar{n}^p}^2 + \lambda\gamma \sigma_{\bar{e}^p, \bar{q}^p} + \lambda\rho_e \sigma_{\bar{n}^p, \bar{q}^p} \\ &\quad + [\gamma(\rho + \rho_e) + \rho_e(\gamma + \gamma_n)] \sigma_{\bar{e}^p, \bar{n}^p} + \sigma_{\bar{e}^k}^2 + \sigma_{\bar{e}^k, \bar{q}^k} + \sigma_{\bar{e}^k, \bar{n}^k} \end{aligned} \quad (23)$$

$$\begin{aligned} \text{Cov}(\bar{n}_f^k, \bar{c}_f^k) &= \gamma_n(\gamma + \gamma_n) \sigma_{\bar{e}^p}^2 + \rho(\rho_e + \rho) \sigma_{\bar{n}^p}^2 + \lambda\gamma_n \sigma_{\bar{e}^p, \bar{q}^p} + \lambda\rho \sigma_{\bar{n}^p, \bar{q}^p} \\ &\quad + [\gamma_n(\rho + \rho_e) + \rho(\gamma + \gamma_n)] \sigma_{\bar{e}^p, \bar{n}^p} + \sigma_{\bar{n}^k}^2 + \sigma_{\bar{e}^k, \bar{n}^k} + \sigma_{\bar{n}^k, \bar{q}^k} \end{aligned} \quad (24)$$

The moments of the idiosyncratic permanent components of earnings and other income for children ( $\sigma_{\bar{e}^k}^2$ ,  $\sigma_{\bar{n}^k}^2$ ,  $\sigma_{\bar{e}^k, \bar{n}^k}$ ) are directly identified from (19), (20) and (22). It then follows that the covariances of the child idiosyncratic consumption-shifters with earnings and other income,  $\sigma_{\bar{e}^k, \bar{q}^k}$  and  $\sigma_{\bar{n}^k, \bar{q}^k}$ , are identified from equations (23) and (24), which leaves equation (21) to identify  $\sigma_{\bar{q}^k}^2$ .

### 3.2 Decomposition of Inequality in Child Generation

Earnings inequality among children responds to: (i) the dispersion of earnings ( $\sigma_{\bar{e}^p}^2$ ) and other income ( $\sigma_{\bar{n}^p}^2$ ) among parents, (ii) the covariance between the two parental income channels,  $\sigma_{\bar{e}^p, \bar{n}^p}$ , (iii) the intensity of the intergenerational pass-through parameters,  $\gamma$  and  $\rho_e$ , and (iv) the variance of the permanent component of child earnings that is independent of parents,  $\sigma_{\bar{e}^k}^2$ . The first three effects account for the impact of parental characteristics on the earnings heterogeneity among children; that is,  $\text{Var}[\bar{e}^k(p)] = \gamma^2 \sigma_{\bar{e}^p}^2 + \rho_e^2 \sigma_{\bar{n}^p}^2 + 2\gamma\rho_e \sigma_{\bar{e}^p, \bar{n}^p}$ . This illustrates that the pass-through parameters, which are often the main focus of the applied literature on intergenerational mobility, are not sufficient on their own to determine parental influences on inequality in subsequent generations.

A similar argument holds for inequality in other income, where the variation contributed by parental outcome variables is  $\text{Var}[\bar{n}^k(p)] = \rho^2 \sigma_{\bar{n}^p}^2 + \gamma_n^2 \sigma_{\bar{e}^p}^2 + 2\rho\gamma_n \sigma_{\bar{e}^p, \bar{n}^p}$ .

For expenditures, the first two rows of equation (21) describe how family heterogeneity drives

dispersion in the offspring generation,  $\text{Var} [\bar{c}^k(p)]$ , while the third row captures the drivers of inequality among children that are independent of parents.

Our model suggests two competing mechanisms affecting consumption inequality — first, a dampening effect whereby the negative covariation between consumption-shifters and income compresses the cross-sectional variance of household expenditures (see [Blundell, Pistaferri and Preston, 2008](#); [Kaplan and Violante, 2010](#)), and second, an intra-family smoothing mechanism, whereby parents attempt to equalize marginal utilities of family members across generations and in effect inflate inequality in the younger generation. We find empirical support for both mechanisms in our results in [Section 4](#).

### 3.3 Estimation

Model parameters are estimated using a generalized method of moments that minimizes the sum of squared deviations between empirical and theoretical second moments. We use an equally weighted distance metric because of the small sample bias associated with using a full variance-covariance matrix featuring higher-order moments (see [Altonji and Segal, 1996](#)). We begin by projecting the logarithm of each outcome variable,  $x_{f,t} \in \{e_{f,t}, n_{f,t}, c_{f,t}\}$  on a full set of year and cohort dummies to account for time and birth effects. The estimated residuals, denoted as  $\hat{x}_{f,t}^{(1)}$ , are referred to as our baseline outcome measures. Next, we regress the baseline outcomes  $\hat{x}_{f,t}^{(1)}$  on a set of observables  $z_{ft}$ ,<sup>5</sup> and denote the fitted values from this step as  $\hat{x}_{f,t}^{(2)}$ . With these in hand, we are able to employ the GMM estimator to recover parameter estimates using either baseline variation,  $\hat{x}_{f,t}^{(1)}$  or fitted variation through observables,  $\hat{x}_{f,t}^{(2)}$ . Comparing different estimates of structural parameters is informative to establish the extent to which the transmission of inequality across generations occurs along observable and unobservable dimensions of heterogeneity.

### 3.4 Data

We use data from the Panel Study of Income Dynamics (PSID). This dataset is often used in the analysis of intergenerational persistence of economic outcomes because the offspring of original sample members become part of the survey sample when they establish separate households. We focus on the nationally representative sample of the PSID (from the Survey Research Centre, SRC) between 1967 and 2014, and exclude samples from the Survey of Economic Opportunity (SEO), immigrant and Latino sub-populations. Our focus on father-son pairs avoids some sample issues associated with the structure of the PSID (see [Hryshko and Manovskii, 2019](#)). For each generation, we only consider income and expenditures between ages 25 and 65 years, to avoid confounding

---

<sup>5</sup>The set of observables  $z_{ft}$  includes dummies for family size, number of children, state of residence, employment status, race and education.

effects related to retirement and unstable teen employment. We also restrict the sample to families with positive head labour earnings, total family income, that work no more than 5,840 hours in a year, and with wages at least half of the federal minimum wage. We select out households that experience annual earnings growth of more than 400% or less than -200%. To reduce noise due to weak labour market attachment and variation in marital status, we sample households with a male head and at least 5 years of observations, possibly non-continuous, when they were married.<sup>6</sup> These restrictions deliver 761 unique father-son pairs for our baseline analysis, although we present results for a variety of alternative restrictions that deliver both larger and smaller sample sizes. Details about data and sampling are in Appendix B.2.

Labour earnings data for the male household head and his wife are readily available for all survey waves of the PSID. Data on transfers from public and private sources for husband and wife are also available for most years since 1969. In contrast, consumption expenditure measures are not consistently available through a single set of variables in the PSID. Expenditure on food is the only category that is observed almost continuously since 1967, and we use food outlays as the consumption measure for the baseline estimation. In Section 6, we examine the robustness of our findings to an alternative consumption measure, suggested by Attanasio and Pistaferri (2014), that relies on 11 major categories of consumption outlays that are reported since 1999. This approach relies on a demand system estimated on food and non-food expenditures and their relative prices, along with household-level demographic and socioeconomic variables, for the period after 1999; by inverting the demand system, one can recover the non-food outlays for the years before 1999. Details about the variables, their availability in the survey and the demand system estimation are in Appendix B.3. We adjust household-level expenditures using the OECD adult equivalence scale.

## 4 Results

### 4.1 Cross-Sectional Variances

Table 1 reports the cross-sectional variances of head earnings, other income and food expenditures for parents and their adult children. These baseline moments are purged of year and cohort effects. The two lifetime-income sources are more dispersed than expenditures in both generations, indicating the presence of cross-sectional consumption smoothing mechanisms. This may occur through taxes and transfers by the government as well as through heterogeneity in saving behaviour of households.

Other income, comprising of wife’s labour earnings and the transfer income of the couple, is

---

<sup>6</sup>The restriction is helpful but not inconsequential, as intergenerational insurance may come into play exactly at the time of relationship breakdown (see Fisher and Low, 2015). In Section 6 we study samples that include observations with household heads of all marital status, but this does not alter our baseline findings.

much more dispersed than head earnings, and this is mainly driven by the excess heterogeneity in the couple’s transfer income (see Table 8). The relative magnitudes of earnings and consumption dispersion reported in Table 1 are consistent with those found in studies by Krueger and Perri (2006) and Attanasio and Pistaferri (2014).<sup>7</sup> These variances, along with the covariances amongst the outcome variables, are used to estimate the parameters of the model. Figure 4 of Appendix C summarizes the within-sample fit of the baseline specification for every moment used in estimation.

Table 1: Cross-Sectional Variances

Variable	Parent	Child
Head Earnings	0.291	0.249
Other Income	0.807	0.535
Consumption	0.097	0.114
<i>No. of Parent-Child Pairs</i>	761	761

The age range used to calculate variances is wider for parents than it is for children since parents are observed for a longer period in PSID data. Therefore, differences in their magnitudes, as shown in Table 1, do not imply a decline in income inequality across generations. Rather, these differences reflect shocks accruing at different stages of the life-cycle. Since we do not observe children in the later part of their working lives, our estimates reflect how parental heterogeneity impacts dispersion among children in the earlier decades of their adult lives.<sup>8</sup> Later on, in Section 4.5 we report variances based on samples where the ages of both parents and children are restricted between 30 and 40 years. These latter variances illustrate the evolution of inequality across generations, showing a relative increase in inequality among children that is consistent with the well-established notion of increasing income inequality for the U.S. over the past decades. The age restriction, however, substantially reduces sample size and in the baseline analysis, we use the wider age range for parents in order to obtain more accurate estimates of parental permanent income.

## 4.2 Baseline Estimates

**Intergenerational elasticities.** Table 2 reports estimates of intergenerational persistence parameters. For the baseline estimates in column (1), where the outcome variables are free of year

<sup>7</sup>Figure 3 in Appendix B shows the evolution of cross-sectional earnings and consumption inequality in our sample over the last four decades.

<sup>8</sup>Life-cycle shocks in later phases of adult life would arguably imply even stronger idiosyncratic dispersion among children. Grawe (2006) and Gouskova, Chiteji and Stafford (2010) show that life-cycle bias is important when estimating intergenerational persistence.

and birth-cohort effects, the elasticity is highest for head earnings, with the pass-through  $\gamma$  estimated at 0.23. The elasticity for other income  $\rho$  is 0.10 and that for consumption-shifters  $\lambda$  is 0.15. The significant pass-through in consumption-shifters is evidence of direct persistence in expenditure and saving propensities across generations. The latter contributes to consumption inequality over and above the income channels.

Table 2: Estimates of Intergenerational Elasticity

Variables	Parameters	Baseline	Observable
		(1)	(2)
Head Earnings	$\gamma$	0.229 (0.028)	0.338 (0.025)
Other Income	$\rho$	0.099 (0.027)	0.248 (0.042)
$\bar{e}_f^p$ on $\bar{n}_f^k$	$\gamma_n$	0.208 (0.035)	0.258 (0.026)
$\bar{n}_f^p$ on $\bar{e}_f^k$	$\rho_e$	0.055 (0.019)	0.112 (0.028)
Consumption Shifters	$\lambda$	0.153 (0.037)	0.452 (0.045)
<i>No. of Parent-Child Pairs</i>	<i>N</i>	761	761

**Note:** Bootstrap standard errors (100 repetitions) in parentheses. *Baseline* refers to data that is purged of year and birth cohort effects,  $\hat{y}_{f,t}^{(1)}$ . These data are then regressed on various controls (viz., dummies for family size, state of residence, number of children, employment status, race and education). *Observable* refers to the fitted values from this regression,  $\hat{y}_{f,t}^{(2)}$ . The average age for parents in the sample is 47 years; that of children is 37 years.

Higher parental earnings are associated with higher levels of other income among offspring, with the cross-elasticity  $\gamma_n$  equal to 0.21. Other household income has a smaller effect on children's earnings, with the elasticity  $\rho_e$  estimated to be less than half that of  $\gamma_n$ , albeit statistically significant. We show in Section 6.4 that ignoring these cross-effects may lead to misleading inference about the role of family influences on cross-sectional inequality in the children's generation.

Column (2) in Table 2 reports estimates of pass-through parameters based only on the predicted components of the outcome variables; that is, they provide a measure of the persistence in parent-child variation that is explained by observable characteristics. The predicted components of

earnings, other income and consumption exhibit higher persistence across generations; in Appendix C we show that, among the observable characteristics, education accounts for a large share of the pass-through in predicted earnings. The latter observation corroborates evidence from previous studies (see for example, Eshaghnia et al., 2021; Landersø and Heckman, 2017; Lefgren, Sims and Lindquist, 2012).

**Permanent income and consumption.** All estimates of variances and covariances for the permanent components of earnings, other income and consumption are reported in Table 3. The importance of jointly estimating income and consumption processes becomes apparent when examining these estimates. The negative covariation between the permanent component of the consumption-shifter, on the one hand, and the two sources of income, on the other, mitigates the impact of income inequality on consumption inequality; that is, the negative covariances compress the distribution of log consumption and drive its overall variance below the variance of log income. The estimates also suggest that higher-income families save proportionally more, and have a lower average propensity to consume out of available resources.<sup>9</sup> Such traits are passed across generations and further mitigate consumption dispersion.

The negative covariation between household consumption-shifters and income sources is better understood in the context of the consumption representation derived in Section 2. The expenditure processes of parents and children in equations (6) and (7) imply one-to-one consumption responses to permanent components embodied in the income fixed effects. Lifetime consumption is also allowed to deviate in response to differences in permanent consumption-shifters  $q_{f,t}$ , which subsume savings and unobserved out-transfers. It follows that the negative covariation between consumption-shifters and income sources captures the lower consumption propensity of higher-income families, thus providing a mechanism to reconcile the model with the cross-sectional observation that consumption is less dispersed than income.

### 4.3 Parental Heterogeneity and the Distribution of Child Outcomes

The quantitative importance of parental heterogeneity for inequality in the next generation depends on three aspects: (i) the level of inequality in the parents' generation, (ii) intergenerational persistence, and (iii) the magnitude of idiosyncratic heterogeneity among kids. We gauge the influence of parental factors in two ways: first, we compute the share of earnings, other income and consumption variances that can be explained through pre-determined parental heterogeneity; second, we show how the cross-sectional distributions of these outcomes change if differences in parental

---

<sup>9</sup>See Straub (2018) and Abbott and Gallipoli (2022) for evidence of high saving rates among the rich over the same sample period. Fan (2006) suggests that this may be motivated by bequest motives. De Nardi, French and Jones (2016) argue that other motives, like healthcare expenditure, may account for the excess savings.

Table 3: Estimates of Variances and Covariances of Fixed Effects

	Parameters	Baseline (1)	Observable (2)
<b><u>Parental Variances</u></b>			
Permanent Head Earnings	$\sigma_{\bar{e}^p}^2$	0.296 (0.020)	0.095 (0.005)
Permanent Other Income	$\sigma_{\bar{n}^p}^2$	0.805 (0.058)	0.084 (0.009)
Permanent Consumption Shifters	$\sigma_{\bar{q}^p}^2$	1.027 (0.064)	0.196 (0.018)
<b><u>Child Idiosyncratic Variances</u></b>			
Permanent Head Earnings	$\sigma_{\bar{e}^k}^2$	0.229 (0.014)	0.041 (0.002)
Permanent Other Income	$\sigma_{\bar{n}^k}^2$	0.511 (0.041)	0.062 (0.004)
Permanent Consumption Shifters	$\sigma_{\bar{q}^k}^2$	0.733 (0.058)	0.105 (0.007)
<b><u>Parental Covariances</u></b>			
Consumption Shifters & Head Earnings	$\sigma_{\bar{e}^p, \bar{q}^p}$	-0.270 (0.026)	-0.120 (0.009)
Consumption Shifters & Other Income	$\sigma_{\bar{n}^p, \bar{q}^p}$	-0.816 (0.060)	-0.115 (0.013)
Head Earnings and Other Income	$\sigma_{\bar{e}^p, \bar{n}^p}$	0.069 (0.017)	0.059 (0.006)
<b><u>Child Idiosyncratic Covariances</u></b>			
Consumption Shifters & Head Earnings	$\sigma_{\bar{e}^k, \bar{q}^k}$	-0.250 (0.024)	-0.058 (0.003)
Consumption Shifters & Other Income	$\sigma_{\bar{n}^k, \bar{q}^k}$	-0.523 (0.046)	-0.069 (0.005)
Head Earnings & Other Income	$\sigma_{\bar{e}^k, \bar{n}^k}$	0.076 (0.017)	0.031 (0.003)
<i>No. of Parent-Child Pairs</i>	<i>N</i>	761	761

**Note:** See note to Table 2.

characteristics are removed.

**Variance Accounting.** Table 4 summarizes the impacts of parental heterogeneity on the variances of children outcomes. Column (1) shows the total cross-sectional variance in each of the children’s outcome variables. In column (2) we report the proportional contribution of parental variables to the dispersion in column (1). Finally, column (3) shows the magnitude of parental contributions when we restrict attention to intergenerational linkages operating through the predicted component of each outcome variable; thus, column (3) shows the proportional parental contribution when considering only the outcomes’ variation predicted through the observable characteristics of each parent-child pair.

Table 4: Percentage of Child Variance Explained by Parental Outcomes

Variables	Child Variance (1)	Parental Role Total	Parental Role via Observables
		(2)	(3)
Head Earnings	0.249	7.9% [3.5%, 12.4%]	6.6% [4.7%, 8.5%]
Other Income	0.535	4.4% [1.4%, 7.4%]	3.6% [2.0%, 5.1%]
Consumption	0.114	30.1% [19.7%, 40.5%]	7.0% [5.1%, 9.0%]

**Note:** Numbers in columns (2) and (3) represent the fraction of total cross-section variance in the child outcome variable in column (1) that is explained by parents. Results in columns (2) and (3) are obtained using estimates from columns (1) and (2) respectively of Tables 2 and 3. Numbers in parentheses are 95% confidence intervals.

To compute these alternative measures, we follow the notation of Section 3.2 and, for each outcome  $x \in \{e, n, c\}$ , we let  $\text{Var}[\bar{x}^k(p)]$  be the variance in the children’s generation that is explained by parental variables while  $\text{Var}(\bar{x}^k)$  denotes the overall cross-sectional variance in the children’s generation. The variance  $\text{Var}[\bar{x}^k(p)]$  can be computed for either our baseline measures of children outcomes or for their fitted values based on observables. We therefore compute two alternative measures of  $\text{Var}[\bar{x}^k(p)]$  using parameter estimates from either column (1) or column (2) of Tables 2 and 3. We denote these measures as  $\text{Var}[\bar{x}^k(p)]_{base}$  and  $\text{Var}[\bar{x}^k(p)]_{observ}$ , respectively.

The baseline measure  $\frac{\text{Var}[\bar{x}^k(p)]_{base}}{\text{Var}(\bar{x}^k)}$  reported in column (2) of Table 4 quantifies the impact of parental factors operating through both observable and unobservable characteristics. On the other hand, the ratio  $\frac{\text{Var}[\bar{x}^k(p)]_{observ}}{\text{Var}(\bar{x}^k)}$ , shown in column (3) of Table 4, measures the share of the variance in the child generation that can be accounted for by observed characteristics of the family.

The largest influence of parental heterogeneity is on consumption dispersion, where it accounts for about 30% of inequality in the children generation. Family factors account for less of the variation in income: respectively, 8% and 4% for head earnings and other income. This suggests that the intergenerational transmission of consumption behaviour, through the elasticity  $\lambda$ , remains a central channel of intra-family persistence even after controlling for income linkages.

A caveat is in order. The finding that roughly 8% of permanent earnings inequality can be explained through family influences does not imply that permanent heterogeneity is less important than other factors for life-cycle outcomes; rather, while our measures quantify the impact of family factors on permanent heterogeneity, the latter still accounts for much of the overall income dispersion. Evidence in Daruich and Kozlowski (2020) shows that, while over 50% of total life-cycle variance in earnings is explained by differences in permanent heterogeneity,<sup>10</sup> removing the correlation between parental and child outcomes would lower earnings inequality by about 7%, a value close to our estimate. The imperfect pass-through of family traits across generations does not imply that permanent income (whether family-related or not) is any less important for inequality. Of course, parental influences can operate through other channels beyond those we explicitly consider.<sup>11</sup> Nonetheless, our estimates of parental impacts on income inequality turn out to be comparable to studies based on alternative approaches. For example, Hufe, Kanbur and Peichl (2021) find that ‘unfair’ inequality in disposable income in the U.S. hovered between 15% and 25% of total inequality for the last five decades, and about half of that is attributable to the education and occupation of parents. In other words, intergenerational concerns can explain about 10% of the total disposable income inequality in their framework.

**The relation between income and consumption persistence.** The value of studying the *joint* evolution of income and consumption becomes apparent when we consider parental impacts on inequality. If we looked at the consumption process in isolation, the 30% parental contribution to inequality would imply an intergenerational elasticity of roughly 0.55, provided consumption inequality is roughly equal in the two generations. Since estimates of the intergenerational consumption elasticity are generally half the required size (see Table 14 in Appendix A), it follows that strong family influences on the inequality of expenditures among the young can only be reconciled through concurring income changes regulated by the variances and covariances of unobserved factors, as shown in equation (21).

The latter observation is especially relevant when we consider the ‘excess inequality’ attributed to observed family characteristics. About 80% of the parental contribution to income and earnings heterogeneity of children occurs through variation in observables; in contrast, heterogeneity

<sup>10</sup>An estimate consistent with findings in Keane and Wolpin (1997); Huggett, Ventura and Yaron (2011).

<sup>11</sup>For a recent example, see Seror (2022) who study the role of parental affection and parent-child interactions in the formation of non-cognitive skills during child development.

A: This sentence is problematic because we know larger  $\lambda$  leads to lower parental influence in consumption inequality due to the negative covariances. We should remove it

A: We can probably think of a better name for this paragraph

A: I have changed this sentence.

through observables account for just 23% of the parental influence in consumption inequality. The discrepancy suggests that, while parental effects have a larger influence on consumption inequality, this enhanced role operates through unobserved characteristics of the family. A lesson from these exercises is that restricting the analysis to either income or consumption alone, and to related observable characteristics, would not necessarily deliver an accurate description of their persistence across generations.

A: I have changed this sentence.

Our findings also draw attention to a subtle distinction between consumption smoothing across generations of a family and consumption differences in the cross-section of families in a given generation. Cross-sectional consumption insurance relies on as a set of formal and informal transfers that dampen the dispersion of household expenditures at a point in time. However, within-family insurance has an often overlooked effect because richer parents, who engage in explicit or in-kind transfers to equalize marginal utilities across generations, can bring about lasting effects on the cross-sectional dispersion of expenditures in the child generation. These effects can be measured once we separately quantify the persistent and idiosyncratic components of permanent income and consumption and we discuss them in the following section in the context of cross-sectional insurance and consumption inequality.

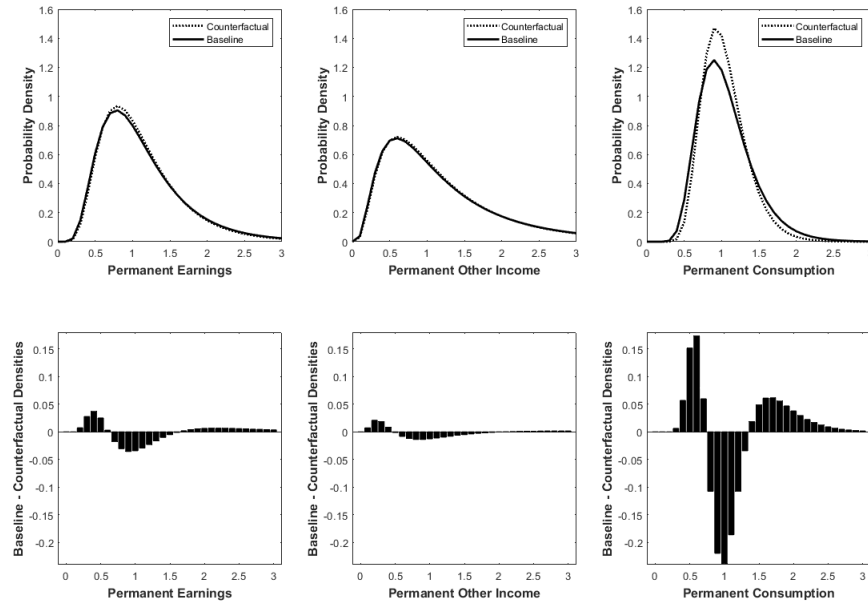


Figure 1: Baseline versus Counterfactual Probability Density Functions

**Note:** Counterfactual refers to the case where all the parental channels have been switched off in the baseline specification. Top panels report density functions. Bottom panels report histograms of changes in local probability mass (the probability mass of the actual distribution minus the corresponding mass of the counterfactual). Outcome variables are net of year and cohort effects.

**Counterfactual Cross-Sectional Distributions.** To visually gauge the excess inequality in the children’s outcomes that our estimates attribute to family background, we plot in Figure 1 the observed cross-sectional distribution of each outcome in the children’s generation and compare it to a counterfactual distribution in the absence of any pass-through from parents. The top panel plots these two distributions, while the bottom panel plots the histogram of frequency differences between the actual and counterfactual distributions.<sup>12</sup> While parental influences appear to increase the spread among families in the tails of the distribution for each outcome variable, the plots also confirms the larger impact of family background on consumption, as opposed to income, inequality in the younger generation.

#### 4.4 Consumption Inequality in the Family and in the Cross-Section

We distinguish between cross-sectional consumption insurance, achieved through formal and informal transfers, and intra-family consumption insurance due to parental influences. These mechanisms induce consumption smoothing in the cross-section and across generations, and our model can be used to assess their empirical importance. To this purpose we quantify the evolution of the cross-sectional dispersion of consumption as opposed to the variance of difference in consumption for two consecutive generations within the same family. We emphasize that intergenerational insurance contributes in subtle ways to cross-sectional consumption inequality: on the one hand it might increase differences between offspring of different families, on the other it closes the within-family gap in consumption. To make this distinction transparent, we recast the lifetime income and consumption of parent and child in a stylized form that highlights alternative types of insurance.

**Changes in cross-sectional consumption inequality.** We begin by expressing lifetime average income ( $\bar{y}$ ) and consumption ( $\bar{c}$ ) of child  $k$  in family  $f$  as a function of those of the parent  $p$  and of an idiosyncratic income component  $\check{y}_f^k$ ,

$$\bar{y}_f^k = \beta_y \bar{y}_f^p + \check{y}_f^k \quad (25)$$

$$\bar{c}_f^k = \bar{c}_f^p + \mu_{GEN} \times \check{y}_f^k \quad (26)$$

where  $\beta_y$  is the intergenerational elasticity of lifetime income, and  $\mu_{CS}$  is the pass-through from the idiosyncratic income  $\check{y}_f^k$  to consumption of the young. Taking parental effects  $\bar{y}_f^p$  and  $\bar{c}_f^p$  as given, we can compute the cross-sectional variance on both sides of (26) to identify  $\mu_{GEN}$  as  $\left[ \frac{\text{Var}(\bar{c}_f^k) - \text{Var}(\bar{c}_f^p)}{\text{Var}(\check{y}_f^k)} \right]^{0.5}$ , which quantifies the overall impact of idiosyncratic income  $\check{y}_f^k$  on the evolution of cross-sectional consumption inequality between two consecutive generations. In the case of

<sup>12</sup>To simulate the distributions, we assume lognormality of the outcome variables and use the parameter estimates in column (1) of Tables 2 and 3. Appendix C.3 provides details about the procedure.

A: Don't we want Insurance in the title?

full pass-through of idiosyncratic income shocks at  $\mu_{GEN} = 1$ , changes in consumption inequality across generations tracks the dispersion of idiosyncratic deviations in full; at the opposite extreme, for  $\mu_{GEN} = 0$ , consumption inequality does not respond at all to the dispersion of idiosyncratic income component. Therefore,  $\mu_{GEN}$  provides a simple gauge of the effects of both formal factors (like government taxes and transfers)<sup>13</sup> and family factors (direct and indirect) on changes in consumption inequality across generations.

**Within-family consumption dispersion.** An different metric for consumption insurance across generations can be obtained by explicitly considering within-family consumption deviations. This requires a change in the way we write and interpret (26). Specifically, one can re-arrange that equation as follows:

$$\bar{c}_f^k - \bar{c}_f^p = \mu_{FAM} \times \check{y}_f^k \quad (27)$$

where the consumption difference in  $(\bar{c}_f^k - \bar{c}_f^p)$  is defined at the level of the family. Taking the variance on both sides of (27), we get the within-family pass-through parameter  $\mu_{FAM} = \left[ \frac{\text{Var}(\bar{c}_f^k - \bar{c}_f^p)}{\text{Var}(\check{y}_f^k)} \right]^{0.5}$ , which quantifies the extent to which the dispersion of consumption deviations between generations of the same family tracks the dispersion of idiosyncratic income shocks in the younger generation.

Expressing the consumption relation as in (27) results in a different unit of observation and therefore delivers an alternative measure of consumption insurance than that from (26). Specifically, equation (27) focuses on intra-family smoothing by restricting the unit of observation on the left-hand side to parent-child consumption deviations. In contrast, the original representation in (26) does not measure the dispersion of within-family consumption deviations but rather focuses on changes in the broad dispersion of lifetime consumption across two generations. In equation (26) there is no explicit notion of family so that the resulting measure can be interpreted as the change in overall consumption inequality across generations, whether or not that change is due to intra-family deviations.

**Estimates of consumption insurance.** It is straightforward to see that  $\mu_{FAM}$  is decreasing in  $\text{Cov}(\bar{c}_f^p, \bar{c}_f^k)$ , while  $\mu_{GEN}$  is invariant to the parent-child consumption covariance. This brings forth the key difference between the two metrics: while  $\mu_{FAM}$  quantifies the cross-sectional heterogeneity of the consumption differences between two generations of the same family,  $\mu_{GEN}$  measures

---

<sup>13</sup>Government taxes and transfers provide various types of insurance, e.g., consumption smoothing over the life-cycle (e.g., fully funded pension scheme and unemployment insurance), consumption smoothing across generations (e.g., pay-as-you-go pension scheme), and reducing cross-sectional resource inequality at a point in time. Of these, the channel of intertemporal insurance over an individual's life-cycle cannot be identified when one considers lifetime averages of income and consumption. We will identify these inter-temporal insurance channels in Section 6.2 using time-variation in income and consumption of individuals within each generation. In this Section, we focus on insurance in lifetime average consumption against permanent shocks to lifetime average income.

the evolution of cross-sectional consumption inequality over two generations without restricting attention to pairwise family linkages. The family linkages do affect cross-sectional inequality across generations but, unlike in the  $\mu_{FAM}$  metric, their contribution is conflated with other influences that shape the evolution of cross-sectional consumption.

In Appendix C.4 we show that as long as the intergenerational elasticity of consumption does not exceed unity, a condition that is met in data, the within-family pass-through  $\mu_{FAM}$  cannot be smaller than the value of the total cross-sectional pass-through  $\mu_{GEN}$ , since the latter reflects the inverse of both family and other sources of insurance at any point in time. This result once again corroborates that within-family insurance is a subset of total cross-sectional insurance.

To estimate empirical counterparts of the insurance metrics described, we note that the only part of the metrics that is not directly measurable from data is the variance of the idiosyncratic shock to income in the children’s generation,  $\text{Var}(\check{y}_f^k)$ . One can estimate it as the variance of the fitted residuals from the OLS regression of  $\bar{y}_f^k$  on  $\bar{y}_f^p$ , summarized in equation (25), or use estimates from a broader model like those presented in Table 3.

Table 5: Measures of Consumption Insurance

Pass-through of Income Shock	Alternative Measures of Income, $y$	
	Head Earnings	Total Family Income
	(1)	(2)
$\mu_{GEN} = \left[ \frac{\text{Var}(\bar{c}_f^k) - \text{Var}(\bar{c}_f^p)}{\text{Var}(\check{y}_f^k)} \right]^{0.5}$	0.28	0.33
$\mu_{FAM} = \left[ \frac{\text{Var}(\bar{c}_f^k - \bar{c}_f^p)}{\text{Var}(\check{y}_f^k)} \right]^{0.5}$	0.78	0.93

**Note:** All columns use pre-tax measures of lifetime average income and food consumption after controlling for year and cohort effects for 761 parent-child pairs in the baseline sample. In column (1),  $\text{Var}(\check{y}_f^k)$  is taken to be the estimate of  $\sigma_{\epsilon^k}^2$  in column (1) of Table 3, while in column (2) it is calculated as the variance of the fitted residuals from the OLS regression of  $\bar{y}_f^k$  on  $\bar{y}_f^p$  for total family income.

Table 6 shows estimates of each of the two insurance metrics,  $\mu_{GEN}$  and  $\mu_{FAM}$  using alternative measures of income,  $y$ . We consider head’s earnings as well as a broad measure total family income provided in the survey. For both these income measures, we find that within-family consumption insurance against idiosyncratic income shocks is much smaller in comparison with the total cross-sectional insurance. In fact, consumption insurance provided by parents is negligible against total family income as the pass-through parameters are close to unity. Consumption smoothing within family is a bit stronger when we consider head’s earnings alone. This is not unexpected since parents can more easily influence the lifetime average earnings of their adult children than the total income

of their household. While parent-child earning persistence is boosted through direct and indirect investments occurring over the life of the offspring, idiosyncratic income variation due to partner choice or other income shocks is more likely to induce consumption deviations within parent-child pairs that are less likely to be insured. It is therefore reasonable to find that the within-family component of consumption smoothing is less prominent when we use broader measures of family income.

Our framework of estimating consumption insurance against shocks to individual fixed effects in income is complementary to the broader literature on consumption insurance that typically estimates partial insurance against permanent shocks to a random walk income process. For example, [Blundell, Pistaferri and Preston \(2008\)](#) find a pass-through of 0.22 and 0.31 from permanent shocks to male earnings and total family earnings respectively to non-durable consumption. Despite the difference in methodology, these figures are comparable to our cross-sectional pass-through,  $\mu_{GEN}$  of 0.28 and 0.33 from shocks to individual fixed effects of male earnings and total family income respectively to food consumption. Moreover, [Blundell, Pistaferri and Preston \(2008\)](#) also find that the impact of measured help from friends and relatives is negligible on the total insurance achieved by households. This is in line with our finding of within-family pass-through of income shocks,  $\mu_{FAM}$  being close to one.

Table 6: Heterogeneity of Measures of Consumption Insurance by Parental Attributes

Pass-through of Income Shock	Alternative Measures of Income, $y$															
	Head Earnings by Parental Attributes								Total Family Income by Parental Attributes							
	Q-1	Q-2	Q-3	Q-4	Below Median	Above Median	No College	Some College	Q-1	Q-2	Q-3	Q-4	Below Median	Above Median	No College	Some College
$\mu_{GEN} = \left[ \frac{\text{Var}(e_t^y) - \text{Var}(e_t^y)}{\text{Var}(y_t^y)} \right]^{0.5}$	0.16	0.58	0.41	0.28	0.38	0.31	0.31	0.30	0.21	0.60	0.53	0.39	0.40	0.41	0.35	0.35
$\mu_{FAM} = \left[ \frac{\text{Var}(e_t^y - e_t^y)}{\text{Var}(y_t^y)} \right]^{0.5}$	0.91	0.84	0.77	0.74	0.89	0.75	0.88	0.77	1.01	1.05	0.84	0.82	1.03	0.84	1.00	0.88
<i>No. of Parent-Child Pairs</i>	192	189	190	190	381	380	405	356	191	190	190	190	381	380	405	356

**Note:** All columns use pre-tax measures of lifetime average income and food consumption after controlling for year and cohort effects, and  $\text{Var}(y_t^y)$  is calculated as the variance of the fitted residuals from the OLS regression of  $y_t^y$  on  $y_t^y$ . The columns Q-1 through Q-4 denote the first to fourth quartiles of the parental income distribution. *No College* refers to the sample of parents whose highest educational attainment is high school graduation with some potential non-academic training, while *Some College* refers to a sample of parents who are at least college dropouts.

## 4.5 The Evolution of Inequality across Generations

The PSID family panels cover, at most, the working life of children born between the 1950s and the early 1980s. This makes it hard to obtain direct estimates of the impact of grandparents on grandchildren and generations further apart. Nevertheless, under a stationarity assumption, our model can be used to examine the projected path of inequality starting from current levels.

Before drawing inference about projected paths, we illustrate observed differences in the dispersion of income and expenditures in the parent and child generations. To limit the confounding influence of life-cycle effects, we restrict the baseline sample to parents and children between age 30 and 40. The cross-sectional variances for this reduced sample, consisting of 404 unique parent-child pairs, are reported in columns (1) and (2) of Table 7. Estimates of the variance for each generation

confirm the well-established finding that earnings inequality in the U.S. has increased over time (Heathcote, Perri and Violante, 2010).

Using equations (4), (5) and (7), it is possible to project the evolution of income and consumption dispersion as a vector autoregressive (VAR) process, where the younger generation’s idiosyncratic fixed effects behave like innovations. One can iterate this VAR system forward until the distribution of outcomes converges to a stationary one. The variances of the resultant long-run distribution are reported in column (3) of Table 7.<sup>14</sup>

Table 7: Steady-state versus Current Inequality

Variable	Parental Variance	Child Variance	Steady-state Variance
	(1)	(2)	(3)
Head Earnings	0.183	0.260	0.265
Other Income	0.876	0.631	0.638
Consumption	0.090	0.117	0.129

**Note:** Estimates based on sample of 404 unique parent-child pairs. Age restricted between 30 and 40 years.

The long-term steady-state variances are higher than the ones observed in the child generation, although differences are not large (columns 2 and 3 in Table 7). The latter result suggests that the moderate values of the estimated pass-through parameters cannot induce much larger dispersion in the long run and, as a result, the initial influence of family background for inequality dissipates over successive generations. To further corroborate the observation that intergenerational elasticities are not large enough to induce significant increases in inequality, we consider the impact of progressively larger values of the pass-through parameters: in Table 18 of Appendix C.5, we show that even with a counterfactually large earnings pass-through  $\gamma$  of 0.50 (more than twice as large as the baseline estimate), the role of parental effects on earnings variance is around 15%. These magnitudes, while significant, imply family linkages that are not, by themselves, strong enough to induce large rises in inequality in future generations.

## 5 Pathways of Intergenerational Influence

Our estimates indicate that parental heterogeneity influences inequality among offspring, with pronounced impacts occurring through consumption heterogeneity. To account for these findings,

<sup>14</sup>Details of the simulation of long-run inequality and its transition path are provided in Appendix C.5.

and to assess the role of alternative mechanisms, we overview some pathways of intergenerational persistence through the lens of the model.

## 5.1 Spousal Earnings and Family Background

*Other income* is defined as the sum of wife’s labour earnings and total transfer income (both public and private transfers) accruing to the couple. To establish how much these components account for the intergenerational linkages in other income, we estimate two versions of the model — (i) using wife earnings alone as the measure of other income, and (ii) considering three separate income processes for head earnings, wife earnings and transfer income. In the latter specification, where we jointly model three income sources along with their covariation within and across generations, an extension of the baseline model is required (details in Appendix D.1).

To facilitate comparisons, we estimate each specification using a common sample of 459 parent-child pairs for which income and expenditure variables can be consistently defined in each model. Table 8 illustrates the contribution of parental factors to inequality in the younger generation under the three alternative specifications of the *other income* process. All specifications suggest that parental effects through other income are largely driven by wife earnings, rather than the transfer component. When only wife earnings are used to measure other income, we find significant pass-through between — (i) earnings of the mother and the wife of the adult child, with elasticity of 0.14, and (ii) earnings of the father and the wife of the adult child, with elasticity of 0.23. Such persistence indicates that parental heterogeneity may induce spousal selection and lead to positive assortative matching in terms of spousal labour market outcomes. This observation is consistent with findings in Fernandez, Fogli and Olivetti (2004), who document preference formation based on maternal characteristics. Allowing for three separate income sources further corroborates our finding that parental factors have a large influence on wife earnings. In this specification the mother-to-wife earnings elasticity is not precisely estimated due to the considerable number of additional parameters. However, the pass-through from father’s earnings and parental transfer income to the child’s wife-earnings remain significant throughout.

The need to obtain estimates for each specification from the same sample imposes restrictions resulting in a 40% reduction in sample size compared to our baseline sample. Nonetheless, we verify that all estimates in columns (2) through (4) of Table 8 are not statistically different from each other and the the results for the baseline specification are statistically indistinguishable under the two alternative samples. Since most of the sample reduction is due to the presence of zeros in the noisy transfer variable, we also check robustness of our finding using a sample requiring only positive wife earnings; this reduces the sample size by only 11% (from 761 to 674 pairs) and the resulting estimates are again similar for the baseline model and Model B (available upon request).

G replace the sentence: we use the same common sample of 459 parent-child pairs for which all income and expenditure variables are strictly positive and can be expressed in logarithms. SENTENCE DRAWS ATTENTION TO SELECTION. SAY HOW WE TRIED TO DEAL WITH THE NONPOSITIVE VALUES?

A: I have changed this paragraph slightly.

Table 8: Parental Importance for Child Inequality: Unpacking *Other Income*

Variable	Role of Parents under Alternative Models			
	Baseline I	Baseline II	Model B	Model C
	761 Pairs (1)	459 Pairs (2)	459 Pairs (3)	459 Pairs (4)
Head Earnings	7.9% [3.5%, 12.4%]	10.6% [4.8%, 16.4%]	14.6% [8.6%, 20.6%]	5.7% [1.1%, 10.4%]
Wife Earnings	-	-	8.1% [2.7%, 13.4%]	3.8% [0.9%, 6.7%]
Transfer Income	-	-	-	0.4% [-0.8%, 1.5%]
Wife Earnings + Transfer Income	4.4% [1.4%, 7.4%]	3.5% [0.1%, 6.8%]	-	-
Consumption	30.1% [19.7%, 40.5%]	24.6% [14.0%, 35.2%]	22.8% [12.6%, 33.0%]	34.8% [18.1%, 51.5%]

**Note:** The three models differ in the definition of *other income*. Baseline model uses the sum of wife earnings and transfer income as the measure of other income, like in our baseline estimation. Model B uses wife earnings only, while Model C uses three separate income processes for head earnings, wife earnings and transfer income. All models use food expenditure as the measure of consumption, and use only cross-sectional variation from time-averaged variables. In the baseline sample we require the sum of wife earnings and transfer income to be positive, which yields 761 pairs. When both wife earnings and transfer income are individually positive, we obtain a sample of 459 pairs. Numbers in parentheses are 95% confidence intervals, calculated using bootstrap standard errors with 100 repetitions. Results for baseline model using 761 pairs are based on parameter estimates in column (1) of Tables 2 and 3, and those for all the three models using 459 pairs are based on parameter estimates from Tables 21 and 22.

## 5.2 Liquidity Constraints

Liquidity constraints can influence intergenerational elasticities and, consequently, parental impacts on inequality. A key mechanism operates through financial constraints that limit parental investments in their children. Access to extra income may translate into larger investments in such families; in turn, this may equalize income and consumption across generations leading to stronger intergenerational pass-through. A large literature, however, highlights the difficulty in empirically identifying the effect of financial constraints on intergenerational mobility, especially from surveys lacking consumption data (see Black and Devereux, 2011, for a summary).

A recurring concern relates to the identification of credit-constrained households in data. While low-income parents may experience frequent episodes of financial hardship, high-income families can also become constrained if their children exhibit high returns to investments. Financing education

for high-return offspring may require higher outlays to invest more than the basic level provided through publicly subsidized education programs (see [Han and Mulligan, 2001](#)). It follows that liquidity constraints can lead to high intergenerational persistence both at the bottom and at the top of the earnings distribution, a pattern consistent with the mobility matrices in Appendix [A.1](#) (see also [Grawe, 2004](#)).

Moreover, intergenerational elasticities can be high for several reasons beyond financial constraints, such as complementarities in human capital production ([Becker et al., 2018](#)). To circumvent the limitations of using income measures in isolation, [Mulligan \(1997\)](#) classifies as ‘unconstrained’ those PSID households that receive substantial bequests, while [Mazumder \(2005\)](#) labels households with above-median net worth as ‘unconstrained’ in SIPP data. Neither of these studies, however, finds significantly larger intergenerational mobility in the unconstrained groups.

Information on family expenditures alongside family income is useful to identify constrained households as it allows to bypass some confounding effects that affect income-only measures. For example, to establish an upper bound on the share of credit-constrained households, [Primiceri and van Rens \(2009\)](#) suggest a procedure based on consumption data that builds on insights from [Blundell and Preston \(1998\)](#). Using repeated cross-sections in the CEX, they find that at most 3% households in the U.S. are severely credit-constrained. While different in focus, earlier work by [Carneiro and Heckman \(2003\)](#) suggests that about 8% of U.S. youth, over a similar sample period, were credit-constrained when accessing higher education. In related work, [Abbott et al. \(2019\)](#) show that liquidity constraints preventing high-ability students from enrolling in college are not widely binding once existing loan and grant programs are accounted for. [Alan, Browning and Ejrnæs \(2018\)](#) also find little evidence of excess sensitivity of consumption to anticipated income changes - a marker of binding liquidity constraints - in a PSID sample of married individuals observed for at least 15 years, with heads aged over 30 years.

In what follows we consider alternative approaches that combine information about income and consumption to establish the prevalence of liquidity constraints in our PSID sample of families. We then examine the effects of removing constrained households from the sample on the estimates of intergenerational persistence and parental influence.

**Using consumption growth.** A credit constraint that binds in period  $t$ , but not  $t + 1$ , would increase consumption growth between the two periods ([Crossley and Low, 2014](#)). This insight suggests constrained households could be recognized from observations where the increase in food expenditure over a two-year interval is above 25%; for example, a household experiencing a  $x\%$  increase in real food outlays between 2010 and 2012 would be labelled as constrained in 2010 if  $x > 25$ . Adopting this criterion, we find that removing constrained observations from the baseline sample does not significantly alter estimates. The analysis (presented in Appendix [D.2.1](#)) points to a limited influence of borrowing constrained observations on estimates of both persistence and

dispersion parameters.

**Measuring the volatility of income and expenditures over the life cycle.** Panel data on income and expenditures make it possible to measure the volatility of consumption and earnings for different households over time. Having joint measures of income and outlays allows one to run a test of ‘excess sensitivity’ of consumption to income changes, which is a well-established indicator of potential liquidity constraints. We then label as liquidity-constrained those households that fall in the top decile according to the ratio of consumption and earnings volatility over the life-cycle. Dropping these households from the baseline sample and re-estimating the model results in little or no changes (see Appendix D.2.2).

G: families?

**Young families.** An interesting observation (Mazumder, 2005; Caucutt and Lochner, 2019; Carneiro et al., 2021) is that the uneven prevalence of credit constraints over the life-cycle may be reflected in intergenerational persistence patterns. In turn, one might expect to see different patterns of persistence among younger households to the extent that they are subject to more frequent binding constraints than older parents. To examine this hypothesis, we re-estimate intergenerational persistence using parental measures computed at different children ages. That is, we use family controls obtained at different stages of the parental life-cycle, capturing life-cycle variation in the parents’ generation. As we consider progressively older parents, we do not find evidence of decreasing parental impacts on the dispersion of children’s outcomes (Appendix D.2.3).

G: check the Carneiro paper; no obvious that what we are doing is an exact check of differential constraints, and perhaps we should explain better.

### 5.3 Parental Motives

The baseline model features intergenerational linkages but does not make parental motives explicit. In what follows we introduce a warm-glow mechanism in the consumption problem (1) and posit that parents can derive utility from transferring resources to their kids. The objective of the household becomes,

$$\max_{\{C_{f,s}, \mathcal{T}_{f,s}\}_{s=t}^T} \mathbb{E}_t \sum_{j=0}^{T-t} \beta^j \left[ \frac{C_{f,t+j}^{1-\sigma}}{1-\sigma} + \mu_1 \cdot \frac{\mathcal{T}_{f,t+j}^{1-\mu_2}}{1-\mu_2} \right]$$

The variable  $\mathcal{T}_{f,t}$  denotes the parental expenditure on the child at time  $t$ . The expenditure can finance an investment in human capital while the child is in the same household or inter-vivos transfers when the child is in a separate household as an adult. In the budget constraint we distinguish between expenditures for own consumption and for children,

$$A_{f,t+1} = (1+r)(A_{f,t} + E_{f,t} + N_{f,t} - C_{f,t} - \mathcal{T}_{f,t}),$$

Without loss of generality, we assume that prices for different expenditures are the same; then, optimality implies that the marginal rate of substitution between own consumption and child expenditures be equal to one and one can show that expenditures of family  $f$  in period  $t$  are,

$$\ln C_{f,t} = -\frac{1}{\sigma} \log \mu_1 + \frac{\mu_2}{\sigma} \ln \mathcal{T}_{f,t} \quad (28)$$

Over our sample period there is no consistent measure of family asset positions ( $A_{f,t}$ ) nor of life-cycle transfers to children ( $\mathcal{T}_{f,t}$ ). However, equation (28) implies that parental expenditures, which we do observe, behave like a sufficient statistic for total parental transfers to the offspring, which are unobserved. Transfers to children, in turn, influence their income and consumption, which suggests that the warm-glow motive introduces a direct link between parental expenditures,  $C_{f,t}$ , and observed child outcomes. Accounting for this additional source of persistence, we show<sup>15</sup> that the three outcome processes for the children can be cast as,

$$\bar{e}_f^k = (\gamma + \lambda_e) \bar{e}_f^p + (\rho_e + \lambda_e) \bar{n}_f^p + \lambda_e \bar{q}_f^p + \check{e}_f^k \quad (29)$$

$$\bar{n}_f^k = (\rho + \lambda_n) \bar{n}_f^p + (\gamma_n + \lambda_n) \bar{e}_f^p + \lambda_n \bar{q}_f^p + \check{n}_f^k \quad (30)$$

$$\bar{c}_f^k = (\lambda + \lambda_e + \lambda_n) \bar{q}_f^p + (\gamma + \gamma_n + \lambda_e + \lambda_n) \bar{e}_f^p + (\rho + \rho_e + \lambda_e + \lambda_n) \bar{n}_f^p + \check{e}_f^k + \check{n}_f^k + \check{q}_f^k \quad (31)$$

Parental expenditures affect offspring income in a log-linear fashion through pass-through parameters  $\lambda_e$  and  $\lambda_n$ , respectively, while their direct effect on child consumption operates through  $\lambda$ , as shown in (31). Equations (29), (30) and (31) collapse back to the baseline processes in (4), (5) and (7) if  $\lambda_e \simeq \lambda_n = 0$ .

Estimates of the extended model suggests that neither  $\lambda_e$  nor  $\lambda_n$  are different from zero (Table 29 in Appendix D). The lack of incremental effects through the explicit transfer channels indicates that the parsimonious baseline specification is sufficient to characterize intergenerational linkages without imposing specific behavioral motives.

More generally, we reject the hypothesis that family expenditures have a direct influence on child outcomes above and beyond what is already captured by the baseline pass-through parameters. Further evidence of this is presented in columns (1) and (2) of Table 9, where we show that accounting for parental motives through their expenditures does not change estimates of the influence of family heterogeneity on inequality.

To be sure, these findings do not imply that altruistic or paternalistic motives are absent or inconsequential.<sup>16</sup> Rather, they suggest that, irrespective of the motives, parent-child linkages and their impact on inequality are adequately summarized through the baseline pass-through of

<sup>15</sup>A detailed discussion of the extended model, and of parameter identification, are in Appendix D.3.

<sup>16</sup>See Altonji, Hayashi and Kotlikoff (1997) for a test of altruism in PSID data.

income and consumption expenditures, with no need to impose additional and explicit behavioral structures.

Table 9: Parental Importance for Child Inequality

Variables	Baseline Model	Extended Model
	(1)	(2)
Head Earnings	7.9% [3.5%, 12.4%]	7.8% [4.3%, 11.3%]
Other Income	4.4% [1.4%, 7.4%]	4.3% [1.6%, 7.0%]
Consumption	30.1% [19.7%, 40.5%]	32.4% [23.7%, 41.3%]

**Note:** Results in column (1) are based on parameter estimates from column (1) of Tables 2 and 3. Results in column (2) are based on parameter estimates from column (1) of Tables 29 and 30 in Appendix D.3. Numbers in parentheses are 95% confidence intervals, calculated using bootstrap with 100 repetitions.

## 6 Robustness

To assess the robustness of our findings we perform several checks. First, we consider whether there are differences across birth-cohorts of children. Second, we assess the importance of the cross-elasticities between earnings and other income by setting  $\gamma_n$  and  $\rho_e$  to zero in the baseline model. Third, we consider a sample of randomly matched parent-child pairs as a placebo test for family linkages. Fourth, we employ alternative measures of expenditure. Fifth, we assess the prevalence and importance of liquidity constraints. Finally, we estimate the model on a larger sample including families with relatively less stable marriages.

### 6.1 Panel Variation with Persistent and Transitory Shocks

Baseline estimates leverage cross-sectional variation in the outcome variables. Through the time-averaging of variables we make sure that per-period mean-zero shocks drop out. However, the individual fixed effects, estimated after averaging the outcome variables, may partly reflect persistent but mean-reverting shocks to income and consumption. To separately identify the variances of such confounding shocks and distinguish them from heterogeneity in individual fixed effects, we set out to estimate a version of the model which takes full advantage of the panel variation.

Estimating the variances of both autoregressive and transitory shocks increases the number of parameters from 17 to 43. For this reason, we implement estimation in two steps: first, we recover

the 26 parameters describing the shock processes using standard panel data methods; then, we perform GMM estimation of the remaining 17 parameters while holding the other 26 fixed. In Appendix E.1 we establish identification and describe the procedure to estimate the shock process parameters in the initial step, along with sensitivity checks to assess the robustness of our findings.

Table 10: Parental Importance for Child Inequality

Variables	Time-Averaged	Panel
	(1)	(2)
Head Earnings	7.9%	12.2%
	[3.5%, 12.4%]	[4.2%, 20.2%]
Other Income	4.4%	1.7%
	[1.4%, 7.4%]	[-1.1%, 4.5%]
Consumption	30.1%	22.0%
	[19.7%, 40.5%]	[8.7%, 35.4%]

**Note:** Results in column (1) are based on parameter estimates from column (1) in Tables 2 and 3. Results in column (2) are based on estimates from column (2) in Tables 31 and 33, Appendix E.1. Numbers in parentheses are 95% confidence intervals, calculated using panel bootstrap with 100 repetitions.

As shown in Table 10, explicitly allowing for autoregressive shocks to income and consumption, as well as transitory innovations, does not materially change the nature of the key estimates. The only statistically significant difference relative to the time-averaged approach is in the parental influence on other income, which becomes statistically indistinguishable from zero in the panel estimation. This is not surprising, however, given the attenuation bias due to the measurement error reintroduced by the panel variation. As discussed before, this problem is especially severe in transfer data used to construct other income.

## 6.2 A Model with Permanent Income as a Random Walk

Intergenerational persistence in the baseline model occurs through the transmission of individual fixed effects that subsume permanent income and consumption. An alternative specification, where persistent autoregressive components are random walks, would result in the following income processes for each generation  $g \in \{p, k\}$ ,

$$e_{f,t}^g = \bar{e}_f^g + \mathcal{E}_{f,t}^g + \varepsilon_{f,t}^g \quad \text{where} \quad \mathcal{E}_{f,t}^g = \mathcal{E}_{f,t-1}^g + \epsilon_{f,t}^g \quad (32)$$

$$n_{f,t}^g = \bar{n}_f^g + \Theta_{f,t}^g + \vartheta_{f,t}^g \quad \text{where} \quad \Theta_{f,t}^g = \Theta_{f,t-1}^g + \theta_{f,t}^g \quad (33)$$

where the random walk components  $\mathcal{E}_{f,t}^g$  and  $\Theta_{f,t}^g$  have i.i.d. innovations  $\epsilon_{f,t}^p$  and  $\theta_{f,t}^p$ . The transitory shocks to earnings and other income are also i.i.d. and denoted as  $\varepsilon_{f,t}^p$  and  $\vartheta_{f,t}^p$ .

In this setting, which requires estimation in first-differences, the growth rate of consumption depends on transitory and permanent innovations to income, and on a consumption-specific transitory shock (see [Blundell, Pistaferri and Preston, 2008](#), for a derivation):

$$\Delta c_{f,t}^g = \omega_{eg} \epsilon_{f,t}^g + \omega_{ng} \theta_{f,t}^g + \psi_{eg} \varepsilon_{f,t}^g + \psi_{ng} \vartheta_{f,t}^g + \xi_{f,t}^g \quad \text{for each } g \in \{p, k\} \quad (34)$$

The equation above has two loading parameters,  $\omega_{eg}$  and  $\omega_{ng}$ , that can be interpreted as inverse measures of consumption insurance against permanent shocks. For example, when  $\omega_{eg}$  is close to zero, permanent shocks to earnings have little effect on expenditure growth, which suggests the presence of consumption smoothing mechanisms. By contrast, a value of  $\omega_{eg}$  close to unity indicates little insurance against innovations to permanent earnings. Similarly, the loading parameters  $\psi_{eg}$  and  $\psi_{ng}$  can be interpreted as inverse measures of insurance against transitory shocks.

Unlike before, intergenerational persistence in the time-differenced model amounts to a correlation between the permanent innovations to the income processes of parent and child, as well as a correlation between the transitory shocks to consumption growth across generations. These linkages can be expressed as,

$$\epsilon_{f,t}^k = \gamma_{\Delta} \epsilon_{f,t}^p + \check{\epsilon}_{f,t}^k \quad (35)$$

$$\theta_{f,t}^k = \rho_{\Delta} \theta_{f,t}^p + \check{\theta}_{f,t}^k \quad (36)$$

$$\xi_{f,t}^k = \lambda_{\Delta} \xi_{f,t}^p + \check{\xi}_{f,t}^k, \quad (37)$$

where the subscript  $\Delta$  on the pass-through parameters highlights the fact that they are identified from growth rates of outcome variables, rather than variation in levels as in the baseline case. Combining equations (32) through (37) yields the following income and consumption growth equations in the two generations:

$$\Delta e_{f,t}^p = \epsilon_{f,t}^p + \Delta \varepsilon_{f,t}^p \quad (38)$$

$$\Delta n_{f,t}^p = \theta_{f,t}^p + \Delta \vartheta_{f,t}^p \quad (39)$$

$$\Delta c_{f,t}^p = \omega_{ep} \epsilon_{f,t}^p + \omega_{np} \theta_{f,t}^p + \psi_{ep} \varepsilon_{f,t}^p + \psi_{np} \vartheta_{f,t}^p + \xi_{f,t}^p \quad (40)$$

$$\Delta e_{f,t}^k = \gamma_{\Delta} \epsilon_{f,t}^p + \check{\epsilon}_{f,t}^k + \Delta \varepsilon_{f,t}^k \quad (41)$$

$$\Delta n_{f,t}^k = \rho_{\Delta} \theta_{f,t}^p + \check{\theta}_{f,t}^k + \Delta \vartheta_{f,t}^k \quad (42)$$

$$\Delta c_{f,t}^k = \omega_{e^k} (\gamma_{\Delta} \epsilon_{f,t}^p + \check{\epsilon}_{f,t}^k) + \omega_{n^k} (\rho_{\Delta} \theta_{f,t}^p + \check{\theta}_{f,t}^k) + \psi_{e^k} \varepsilon_{f,t}^k + \psi_{n^k} \vartheta_{f,t}^k + (\lambda_{\Delta} \xi_{f,t}^p + \check{\xi}_{f,t}^k) \quad (43)$$

All fixed effects cancel out through time-differencing. Therefore, their variances and covariances, and any intergenerational linkage operating through them, are not identified. Appendix E.2 derives the identification results and shows parameter estimates for this alternative specification. We find no evidence of intergenerational persistence in either permanent innovations to income or in transitory shocks to consumption growth. Estimates of pass-through parameters  $\gamma_{\Delta}$ ,  $\rho_{\Delta}$  and  $\lambda_{\Delta}$  are statistically indistinguishable from zero. This might partly be due to the well-known problem that differencing exacerbates attenuation bias due to measurement error. This is further evidence that the baseline model of intergenerational linkages in individual fixed effects delivers a practical and informative representation of cross-generation persistence of inequality.

### 6.3 Estimates by Child Birth-Cohort

Our baseline sample includes children born between 1952 and 1981. To assess whether parental impacts on inequality in child outcomes have changed over time, we split the baseline sample in two 15-year children birth-cohorts and separately estimate the model on each subsample. Namely, we use one birth-cohort running between 1952 and 1966 and another covering 1967 through 1981. Table 11 shows that parental influences on cross-sectional heterogeneity in the child generation have remained roughly stable across these birth cohorts.<sup>17</sup>

Table 11: Parental Importance by Child-Cohort

Variables	All Cohorts (1)	1952-1966 Cohort (2)	1967-1981 Cohort (3)
Head Earnings	7.9% [3.5%, 12.4%]	8.0% [3.2%, 12.7%]	8.3% [3.0%, 13.6%]
Other Income	4.4% [1.4%, 7.4%]	3.2% [0.2%, 6.2%]	8.3% [0.5%, 16.1%]
Consumption	30.1% [19.7%, 40.5%]	33.6% [21.2%, 46.6%]	23.9% [14.6%, 33.2%]
<i>No. of Parent-Child Pairs</i>	761	467	294

**Note:** Numbers in parentheses are 95% confidence intervals, calculated using bootstrap standard errors with 100 repetitions.

<sup>17</sup>In Appendix E.3 we present further robustness of estimates by child birth-cohorts where we control for life-cycle bias by studying parents and children between ages 30 and 40 years. Although such sampling restriction reduces the sample size by more than half and estimates become noisier, our qualitative findings survive.

## 6.4 Restricting Cross-Effects between Income Sources

We consider a restricted version of the baseline model that does not allow parental earnings to affect other income of the child, nor parent's other income to affect child's earnings; that is, we impose both  $\gamma_n$  and  $\rho_e$  to be zero. Column (2) in Table 12 reports elasticity estimates under these restrictions. The point estimate of the earnings elasticity changes significantly in the restricted model, overstating the importance of parental factors for earnings inequality among children. Most of the difference relative to the baseline can be attributed to the restriction that  $\gamma_n = 0$ , since the magnitude of  $\rho_e$  is already close to zero in the baseline model. By restricting  $\gamma_n$  to be zero, we decrease its value below the positive baseline estimate and mechanically push up the estimate of  $\gamma$  so as to guarantee a fairly constant value of  $(\gamma + \gamma_n)$ , the total intergenerational pass-through from parental earnings to child outcomes. This results in the contribution of parental heterogeneity to children's inequality to be significantly larger for earnings and smaller for consumption (see column (2) of Table 13). The exercise highlights the importance of allowing for cross-effects above and beyond the direct channels captured by  $\gamma$  and  $\rho$  when drawing inference about intergenerational elasticity parameters.

Table 12: Robustness: Intergenerational Elasticity Estimates

Parameters	Baseline (1)	$\gamma_n = \rho_e = 0$ (2)	Random Match (3)	Imputed Consumption (4)	All Marital Status (5)	Post-tax Income (6)
Head Earnings: $\gamma$	0.229 (0.028)	0.340 (0.027)	-0.018 (0.028)	0.256 (0.024)	0.217 (0.029)	0.225 (0.026)
Other Income: $\rho$	0.099 (0.027)	0.120 (0.028)	-0.039 (0.025)	0.096 (0.028)	0.103 (0.035)	0.091 (0.028)
$\bar{e}_f^p$ on $n_{f,t}^k$ : $\gamma_n$	0.208 (0.035)	0	-0.007 (0.035)	0.237 (0.031)	0.239 (0.039)	0.199 (0.039)
$\bar{n}_f^p$ on $e_{f,t}^k$ : $\rho_e$	0.055 (0.019)	0	-0.015 (0.023)	0.052 (0.015)	0.058 (0.015)	0.044 (0.014)
Consumption Shifters: $\lambda$	0.153 (0.037)	0.108 (0.029)	-0.048 (0.034)	0.127 (0.033)	0.170 (0.042)	0.119 (0.033)
No. of Parent-Child Pairs	761	761	761	761	1038	755

**Note:** Bootstrap standard errors (100 repetitions) in parentheses. Variables have been purged of year and cohort fixed effects.

## 6.5 Placebo Test: Random Matching of Parents and Children

It is conceivable that spurious correlations in the data may affect estimates of parent-child pass-through parameters. To account for this possibility we perform a placebo test using a sample in which parents and children are randomly matched. Estimates based on this sample imply the absence of any significant intergenerational pass-through and virtually no role of parental heterogeneity for inequality among the children, as seen in column (3) of Tables 12 and 13. This finding

confirms that genuine family linkages, rather than spurious correlations, drive the baseline results.

## 6.6 Alternative Measures of Consumption Expenditure

Our baseline analysis uses food expenditure as the consumption measure because food expense is available for most survey rounds of the PSID. However, other components of consumption might exhibit different properties. We examine the importance of other expenditure categories in two ways. First, we impute total consumption using the procedure suggested by [Attanasio and Pistaferri \(2014\)](#) — this approach exploits rich consumption expenditure information available in the PSID after 1997 to approximate households’ outlays in the earlier years of the survey. We report results for this alternative consumption measure in column (4) of Tables [12](#) and [13](#). Estimates based on this broader range of expenditures suggest a stronger role of parental heterogeneity for consumption dispersion among children, with roughly half of the total dispersion due to family linkages. The higher estimate of the parental contribution to consumption inequality is arguably an upper bound of their true contribution, as it reflects latent persistence of observable characteristics used to impute total consumption. In a second sensitivity exercise, we restrict the sample to the post-1997 period, when there is no need for imputation of non-food consumption. Albeit less precise due to the smaller sample size, estimates from this sample suggest a parental contribution to consumption inequality of roughly 24% (not shown here), comparable to the baseline estimate.

Table 13: Robustness: Importance of Parental Heterogeneity for Child Inequality

Variables	Baseline	$\gamma_n = \rho_e = 0$	Random Match	Imputed Consumption	All Marital Status	Post-tax Income
	(1)	(2)	(3)	(4)	(5)	(6)
Head Earnings	7.9%	13.5%	0.1%	9.3%	6.4%	7.0%
	[3.5% 12.4%]	[9.4% 17.6%]	[-0.8% 1.0%]	[6.0% 12.6%]	[3.4% 9.4%]	[4.0% 10.1%]
Other Income	4.4%	2.2%	0.2%	5.0%	2.5%	3.4%
	[1.4% 7.4%]	[0.2% 4.1%]	[-0.4% 0.9%]	[2.2% 7.8%]	[0.9% 4.2%]	[0.7% 6.1%]
Consumption	30.1%	19.6%	0.2%	47.6%	26.1%	25.6%
	[19.7% 40.5%]	[13.5% 25.7%]	[-0.9% 1.3%]	[35.4% 59.8%]	[17.2% 35.0%]	[17.4% 33.8%]
<i>No. of Parent-Child Pairs</i>	761	761	761	761	1038	755

**Note:** Results in columns (1) through (5) are based on parameter estimates in Table [12](#) and Appendix Table [43](#), while those in column (6) are based on column (6) of Table [12](#) and column (3) of Appendix Table [45](#). Numbers in parentheses are 95% confidence intervals, calculated using bootstrap standard errors with 100 repetitions.

## 6.7 Relaxing Marital Status Restrictions

The baseline sample, consisting of 761 parent-child pairs, is restricted to households with at least 5 (not necessarily continuous) years of observations during which the head was married. This restriction does not limit the sample to ‘always married’ households, but does concentrate on relatively stable families. To assess how much of a bias is introduced by sample selection due

to marital status of household heads, we estimate the baseline specification using all households observed at least 5 years regardless of their marital status. This increases the number of parent-child pairs from 761 to 1038. Estimates of parental effects on child inequality in this larger sample are reported in column (5) of Table 13 and are not statistically different from the baseline. This suggests that marital selection bias is not quantitatively large in the baseline sample, which has the advantage of reducing noise in the ‘other income’ measure.

## 6.8 Income Taxation

To explore if income taxes mitigate parental influences in the children’s generation, we consider a post-tax income measure where the total household earnings tax burden is split between head earnings and other income (based on the proportion of head and wife earnings, respectively).<sup>18</sup> The last columns of Tables 12 and 13 show the impact of income taxes on the intergenerational elasticity parameters and the role of parents for inequality in the children’s generation. We find marginal decrease in both the pass-through parameters and the role of parents for child inequality, but none of the reductions are statistically significant. Consistent with intuition, we also find that federal income taxes provide additional consumption insurance, that is, the amount of residual insurance in post-tax income is marginally lower than in pre-tax income due to the lower dispersion in the idiosyncratic component of child earnings.<sup>19</sup>

## 7 Conclusion

This paper examines the importance of family background for understanding income and consumption inequality. We estimate the intergenerational elasticities of earnings, other income and consumption, and document their significance for the persistence of inequality across generations. Our main finding is that the quantitative contribution of idiosyncratic heterogeneity to cross-sectional inequality is significantly larger than that of parental effects. Our estimates imply that intergenerational persistence is not, by itself, high enough to induce further large increases in inequality over time and across generations. This emphasizes the prominent role of idiosyncratic heterogeneity, which diffuses and attenuates the impact of family background on the cross-sectional distributions of life-cycle income and consumption.

In reaching this conclusion, we highlight the importance of jointly estimating the income and

---

<sup>18</sup>We consider two other alternative splits of the tax burden: one where the entire tax burden is assumed to be incident on head earnings and another where it is incident only on other income. Results for all three cases are compared in Appendix E.5.

<sup>19</sup>When post-tax head earnings is used as the measure of income instead of pre-tax head earnings, our within-generational pass-through  $\mu_{GEN}$  increases from 0.28 to 0.33, while the within-family pass-through  $\mu_{FAM}$  increases from 0.78 to 0.88.

expenditure processes, and of accounting for cross-effects between sources of income and consumption. Accounting for such cross-effects reveals important channels of parental influence, for example, marital sorting and income-dependent propensities to consume or save.

## References

- Aaronson, Daniel, and Bhashkar Mazumder.** 2008. “Intergenerational Economic Mobility in the United States, 1940 to 2000.” *Journal of Human Resources*, 43(1): 139–172.
- Abbott, Brant, and Giovanni Gallipoli.** 2022. “Permanent-Income Inequality.” *Quantitative Economics*.
- Abbott, Brant, Giovanni Gallipoli, Costas Meghir, and Giovanni L. Violante.** 2019. “Education Policy and Intergenerational Transfers in Equilibrium.” *Journal of Political Economy*, 127: 2569–2624.
- Alan, Sule, Martin Browning, and Mette Ejrnæs.** 2018. “Income and consumption: a micro semistructural analysis with pervasive heterogeneity.” *Journal of Political Economy*, 126(5): 1827–1864.
- Altonji, Joseph G., and Lewis M. Segal.** 1996. “Small-Sample Bias in GMM Estimation of Covariance Structures.” *Journal of Business & Economic Statistics*, 14(3): 353–366.
- Altonji, Joseph G., Fumio Hayashi, and Laurence J. Kotlikoff.** 1997. “Parental Altruism and Inter Vivos Transfers: Theory and Evidence.” *Journal of Political Economy*, 105(6): 1121–1166.
- Andreski, Patricia, Geng Li, Mehmet Zahid Samancioglu, and Robert Schoeni.** 2014. “Estimates of annual consumption expenditures and its major components in the PSID in comparison to the CE.” *American Economic Review*, 104(5): 132–135.
- Attanasio, Orazio, and Luigi Pistaferri.** 2014. “Consumption inequality over the last half century: some evidence using the new PSID consumption measure.” *The American Economic Review: Papers and Proceedings*, 104(5): 122–126.
- Attanasio, Orazio P., and Luigi Pistaferri.** 2016. “Consumption Inequality.” *Journal of Economic Perspectives*, 30(2): 3–28.
- Becker, Gary S., Scott Duke Kominers, Kevin N. Murphy, and Jorg L. Spenkuch.** 2018. “A Theory of Intergenerational Mobility.” *Journal of Political Economy*, 126(S1): S7–S25.
- Bello, Salvatore Lo, and Iacopo Morchio.** 2016. “Like Father, Like Son: Occupational Choice, Intergenerational Persistence and Misallocation.” *Working Paper*.

- Black, Sandra E, and Paul J Devereux.** 2011. “Recent developments in intergenerational mobility.” In *Handbook of Labor Economics*. Vol. 4, , ed. David Card and Orley Ashenfelter, 773–1823. Amsterdam:Elsevier.
- Blundell, Richard, and Ian Preston.** 1998. “Consumption and income uncertainty.” *The Quarterly Journal of Economics*, 113(2): 603–640.
- Blundell, Richard, Luigi Pistaferri, and Ian Preston.** 2008. “Consumption Inequality and Partial Insurance.” *The American Economic Review*, 98(5): 1887–1921.
- Boar, Corina.** 2021. “Dynastic Precautionary Savings.” *Review of Economic Studies*, 88: 2735–2765.
- Bound, John, Charles Brown, Greg J. Duncan, and William L. Rodgers.** 1994. “Evidence on the Validity of Cross-sectional and Longitudinal Labor Market Data.” *Journal of Labor Economics*, 12(3): 345–368.
- Carneiro, Pedro, and James J Heckman.** 2003. “Human Capital Policy.” NBER Working Paper w9495.
- Carneiro, Pedro, Italo López García, Kjell G Salvanes, and Emma Tominey.** 2021. “Intergenerational mobility and the timing of parental income.” *Journal of Political Economy*, 129(3): 757–788.
- Caucutt, Elizabeth, and Lance John Lochner.** 2019. “Early and Late Human Capital Investments, Borrowing Constraints, and the Family.” forthcoming, *Journal of Political Economy*.
- Charles, Kerwin Kofi, Sheldon Danziger, Geng Li, and Robert Schoeni.** 2014. “The Intergenerational Correlation of Consumption Expenditures.” *American Economic Review*, 104(5): 136–140.
- Charles, Kerwin Kofi, and Erik Hurst.** 2003. “The Correlation of Wealth across Generations.” *Journal of Political Economy*, 111(6): 1155–1182.
- Chetty, Raj, Nathaniel Hendren, Patrick Kline, Emmanuel Saez, and Nicholas Turner.** 2014. “Is the United States Still a Land of Opportunity? Recent Trends in Intergenerational Mobility.” *American Economic Review: Papers & Proceedings*, 104(5): 141–147.
- Corak, Miles.** 2013. “Income Inequality, Equality of Opportunity, and Intergenerational Mobility.” IZA Discussion Paper Series No. 7520.
- Corak, Miles, and Patrizio Piraino.** 2010. “Intergenerational Earnings Mobility and the Inheritance of Employers.” IZA Discussion Paper Series 4876.
- Crossley, Thomas F., and Hamish W. Low.** 2014. “Job Loss, Credit Constraints, and Consumption Growth.” *The Review of Economics and Statistics*, 96(5): 876–884.
- Cunha, Flavio, James J Heckman, and Susanne M Schennach.** 2010. “Estimating the technology of cognitive and noncognitive skill formation.” *Econometrica*, 78(3): 883–931.

- Daruich, Diego, and Julian Kozlowski.** 2020. "Explaining intergenerational mobility: The role of fertility and family transfers." *Review of Economic Dynamics*, 36(April): 220–245.
- De Nardi, Mariacristina, Eric French, and John Bailey Jones.** 2016. "Savings After Retirement: A Survey." *Annual Review of Economics*, 8: 177–204.
- Eshaghnia, Sadegh, James J. Heckman, Rasmus Landersø, Rafeh Qureshi, and Victor Ronda.** 2021. "The Intergenerational Transmission of Lifetime Wellbeing." *Working Paper*.
- Fan, Simon C.** 2006. "Do the Rich Save More? A New View Based on Intergenerational Transfers." *Southern Economic Journal*, 73(2): 362–373.
- Fernandez, Raquel, Alessandra Fogli, and Claudia Olivetti.** 2004. "Mothers and Sons : Preference Formation and Female Labor Force Dynamics." *The Quarterly Journal of Economics*, 119(4): 1249–1299.
- Fisher, Hayley, and Hamish Low.** 2015. "Financial implications of relationship breakdown: Does marriage matter?" *Review of Economics of the Household*, 13(4): 735–769.
- Flavin, Marjorie, and Takashi Yamashita.** 2002. "Owner-Occupied Housing and the Composition of the Household Portfolio." *The American Economic Review*, 92(1): 345–362.
- Gayle, George-Levi, Limor Golan, and Mehmet A. Soytas.** 2018. "What is the Source of the Intergenerational Correlation in Earnings?" *Working Paper*.
- Gouskova, Elena, Ngina Chiteji, and Frank Stafford.** 2010. "Estimating the intergenerational persistence of lifetime earnings with life course matching: Evidence from the PSID." *Labour Economics*, 17(3): 592–597.
- Grawe, Nathan D.** 2004. "Reconsidering the Use of Nonlinearities in Intergenerational Earnings Mobility as a Test for Credit Constraints." *The Journal of Human Resources*, 29(3): 813–827.
- Grawe, Nathan D.** 2006. "Lifecycle bias in estimates of intergenerational earnings persistence." *Labour Economics*, 13(5): 551–570.
- Haider, Steven, and Gary Solon.** 2006. "Life-cycle variation in the association between current and lifetime earnings." *American Economic Review*, 96(4): 1308–1320.
- Han, Song, and Casey B. Mulligan.** 2001. "Human Capital, Heterogeneity and Estimated Degrees of Intergenerational Mobility." *The Economic Journal*, 111(April): 207–243.
- Heathcote, Jonathan, Fabrizio Perri, and Giovanni L Violante.** 2010. "Unequal we stand: An empirical analysis of economic inequality in the United States, 1967 – 2006." *Review of Economic Dynamics*, 13(1): 15–51.
- Hertz, Tom.** 2007. "Trends in the intergenerational elasticity of family income in the United States." *Industrial Relations*, 46(1): 22–50.
- Hryshko, Dmytro, and Iouri Manovskii.** 2019. "How much consumption insurance in the U.S.?" Univ. of Alberta and Univ. of Pennsylvania.

- Hufe, Paul, Ravi Kanbur, and Andreas Peichl.** 2021. “Measuring Unfair Inequality: Reconciling Equality of Opportunity and Freedom from Poverty.” *Review of Economic Studies*, forthcoming.
- Huggett, Mark, Gustavo Ventura, and Amir Yaron.** 2011. “Sources of Lifetime Inequality.” *American Economic Review*, 101(7): 2923–2954.
- Kaplan, Greg, and Giovanni L. Violante.** 2010. “How much consumption insurance beyond self-insurance?” *American Economic Journal: Macroeconomics*, 2(4): 53–87.
- Keane, Michael P., and Kenneth I. Wolpin.** 1997. “The Career Decisions of Young Men.” *Journal of Political Economy*, 105(3): 473–522.
- Koeniger, Winfried, and Carlo Zanella.** 2022. “Opportunity and inequality across generations.” *Journal of Public Economics*, 208(104623).
- Krueger, Alan B.** 2012. “The Rise and Consequences of Inequality in the United States.” *Discussion paper, Center for American Progress, Presentation made on January 12th*.
- Krueger, Dirk, and Fabrizio Perri.** 2006. “Does Income Inequality Lead to Consumption Inequality? Evidence and Theory.” *The Review of Economic Studies*, 73(1): 163–193.
- Landersø, Rasmus, and James J. Heckman.** 2017. “The Scandinavian Fantasy: The Sources of Intergenerational Mobility in Denmark and the US.” *Scandinavian Journal of Economics*, 119(1): 178–230.
- Lee, Chul-In, and Gary Solon.** 2009. “Trends in Intergenerational Income Mobility.” *Review of Economics and Statistics*, 91(4): 766–772.
- Lee, Sang Yoon Tim, and Ananth Seshadri.** 2019. “On the Intergenerational Transmission of Economic Status.” *Journal of Political Economy*, 127(2): 855–921.
- Lefgren, Lars, David Sims, and Matthew J Lindquist.** 2012. “Rich Dad, Smart Dad : Decomposing the Intergenerational Transmission of Income.” *Journal of Political Economy*, 120(2): 268–303.
- Li, Geng, Robert F. Schoeni, Sheldon Danziger, and Kerwin Kofi Charles.** 2010. “New expenditure data in the PSID: comparisons with the CE.” *Monthly Labor Review*, February: 29–39.
- Lochner, Lance, and Youngmin Park.** 2021. “Earnings Dynamics and Intergenerational Transmission of Skill.” *Journal of Econometrics*, forthcoming.
- Mayer, Susan E., and Leonard M. Lopoo.** 2005. “On the Intergenerational Transmission of Economic Status.” *The Journal of Human Resources*, 40(1): 169–185.
- Mazumder, Bhashkar.** 2005. “Fortunate Sons: New Estimates of Intergenerational Mobility in the United States Using Social Security Earnings Data.” *The Review of Economics and Statistics*, 87(2): 235–255.

- Mulligan, Casey B.** 1997. “Parental Priorities and Economic Inequality.” *University of Chicago Press*.
- Peters, H Elizabeth.** 1992. “Patterns of Intergenerational Mobility in Income and Earnings.” *The Review of Economics and Statistics*, 74(3): 456–466.
- Primiceri, Giorgio E., and Thijs van Rens.** 2009. “Heterogeneous life-cycle profiles, income risk and consumption inequality.” *Journal of Monetary Economics*, 56: 20–39.
- Rauh, Christopher.** 2017. “Voting, education, and the Great Gatsby Curve.” *Journal of Public Economics*, 146: 1–14.
- Restuccia, Diego, and Carlos Urrutia.** 2004. “Intergenerational persistence of earnings: The role of early and college education.” *American Economic Review*, 94(5): 1354–1378.
- Seror, Avner.** 2022. “Child Development in Parent-Child Interactions.” *Journal of Political Economy*, forthcoming.
- Shorrocks, A. F.** 1978. “The Measurement of Mobility.” *Econometrica*, 46(5): 1013–1024.
- Straub, Ludwig.** 2018. “Consumption, Savings, and the Distribution of Permanent Income.” *Working Paper*.
- Waldkirch, Andreas, Serena Ng, and Donald Cox.** 2004. “Intergenerational Linkages in Consumption Behavior.” *Journal of Human Resources*, 39(2): 355–381.

# Appendix

There are five appendices, [A](#) through [E](#) corresponding to Sections [2](#) through [6](#) in the main paper respectively.

## A Appendix to Section [2](#)

There are two main sections to this appendix. In section [A.1](#), we present reduced-form evidence of the time trends and cross-sectional heterogeneity of intergenerational persistence in earnings, as common in the literature, and also consumption, which is more closely tied to welfare. In section [A.2](#), we provide detailed derivation of the consumption process our baseline specification under alternative assumptions of quadratic and CRRA utility functions.

### A.1 Intergenerational Persistence: Reduced-Form Evidence

**Evolution of Intergenerational Elasticities.** A natural way to measure the impact of parental economic circumstances on a child’s adult outcomes is to estimate the intergenerational elasticity of such outcomes. By definition, this elasticity measures the percentage change in the child’s variable following one percentage change in the corresponding parental variable, and is obtained by regressing a logged measure of the child’s variable on its parental counterpart.

We are interested in knowing the persistence in permanent earnings and consumption, but we do not directly observe the long-term (permanent) earnings and consumption of any individual. An adult child’s earnings are observed only over a limited range of ages. Hence we must proxy these life-cycle variables by some function of the current (yearly) variables that are actually observable.<sup>[20](#)</sup> As in [Lee and Solon \(2009\)](#) we use adult children’s data for all the available years, along with a full set of age controls. We centre the child’s age around 40 years to minimise the bias from heterogeneity in growth rates, and interpret the estimated intergenerational elasticity as an average value as successive cohorts of children pass through age 40.<sup>[21](#)</sup> In fact, these intergenerational elasticities at age 40 (for a given year) can be interpreted as an asymmetrical moving average of the cohort-specific elasticities for the cohorts of adult children who are observed for that particular year. It is asymmetrical because the older cohorts weigh more in a particular year’s estimate owing

---

<sup>20</sup>A simpler way of dealing with this issue is to take into account the relevant variable at a particular age (say 30) for all children, like in [Mayer and Lopoo \(2005\)](#). The downside of conditioning on a specific age is that one has to throw out much valuable information (that is, all the data available for other ages). Moreover, transitory shocks occurring at the specific age may introduce some bias in the estimated parameter.

<sup>21</sup>Classical measurement error in the dependent variable (here, the child variable) is usually not a problem. However, [Haider and Solon \(2006\)](#) shows that using current variables as a proxy for a child’s permanent (lifetime) earnings or income may entail non-classical measurement error but the extent of the measurement error bias in the left-hand-side variable is the lowest if the current variable is measured at around age 40. So, we centre the child’s age around age 40.

to the fact that cohorts enter as they turn 25 years of age but never leave till the end of the PSID dataset.<sup>22</sup>

We also need to use a suitable proxy for the long-run parental variable serving as the principal regressor. Using the current measure of the parental variable would introduce an attenuation bias in the estimation of the long-term intergenerational elasticity of the child's variable. As in [Lee and Solon \(2009\)](#), we use the average log annual value of the parental variable over the years when the child was between age 15 and 17 as a proxy for the long-run value of the parent's process. We choose 15 years as the starting child age for a parental observation because our focus is on how parental circumstances in the formative years affects outcomes.<sup>23</sup> An alternative would have been to take the average of the parental variable (earnings or consumption) for the parents' entire lifetime (till 65 years of age). This would confound a number of effects, in particular, the effect of parental outcomes when children are at home with realisations of parental outcomes after children left home. The latter contemporaneous pass-through may be important for consumption smoothing across generations, but conceptually it is a different mechanism. A further issue with using the average over the entire lifetime is that this would impose that siblings born at different life-stages of the parent face the same parental inputs. Obviously, the age of the parents of different children born in a particular cohort will not be the same when the children reach the age range between 15 and 17. Therefore, we also control for the age of the parental household head.

We define the dependent variable  $\zeta_{fht}$  as the outcome variable — earnings or consumption, of the child  $f$  born in year  $h$  observed in year  $t$ . We run the regression:

$$\zeta_{fht} = \mu D_t + \beta_t x_{fh} + \gamma a_{fh}^p + \delta a_{fht}^k + \epsilon_{fht} \quad (\text{A.1})$$

The regressor,  $x_{fh}$  is the average value of the parent's outcome variable when the child  $f$  from cohort  $h$  is between 15 and 17 years of age. As controls, we include year dummies  $D_t$ , and quartics in the average parental age when the child is age 15-17 years,  $a_{fh}^p$ , and also quartics in the age of the child in year  $t$ , centred around 40 years (that is, a quartic in  $t - h - 40$ ),  $a_{fht}^k$ . The error term  $\epsilon_{fht}$  reflects factors like luck in labour and marriage markets, intergenerational transmission of genetic traits and other environmental factors (see [Peters, 1992](#)). We allow the coefficient  $\beta$  to vary by year to capture the time variation in intergenerational persistence. It should be noted that the choice of the normalization age for  $a_{fht}^k$  affects the point estimate of  $\beta_t$  in each year but not the time trend.

In [Table 14](#) we report the actual year-specific estimates from 1990 through 2010. We can obtain estimates starting from 1977 onwards, but in earlier years of the PSID the average age of the children samples is quite low, as we only observe independent children for very few years. This

---

<sup>22</sup>This asymmetry can be easily removed by making cohorts exit after a certain age, but that would lead to missing out on valuable information for those omitted cohorts. An alternative to this time-conditional estimation is to estimate cohort-specific elasticities using lifetime average of earnings (or consumption) for the adult children.

<sup>23</sup>Data availability then implies that is the oldest cohort of children are those born in 1952, with available parental observations starting from 1967 (documented in the 1968 interview).

is problematic because one would have to rely on extremely short snapshots of early adulthood to infer child outcomes. For this reason we only report point estimates of the elasticities from the year 1990 onwards. This guarantees that the cross-section of children in any given year includes a larger number of individuals at later stages of their working life. This also guarantees that children panels are longer, and hence less susceptible to initial conditions bias. It is interesting to note that the estimated elasticities lie in a fairly narrow range in the last 30 years. This absence of either a positive or a negative trend is the basis of our time-stationary model of economic persistence in Section 2.

Table 14: Estimates of Intergenerational Elasticities by Year

Year	Head Earnings	Total Consumption	Food Consumption
1990	0.30***	0.48***	0.25***
1991	0.34***	0.45***	0.24***
1992	0.29***	0.47***	0.27***
1993	0.30***	0.48***	0.29***
1994	0.29***	0.49***	0.25***
1995	0.29***	0.48***	0.27***
1996	0.25***	0.45***	0.25***
1998	0.24***	0.44***	0.24***
2000	0.30***	0.45***	0.25***
2002	0.31***	0.48***	0.23***
2004	0.29***	0.41***	0.19***
2006	0.30***	0.46***	0.23***
2008	0.35***	0.47***	0.26***
2010	0.37***	0.49***	0.29***

**Note:** \*\*\*, \*\* and \* denote statistical significance at 1%, 5% and 10% levels respectively. Standard errors (not reported) are clustered at the level of the unique parent identity.

**Heterogeneity of Intergenerational Persistence.** An alternative way to study the extent of intergenerational economic persistence is through *mobility matrices*. Mobility matrices show the heterogeneity in intergenerational persistence across the income or consumption distribution that is averaged out in the regression analysis above and the GMM analysis later on. The basic idea is to study the probability that an adult child will fall into various quantiles in the income or consumption distribution, given the quantile in which the parent of that child belonged. If the probability of a child being placed in the same quantile as the parent is high, we say that intergenerational persistence is high for that quantile of the distribution. If there were to be perfect

intergenerational mobility then each cell in the mobility matrix would have a conditional probability of 25%, and on the other hand if there were perfect persistence in intergenerational well-being then all the diagonal cells would read 100% while the off-diagonal cells would have a zero probability.

To accomplish the construction of such mobility matrices we first regress parental earnings (or consumption) on the full set of year dummies and the quartic of parental age. The residuals from these regressions are then averaged across the years for each parent and these average residuals are finally used to place each parent in one of the four quartiles of the parental distribution. Similar exercise with the adult children is performed, and finally the two quartile positions of the parents and children are cross-tabulated. A cell  $c_{i,j}$  in a mobility matrix at the intersection of the  $i^{th}$  row and the  $j^{th}$  column  $\forall i, j = 1(1)4$  is given by

$$c_{i,j} = Prob[child \in Q_{k,i} | parent \in Q_{p,j}] \times 100$$

where  $Q_{k,i}$  denotes the  $i^{th}$  quartile of the child distribution and  $Q_{p,j}$  denotes the  $j^{th}$  quartile of the parental distribution. One should note that the sum of each column in a mobility matrix must add up to 100. This is because the sum is essentially the integration of the conditional distribution for the child over the entire range of that distribution. However, the sum of each row need not add up to 100.

The mobility matrices for household head's labour earnings, total family consumption and food consumption are provided below. There are two important observations to be made from the tables. First, the mobility matrix of labour earnings show more mobility than that of total consumption. This implies the presence of other channels of intra-family linkages in consumption that are over and above earnings. Note that this finding is consistent with the intergenerational elasticities above. The contributions of these different channels of persistence will be explicitly quantified in the more structural model in Section 2. Secondly, there is a lot of heterogeneity in economic persistence across the conditional distributions, with the most persistence being observed at the two tails of the distributions, e.g., among children whose parents were in the lowest quartile of the parental distribution, at least about 39% are also in the lowest quartile. There is much more mobility in the middle of the distributions.

**Mobility Matrix of Head Earnings**

<div style="text-align: center;"> <div style="transform: rotate(-45deg); display: inline-block;"> Parent Child </div> </div>	$Q_{p,1}$	$Q_{p,2}$	$Q_{p,3}$	$Q_{p,4}$
$Q_{k,1}$	<b>45.98</b>	27.88	17.29	9.56
$Q_{k,2}$	25.41	<b>29.64</b>	27.17	15.93
$Q_{k,3}$	19.75	24.80	<b>30.44</b>	23.10
$Q_{k,4}$	8.86	17.69	25.10	<b>51.41</b>

**Mobility Matrix of Total Consumption**

Child \ Parent	$Q_{p,1}$	$Q_{p,2}$	$Q_{p,3}$	$Q_{p,4}$
$Q_{k,1}$	<b>53.02</b>	27.79	9.75	4.95
$Q_{k,2}$	26.53	<b>32.04</b>	25.65	13.65
$Q_{k,3}$	16.28	26.51	<b>35.40</b>	23.55
$Q_{k,4}$	4.17	13.67	29.20	<b>57.84</b>

**Mobility Matrix of Food Consumption**

Child \ Parent	$Q_{p,1}$	$Q_{p,2}$	$Q_{p,3}$	$Q_{p,4}$
$Q_{k,1}$	<b>40.00</b>	26.24	21.53	10.17
$Q_{k,2}$	27.03	<b>30.19</b>	20.26	20.75
$Q_{k,3}$	21.11	24.00	<b>32.07</b>	23.30
$Q_{k,4}$	11.86	19.57	26.14	<b>45.78</b>

Mobility matrices, while good at highlighting distributional heterogeneity in intergenerational persistence, as such cannot provide a summary statistic for measuring the overall mobility in the economy. Using the fact that in the case of perfect persistence the mobility matrix is nothing but the identity matrix of size  $m$ , where  $m$  is the number of quantiles used to construct the mobility matrix (in our case of quartiles,  $m = 4$ ), (Shorrocks, 1978) provides a simple measure of the distance of the estimated mobility matrix ( $M$ ) from the identity matrix as follows:

$$\text{Normalized Trace Index, } NTI = \frac{m - \text{trace}(M)}{m-1}$$

The *NTI* measure is **0.81** for the labour earnings transition matrix, while that for total consumption expenditure and food consumption stand lower at **0.74** and **0.84** respectively. This corroborates the higher persistence of total consumption than earnings and food consumption.

## A.2 Derivation of the Consumption Process

In this appendix we derive the analytical approximation of the optimal consumption processes. Assuming a quadratic utility function and  $\beta(1+r) = 1$ , we solve the maximization problem (1) and derive consumption at time  $t$  as the annuity value of lifetime resources, as follows:

$$C_{f,t} = \frac{r}{(1+r) - (1+r)^{-(T-t)}} \left[ A_{f,t} + \sum_{j=0}^{T-t} \left( \frac{1}{1+r} \right)^j \mathbb{E}_t(E_{f,t+j}) + \sum_{j=0}^{T-t} \left( \frac{1}{1+r} \right)^j \mathbb{E}_t(N_{f,t+j}) \right]$$

To express consumption expenditure in terms of logs, we use a first order Taylor series approximation of the logarithm of each variable around unity. For any variable  $x$ ,  $\ln(x) \simeq \ln(1) + \frac{x-1}{1} = x - 1 \implies x \simeq 1 + \ln(x)$ . This approximation holds only for values of  $x$  close to unity. Since in the empirical implementation of the model, we de-mean all the log variables, this approximation is valid on average. Denoting  $\ln(C_{f,t})$ ,  $\ln(A_{f,t})$ ,  $\ln(E_{f,t})$  and  $\ln(N_{f,t})$  by  $c_{f,t}$ ,  $a_{f,t}$ ,  $e_{f,t}$  and  $n_{f,t}$  respectively, and using the time-series processes we assumed for  $e_{f,t}$  and  $n_{f,t}$ , we get,

$$\begin{aligned} 1 + c_{f,t} &\simeq (1 + \bar{e}_f) + (1 + \bar{n}_f) + \\ &\frac{r}{(1+r) - (1+r)^{-(T-t)}} \left\{ (1 + a_{f,t}) + \sum_{j=0}^{T-t} \left( \frac{1}{1+r} \right)^j \mathbb{E}_t[(\mathcal{E}_{f,t+j} + \varepsilon_{f,t+j}) + (\Theta_{f,t+j} + \vartheta_{f,t+j})] \right\} \\ \implies c_{f,t} &\simeq 1 + \bar{e}_f + \bar{n}_f + \frac{r}{(1+r) - (1+r)^{-(T-t)}} [(1 + a_{f,t}) + (\varepsilon_{f,t} + \vartheta_{f,t})] \\ &+ \frac{r}{(1+r) - (1+r)^{-(T-t)}} \left[ \frac{(1+r) - \alpha_e^{T-t+1} (1+r)^{-(T-t)}}{1+r - \alpha_e} \mathcal{E}_{f,t} \right] \\ &+ \frac{r}{(1+r) - (1+r)^{-(T-t)}} \left[ \frac{(1+r) - \alpha_n^{T-t+1} (1+r)^{-(T-t)}}{1+r - \alpha_n} \Theta_{f,t} \right] \end{aligned}$$

The last step follows from the fact that the shocks  $\varepsilon$  and  $\vartheta$  are transitory with expectation zero and hence do not contribute to the discounted sum beyond their current period realizations, while the persistent shocks  $\mathcal{E}$  and  $\Theta$  are serially correlated to their past period's value through their fractional persistence parameters  $\alpha_e$  and  $\alpha_n$  respectively.

Let  $q_{f,t} \equiv 1 + d_t(r) (1 + a_{f,t})$  with  $d_t(r) \equiv \frac{r}{(1+r) - (1+r)^{-(T-t)}}$ , and  $d_t(r, \alpha_x) \equiv \frac{(1+r) - \alpha_x^{T-t+1} (1+r)^{-(T-t)}}{1+r - \alpha_x}$  for each  $x \in \{e, n\}$ . Then we can write the approximate log-consumption processes for an individual as:

$$c_{f,t} \simeq q_{f,t} + \bar{e}_f + \bar{n}_f + d_t(r) [\varepsilon_{f,t} + \vartheta_{f,t} + d_t(r, \alpha_e) \mathcal{E}_{f,t} + d_t(r, \alpha_n) \Theta_{f,t}]$$

For a large enough  $T$  relative to  $t$ ,  $d_t(r) \simeq \frac{r}{1+r}$  and  $d_t(r, \alpha_x) \simeq \frac{1+r}{1+r - \alpha_x}$  for each  $x \in \{e, n\}$ . Thus, for individuals who are sufficiently away from their demise, we can approximate their log-consumption as:

$$c_{f,t} \simeq q_{f,t} + \bar{e}_f + \bar{n}_f + \frac{r}{1+r} (\varepsilon_{f,t} + \vartheta_{f,t}) + \frac{r}{1+r-\alpha_e} \mathcal{E}_{f,t} + \frac{r}{1+r-\alpha_n} \Theta_{f,t} \quad (\text{A.2})$$

**CRRA Utility Function.** Relaxing the assumption of a quadratic utility function, we can still arrive at the same log-consumption equation as (A.2) with a more general utility function, after a linear approximation of the Euler equation. For example, in the case of constant relative risk aversion (CRRA) utility function, the Euler equation is given by  $C_{f,t}^{-\sigma} = \beta (1+r) \mathbb{E}_t (C_{f,t+1}^{-\sigma})$ , where  $\sigma > 0$  is the parameter capturing the degree of risk aversion as also the intertemporal elasticity of substitution. Maintaining the assumption  $\beta (1+r) = 1$ , we get from the Euler equation  $\mathbb{E}_t \left[ \left( \frac{C_{f,t+1}}{C_{f,t}} \right)^{-\sigma} \right] = 1$ . We define the function  $h(g_c) = (1+g_c)^{-\sigma}$ , where  $g_c = \frac{C_{f,t+1}}{C_{f,t}} - 1$  such that  $\mathbb{E}_t [h(g_c)] = 1$ . A first order Taylor series expansion of  $h(g_c)$  around  $g_c^* = 0$  yields  $h(g_c) \approx 1 - \sigma g_c$ . Taking expectations on both sides of this approximate equation, we get  $\mathbb{E}_t (g_c) = 0$ , implying  $C_{f,t} = \mathbb{E}_t (C_{f,t+1})$ . This is exactly the same as the Euler equation that one obtains from quadratic utility function without any approximation. Now, since we did not derive explicitly the consumption expression from this Euler equation in the paper, we provide the derivation here. Iterating forward the per-period budget constraint  $A_{f,t+1} = (1+r)(A_{f,t} + Y_{f,t} - C_{f,t})$  (where  $Y_{f,t} = E_{f,t} + N_{f,t}$ ) by one period and combining it with the Euler equation  $C_{f,t} = \mathbb{E}_t (C_{f,t+1})$ , we get,

$$\begin{aligned} \left(1 + \frac{1}{1+r}\right) C_{f,t} &= A_{f,t} - \left(\frac{1}{1+r}\right)^2 \mathbb{E}_t (A_{f,t+2}) + \left[ Y_{f,t} + \frac{1}{1+r} \mathbb{E}_t (Y_{f,t+1}) \right] \\ &\vdots \\ \Rightarrow \left[ 1 + \frac{1}{1+r} + \left(\frac{1}{1+r}\right)^2 + \dots \infty \right] C_{f,t} &= A_{f,t} - \lim_{k \rightarrow \infty} \left(\frac{1}{1+r}\right)^k \mathbb{E}_t (A_{f,t+k}) + \sum_{j=0}^{\infty} \left(\frac{1}{1+r}\right)^j \mathbb{E}_t (Y_{f,t+j}) \\ \Rightarrow \left[ \frac{1+r}{r} \right] C_{f,t} &= A_{f,t} + \sum_{j=0}^{\infty} \left(\frac{1}{1+r}\right)^j \mathbb{E}_t (Y_{f,t+j}) \\ \Rightarrow C_{f,t} &= \frac{r}{1+r} \left[ A_{f,t} + \sum_{j=0}^{\infty} \left(\frac{1}{1+r}\right)^j \mathbb{E}_t (Y_{f,t+j}) \right] \end{aligned}$$

Note that in the above derivation we have assumed the no-Ponzi condition that prevents an individual from continuously borrowing and rolling over his debt to future periods,  $\lim_{k \rightarrow \infty} \left(\frac{1}{1+r}\right)^k \mathbb{E}_t (A_{f,t+k}) = 0$ .

## B Appendix to Section 3

This appendix complements Section 3 in the main paper by providing further details of the baseline model identification (section B.1), the data and sampling restrictions used for estimation (section B.2), and the imputation of the consumption expenditure data (section B.3).

### B.1 Identification

(i) **Over-identifying moment restrictions.** Some additional cross-generational moments can be used as over-identifying restrictions for the parameter estimates:

$$\text{Cov}(\bar{e}_f^p, \bar{c}_f^k) = (\gamma + \gamma_n) \sigma_{\bar{e}^p}^2 + \lambda \sigma_{\bar{e}^p, \bar{q}^p} + (\rho + \rho_e) \sigma_{\bar{e}^p, \bar{n}^p} \quad (\text{B.1})$$

$$\text{Cov}(\bar{n}_f^p, \bar{c}_f^k) = (\rho + \rho_e) \sigma_{\bar{n}^p}^2 + \lambda \sigma_{\bar{n}^p, \bar{q}^p} + (\gamma + \gamma_n) \sigma_{\bar{e}^p, \bar{n}^p} \quad (\text{B.2})$$

$$\text{Cov}(\bar{c}_f^p, \bar{e}_f^k) = \gamma (\sigma_{\bar{e}^p}^2 + \sigma_{\bar{e}^p, \bar{q}^p} + \sigma_{\bar{e}^p, \bar{n}^p}) + \rho_e (\sigma_{\bar{n}^p}^2 + \sigma_{\bar{n}^p, \bar{q}^p} + \sigma_{\bar{e}^p, \bar{n}^p}) \quad (\text{B.3})$$

$$\text{Cov}(\bar{c}_f^p, \bar{n}_f^k) = \gamma_n (\sigma_{\bar{e}^p}^2 + \sigma_{\bar{e}^p, \bar{q}^p} + \sigma_{\bar{e}^p, \bar{n}^p}) + \rho (\sigma_{\bar{n}^p}^2 + \sigma_{\bar{n}^p, \bar{q}^p} + \sigma_{\bar{e}^p, \bar{n}^p}) \quad (\text{B.4})$$

(ii) **A graphical example.** One insight of our identification argument is that we can use elements of the covariance structure to jointly harness information about cross-sectional inequality and covariation of permanent income across generations. To illustrate how this works in practice, it helps to consider the relationships in Figure 2 where the y-axis measures the parental permanent earnings variance,  $\sigma_{\bar{e}^p}^2$ , and the x-axis represents the intergenerational earnings persistence,  $\gamma$ . To identify this pair of parameters we only use three empirical moments:  $\text{Var}(\bar{e}_f^p)$ ,  $\text{Cov}(\bar{e}_f^p, \bar{e}_f^k)$  and  $\text{Var}(\bar{e}_f^k)$ .

From moment condition (8), the variance of parental earnings ( $\sigma_{\bar{e}^p}^2$ ) is uniquely identified by  $\text{Var}(\bar{e}_f^p)$ : its value is shown as the horizontal dashed line in Figure 2. The moment condition (19) captures the tradeoff between  $\gamma$  and  $\sigma_{\bar{e}^p}^2$ , holding constant other persistence and variance parameters (i.e.,  $\rho_e$ ,  $\sigma_{\bar{n}^p}^2$ ,  $\sigma_{\bar{e}^p, \bar{n}^p}$  and  $\sigma_{\bar{e}^k}^2$ ). This is plotted as the negatively sloped dotted line in Figure 2. The intersection of the dotted line with the dashed line uniquely identifies the persistence parameter,  $\gamma$ . However, our model features an additional restriction: the exact location of the pair  $(\gamma, \sigma_{\bar{e}^p}^2)$  needs to be consistent with the moment condition (14), imposing an additional tradeoff between the two parameters (shown by the solid line). That is,  $\sigma_{\bar{e}^p}^2$  and  $\gamma$  must be such that both the solid and the dotted lines intersect the dashed line at a common location. One can verify that the location where all three moment conditions hold in Figure 2 corresponds to the baseline parameter estimates presented in Section 4.

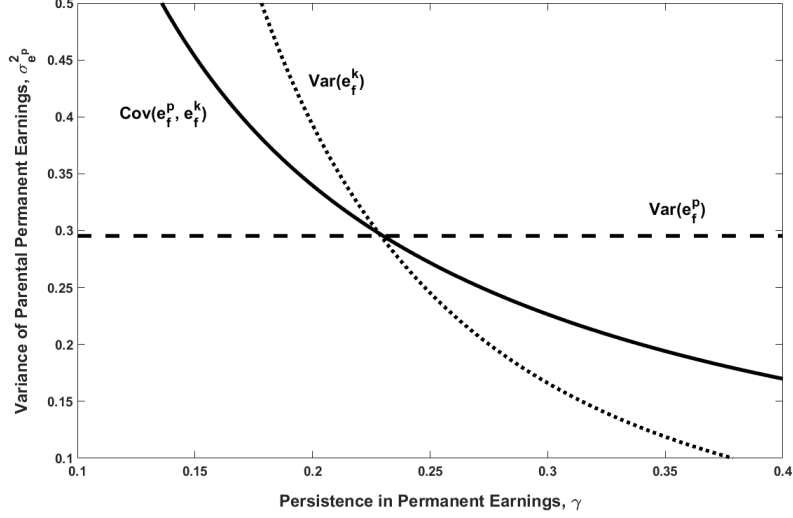


Figure 2: Identification of Persistence and Dispersion Parameters

## B.2 Data and Sampling

The Panel Study of Income Dynamics (PSID) is administered by the University of Michigan's Survey Research Center (SRC). This longitudinal survey began in 1968 with a national probability sample of almost 5,000 U.S. families. The sampled families were re-interviewed annually between 1968 and 1997. After 1997 they were re-interviewed biennially. We focus our study only on the non-Latino, non-immigrant households within the SRC component of the PSID, and exclude those in the Survey of Economic Opportunity (SEO) component where poor households were over-sampled.

PSID data have been used by different authors for intergenerational analyses because, by design, this survey follows the children of original sample members when they become independent from their original family. This allows to follow children from the original sample as they grow into adulthood and become household heads themselves. To reduce noise due to weak labour market participation and marital status, our main analysis for household heads focuses on observations for married male individuals between 25 and 65 years of age, who have at least 5 years of data in the PSID, have non-negative labour earnings and total family income, work for less than 5840 hours annually, have wages greater than half of the federal minimum wage, and do not have annual earnings growth rates of more than 400 percent. Our analysis pertains to children born between 1952 and 1981. To avoid over-representation of children who left their homes at a later stage of their lives, the sample excludes children born before 1952 (that is, those children who were older than 16 at the time of the first 1968 PSID interview). The first year in which child income is observed is 1977 (as reported in the 1978 interview) - the year in which the 1952 birth-cohort reached age 25. Consequently, we can observe the 1952 cohort between ages 25 and 62, while the 1981 cohort can only be observed between ages 25 and 33 years. Parents who are older than 65 are dropped

from the analysis to avoid complications related to retirement decisions. In robustness checks, we consider various alternative samples, e.g., restrict age range from 30 to 40 years for both parents and children, and look at different cohorts of children separately. Our model estimates remain qualitatively similar under all these alternative samples.

The labour earnings data for the male household head and his wife, and the total transfer income data for the couple are readily available for most survey rounds of the PSID. In contrast, the family consumption data is quite sparse across the survey years and not presented as a single variable in the PSID. Different consumption expenditure categories have to be suitably summed up (using appropriate weights depending on the frequency of consumption in a particular category, e.g., yearly, monthly, weekly, etc.) to arrive at an aggregate measure of consumption expenditure.

There are 11 major categories of consumption variables, namely, (i) food, (ii) housing, (iii) child-care, (iv) education, (v) transportation, (vi) healthcare, (vii) recreation and entertainment, (viii) trips and vacation, (ix) clothing and apparel, (x) home repairs and maintenance, and (xi) household furnishings and equipment. Of these, food and housing are most consistently observed across the years - expenditure on food is observed from the 1968 interview through the 2015 interview, barring only 1973, 1988 and 1989. Housing expenditure is observed in all years except 1978, 1988 and 1989. Child-care expenditure data is available for 25 rounds of interview - 1970-1972 (3 interview years), 1976, 1977, 1979 and 1988-2015 (19 interview years). Education, transportation and health-care are only reported by the last 9 PSID interviews (biennially from 1999 through 2015). The rest of the categories from (vii) through (xi) are observed for only the last 6 interviews (biennially from 2005 to 2015).

The uneven availability of expenditure categories in different waves of the PSID suggests that a simple sum of the expenditure categories for different years would not provide an accurate approximation of total consumption because every year reports different subsets of consumption expenditures. There are two ways to account for this problem in the calculation of the total consumption variable: either take the measure of consumption to be equal to just the expenditure on food, the most consistently observed category (although that would ignore variation in the consumption of non-durable goods other than food); or impute the consumption of the missing categories.

### B.3 Imputation of Consumption Expenditure Data

To assess the quality of consumption survey data, [Andreski et al. \(2014\)](#) compare expenditure data from the Consumption Expenditure Survey (CEX) and the PSID. They find that expenditures in individual categories of consumption may vary non-trivially across the two datasets, e.g., reported home repairs and maintenance expenditures are approximately twice as large in the PSID as the are in the CEX, and the PSID home insurance expenditures are 40 to 50 percent higher than their CEX counterparts. However, despite these inconsistencies within individual categories (due to differences in survey methodologies and sampling techniques), [Li et al. \(2010\)](#) show that the

average expenditure since 1999 in PSID and CEX have been fairly close to each other. Moreover, the consumption expenditures in the two datasets vary in a similar way with observable household characteristics like age of household head, household size, educational attainment, marital status, race and home ownership. This average consistency between PSID and CEX data, as well as the fact that total consumption seems to be close to the aggregate consumption estimates in the NIPA (National Income and Product Accounts) data, suggests that PSID expenditure data can be used to draw information about households consumption behaviour.

[Attanasio and Pistaferri \(2014\)](#) (henceforth AP) suggest to impute consumption data for the missing consumption categories in the PSID before 1999 by using the more detailed data available post-1999. Their backward extrapolation is consistent with theories of consumer demand in the sense that the allocation of total resources spent in a given period over different commodities is made dependent on relative prices and taste-shifters, e.g., demographic and socio-economic variables. However, this specification implicitly assumes homotheticity of consumer preferences over different commodities. To relax that assumption, we include log total income in the imputation regression as a control. We use this slightly modified approximated demand system to total consumption expenditures before 1999:

$$\ln(\tilde{C}_{ft}) = Z'_{ft}\omega + p'_t\pi + g(F_{ft}; \lambda) + \epsilon_{ft}, \quad (\text{B.5})$$

where  $\tilde{C}_{ft}$  is consumption net of food expenditure,  $Z_{ft}$  are the socioeconomic controls (viz., dummies for age, education, marital status, race, state of residence, employment status, self-employment, head's hours worked, homeownership, disability, family size, and the number of children in the household) and total family income,  $p_t$  are the relative prices (the overall CPI and the CPIs for food at home, food away from home, and rent),  $F_{ft}$  is the total food expenditure (i.e., sum of food at home, food away from home, and food stamps) that is observed in the PSID consistently through the years,  $g(\cdot)$  is a polynomial function, and  $\epsilon_{ft}$  is the error term. The subscripts  $f$  and  $t$  denotes family identity and year respectively. This equation is estimated using data from the 1999-2015 PSID waves, where the net consumption measure  $\tilde{C}_{ft}$  is the sum of annualized expenditures on home insurance, electricity, heating, water, other miscellaneous utilities, car insurance, car repairs, gasoline, parking, bus fares, taxi fares, other transportation, school tuition, other school expenses, child care, health insurance, out-of-pocket health, and rent. While performing the imputation we skip the consumption expenditure categories that were added to the PSID from the 2005 wave. This is done to keep the measure of consumption consistent over the years and to also maximize the number of categories that can be used. Moreover, the categories added from the 2005 wave collectively constitute a very small fraction of total consumption. In the definition of net consumption we have excluded food expenditure to avoid endogeneity issues in the regression. The measure for rent equals the actual annual rent payments for renters and is imputed to 6% of the self-reported house value (see [Flavin and Yamashita, 2002](#)) for the homeowners.

After estimating the logarithm of the net consumption equation by running a pooled OLS regression on equation (B.5), we construct a measure of imputed total consumption as follows

$$\hat{C}_{ft} = F_{ft} + \exp \left\{ Z'_{ft} \hat{\omega} + p'_t \hat{\pi} + g \left( F_{ft}; \hat{\lambda} \right) \right\}. \quad (\text{B.6})$$

This measure is corrected for inflation by dividing it by the overall CPI. Finally the measure is transformed into adult-equivalent values using the OECD scale,  $(1 + 0.7(A - 1) + 0.5K)$ , where  $A$  is the number of adults and  $K$  the number of children in the household unit.

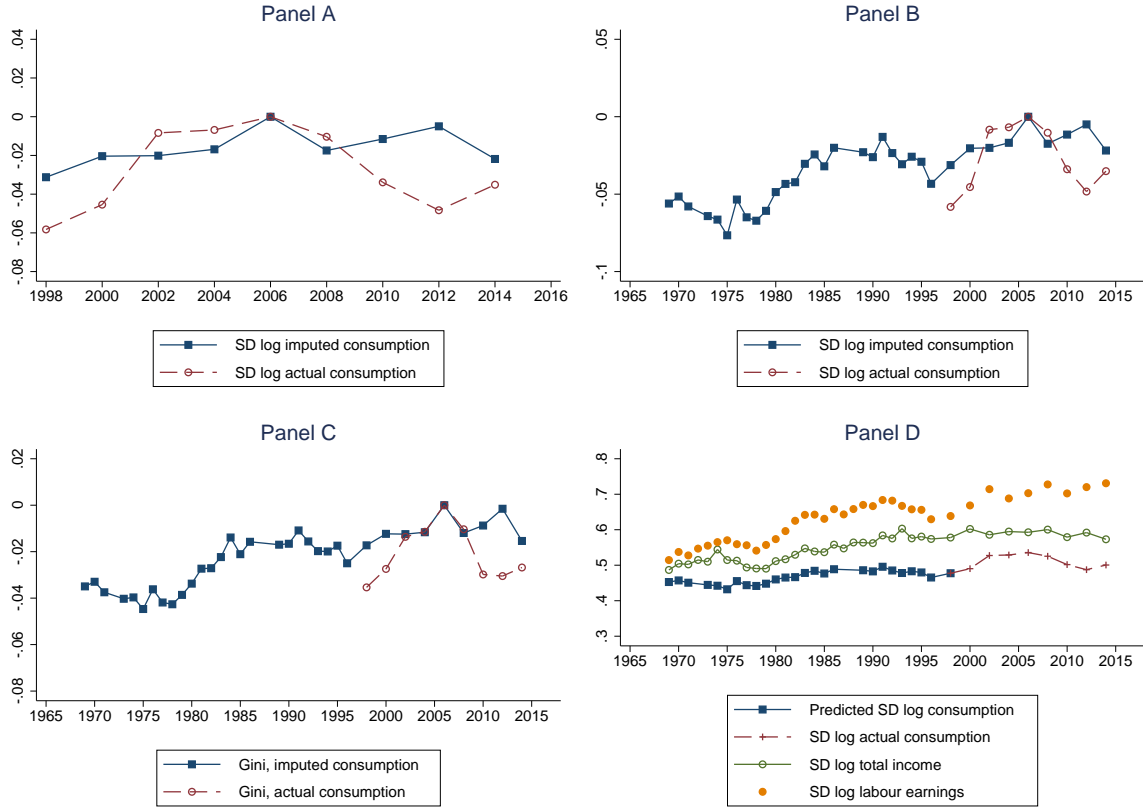


Figure 3: Quality Assessment of Consumption Imputation

**Note:** In Panels A, B and C, series are normalized to values in 2006 for ease of comparison.

A key question is how well the imputed consumption values match with the observed values during the period when both data series are available. A natural choice for a measure of the goodness of fit is the  $R^2$  of the regression (B.5), which is found to be 0.47. However, what we are really interested in is matching the standard deviations of the observed and imputed series because we would be using only the second order moments of income and consumption for estimating our model in Section 2. Like AP, we find that our imputed consumption series can match the observed

series quite closely in terms of standard deviation, and similarly well for a more general non-linear measure like the Gini coefficient. Figure 3 presents the Gini coefficients (normalized to their initial values in 2006) of the logs of imputed and actual consumption (in Panel C), and also compares the standard deviations of actual and imputed consumption with those of real income and labour earnings (in Panels A, B, and D). The top-coded values for total family income and the household heads' labour earnings in the PSID are replaced with the estimates obtained from fitting a Pareto distribution to the upper tail of the corresponding distribution.

## C Appendix to Section 4

This appendix is comprised of the following main sections. Section C.1 shows the values of the empirical moments that are used to estimate the parameters of the baseline specification, along with the internal fit of those moments from the GMM estimation. In Section C.2, we show the intergenerational persistence in observable characteristics and the specific role of education in driving the intergenerational linkages in our data. Section ?? presents details for computing the importance of parental heterogeneity in explaining cross-sectional dispersion in the children's generation. Section C.5 provides details of the long run evolution of inequality across generations.

### C.1 Empirical Moments and Baseline Fit

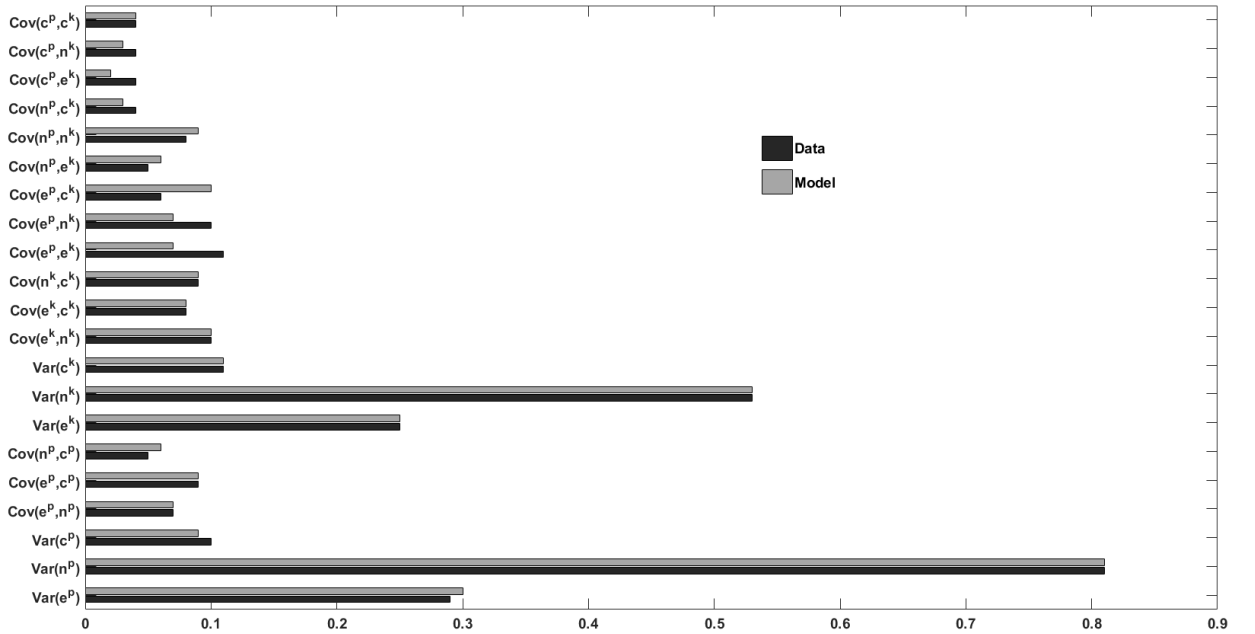


Figure 4: Internal Fit of Baseline Model

**Note:** Both the data and the model estimates correspond to the *Baseline* case where the raw data is purged of only birth cohort and year fixed effects. The average age for parents is 47 years, while that for children is 37 years for 760 unique parent-child pairs in the PSID.

The GMM minimizes the distance between the empirical moments and the analytical moments implied by the statistical model. If the parameters were exactly identified then the GMM estimates would be nothing but the solution of the system of moment restrictions. However, with over-identification, the GMM becomes relevant in the sense that it minimizes the error from all over-identifying restrictions. Hence, it is important that we study the empirical moments which

essentially gives the estimates via the GMM. In Figure 4, we present the cross-sectional empirical moments for the baseline case along with the internal fit of the model.

## C.2 Role of Observable Characteristics in Persistence

How much of the intra-family linkages in earnings, other income and consumption can be explained by observable characteristics of the two generations? Observables like race and educational attainment has long been argued to be significant determinants of intergenerational mobility. Table 15 shows the high degree of persistence in a host of observable characteristics across the two generations in our sample. So a natural question to ask is — if the observables are themselves persistent over generations, how do they influence the persistence in economic outcomes in turn. We have addressed this question in the main paper. Here, in Table 17 we study the role of education alone in driving the intergenerational linkages in income and consumption vis-a-vis the other observable characteristics. We also present the intergenerational mobility matrix for educational attainment in Table 16.

Table 15: Persistence of Observable Characteristics

Observed Variable	Persistence
Family Size	0.32
State of Residence	0.71
No. of Children	0.38
Employment Status	0.86
Race	0.98
Education	0.50

Table 16: Mobility Matrix for Education

<div> <div>Parent</div> <div>Child</div> </div>	<12 years	High School	College Dropout	College & above
<12 years	<b>21.88</b>	4.91	0.00	0.00
High School	40.49	<b>39.96</b>	19.23	7.78
College Dropout	20.90	25.60	<b>42.35</b>	14.93
College & above	16.74	29.53	38.42	<b>77.29</b>

Table 17: Role of Education among Observables

	Parameters	All Observables (2)	Education Only (3)	Observables except Education (4)
Head Earnings	$\gamma$	0.338 (0.025)	0.255 (0.031)	0.304 (0.025)
Other Income	$\rho$	0.248 (0.042)	0.188 (0.029)	0.208 (0.058)
$\bar{e}_f^p$ on $\bar{n}_f^k$	$\gamma_n$	0.258 (0.026)	0.185 (0.017)	0.276 (0.037)
$\bar{n}_f^p$ on $\bar{e}_f^k$	$\rho_e$	0.112 (0.028)	0.196 (0.044)	0.055 (0.027)
Consumption Shifters	$\lambda$	0.452 (0.045)	0.413 (0.029)	0.358 (0.076)
<i>No. of Parent-Child Pairs</i>	$N$	761	761	761

**Note:** Bootstrap standard errors with 100 repetitions are reported in parentheses. *All Observables* refers to the total fitted value of the regression of the data (purged off of year and birth cohort effects) on dummies for family size, state of residence, number of children, employment status, race and education. *Education Only* refers to the fitted value of the regression of the data on education only, while *Observables except Education* refers to the fitted value of the other observable control variables. The average age for parents is 47 years, while that for children is 37 years in the sample.

### C.3 The Impact of Parental Factors on Inequality

In order to compare the actual distribution of outcomes for children with the counterfactual distributions where parental effects are shut down, we assume that the permanent parental and idiosyncratic child components of earnings, other income and consumption jointly follow a Gaussian distribution in logarithms<sup>24</sup>:

$$\begin{pmatrix} \bar{e}_f^p \\ \bar{n}_f^p \\ \bar{q}_f^p \\ \check{e}_f^k \\ \check{n}_f^k \\ \check{q}_f^k \end{pmatrix} \sim \mathbf{N} \left[ \begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_{\bar{e}^p}^2 & \sigma_{\bar{e}^p, \bar{n}^p} & \sigma_{\bar{e}^p, \bar{q}^p} & 0 & 0 & 0 \\ \sigma_{\bar{e}^p, \bar{n}^p} & \sigma_{\bar{n}^p}^2 & \sigma_{\bar{n}^p, \bar{q}^p} & 0 & 0 & 0 \\ \sigma_{\bar{e}^p, \bar{q}^p} & \sigma_{\bar{n}^p, \bar{q}^p} & \sigma_{\bar{q}^p}^2 & 0 & 0 & 0 \\ 0 & 0 & 0 & \sigma_{\check{e}^k}^2 & \sigma_{\check{e}^k, \check{n}^k} & \sigma_{\check{e}^k, \check{q}^k} \\ 0 & 0 & 0 & \sigma_{\check{e}^k, \check{n}^k} & \sigma_{\check{n}^k}^2 & \sigma_{\check{n}^k, \check{q}^k} \\ 0 & 0 & 0 & \sigma_{\check{e}^k, \check{q}^k} & \sigma_{\check{n}^k, \check{q}^k} & \sigma_{\check{q}^k}^2 \end{pmatrix} \right]$$

<sup>24</sup>The mean of the logarithmic variables are zero because we consider de-measured variables net of year and cohort fixed effects.

Then, by the property of a joint Normal distribution, any linear combination of the constituent random variables also follows a Normal distribution. For example, we can assume that the idiosyncratic part of permanent child consumption,  $(\check{c}_f^k + \check{n}_f^k + \check{q}_f^k)$ , follows a Normal distribution with zero mean and variance equal to  $\sigma_{\check{c}^k}^2 + \sigma_{\check{n}^k}^2 + \sigma_{\check{q}^k}^2 + 2(\sigma_{\check{c}^k, \check{n}^k} + \sigma_{\check{c}^k, \check{q}^k} + \sigma_{\check{n}^k, \check{q}^k})$ . Such child idiosyncratic components are, by definition, independent of any parental influence, and hence can be used to generate the counterfactual distribution for the children. Now, since the logarithmic random variables follow the Gaussian distribution (by assumption), they will follow the lognormal distribution in their levels. Figure 1 of the main paper reports the difference between the probability density functions with and without parental influence.

## C.4 Measuring Intergenerational Consumption Insurance

Consider the intergenerational elasticity of consumption,  $\beta_c$ , that can be estimated from the regression:  $\bar{c}_f^k = \beta_c \bar{c}_f^p + \check{c}_f^k$ . The estimated value of  $\beta_c$  is given as follows:

$$\begin{aligned}
\hat{\beta}_c &= \frac{\text{Cov}(\bar{c}_f^p, \bar{c}_f^k)}{\text{Var}(\bar{c}_f^p)} \leq 1 \\
\implies \text{Var}(\bar{c}_f^p) &\geq \text{Cov}(\bar{c}_f^p, \bar{c}_f^k) \\
\implies 2\text{Var}(\bar{c}_f^p) &\geq 2\text{Cov}(\bar{c}_f^p, \bar{c}_f^k) \\
\implies \text{Var}(\bar{c}_f^p) - 2\text{Cov}(\bar{c}_f^p, \bar{c}_f^k) &\geq -\text{Var}(\bar{c}_f^p) \\
\implies \text{Var}(\bar{c}_f^k) + \text{Var}(\bar{c}_f^p) - 2\text{Cov}(\bar{c}_f^p, \bar{c}_f^k) &\geq \text{Var}(\bar{c}_f^k) - \text{Var}(\bar{c}_f^p) \\
\implies \text{Var}(\bar{c}_f^k - \bar{c}_f^p) &\geq \text{Var}(\bar{c}_f^k) - \text{Var}(\bar{c}_f^p) \\
\implies \frac{\text{Var}(\bar{c}_f^k - \bar{c}_f^p)}{\text{Var}(\check{y}_f^k)} &\geq \frac{\text{Var}(\bar{c}_f^k) - \text{Var}(\bar{c}_f^p)}{\text{Var}(\check{y}_f^k)} \\
\implies \left[ \frac{\text{Var}(\bar{c}_f^k - \bar{c}_f^p)}{\text{Var}(\check{y}_f^k)} \right]^{0.5} &\geq \left[ \frac{\text{Var}(\bar{c}_f^k) - \text{Var}(\bar{c}_f^p)}{\text{Var}(\check{y}_f^k)} \right]^{0.5} \\
\implies \mu_{FAM} &\geq \mu_{GEN}
\end{aligned}$$

As an extreme case, consider an economy where child consumption is exactly equal to parental consumption, with no idiosyncratic deviation. That is, there is no uncertainty regarding consumption beyond the family heterogeneity at birth, and any cross-sectional inequality existing in the parental generation will be passed one-for-one to the children's generation. In such a case,  $\text{Var}(\bar{c}_f^k) = \text{Var}(\bar{c}_f^p) = \text{Cov}(\bar{c}_f^p, \bar{c}_f^k)$ , implying,  $\mu_{GEN} = \mu_{FAM} = 0$ , that is, perfect consumption insurance against lifetime average income shocks idiosyncratic to the children's generation.

## C.5 Evolution of Inequality across Generations

**Deriving Steady-State Inequality.** Earnings, other income and consumption shifters evolve through generations of family  $f$  according to the following vector autoregressive process:

$$\begin{bmatrix} \bar{e}_f^{k_t} \\ \bar{n}_f^{k_t} \\ \bar{q}_f^{k_t} \end{bmatrix} = \begin{bmatrix} \gamma & \rho_e & 0 \\ \gamma_n & \rho & 0 \\ 0 & 0 & \lambda \end{bmatrix} \cdot \begin{bmatrix} \bar{e}_f^{k_{t-1}} \\ \bar{n}_f^{k_{t-1}} \\ \bar{q}_f^{k_{t-1}} \end{bmatrix} + \begin{bmatrix} \check{e}_f^{k_t} \\ \check{n}_f^{k_t} \\ \check{q}_f^{k_t} \end{bmatrix}.$$

The superscript  $\{k_t\}$  identifies the  $t^{th}$  generation of kids. Since  $k_1$  denotes the first generation of kids, we define  $k_0$  to be the parents' generation in our data, that is,  $\bar{x}_f^{k_0} \equiv \bar{x}_f^p$  for any variable  $x \in \{e, n, q\}$ . The joint distribution of the covariance-stationary idiosyncratic shocks is

$$\begin{bmatrix} \check{e}_f^{k_t} \\ \check{n}_f^{k_t} \\ \check{q}_f^{k_t} \end{bmatrix} \sim N \left[ \begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_{\check{e}^k}^2 & \sigma_{\check{e}^k, \check{n}^k} & \sigma_{\check{e}^k, \check{q}^k} \\ \sigma_{\check{e}^k, \check{n}^k} & \sigma_{\check{n}^k}^2 & \sigma_{\check{n}^k, \check{q}^k} \\ \sigma_{\check{e}^k, \check{q}^k} & \sigma_{\check{n}^k, \check{q}^k} & \sigma_{\check{q}^k}^2 \end{pmatrix} \right]$$

Using parameter estimates, we simulate the VAR forward, iterating until convergence.<sup>25</sup> This delivers simulated data series for  $\bar{e}_f^{k_t}$ ,  $\bar{n}_f^{k_t}$ ,  $\bar{q}_f^{k_t}$ ,  $\check{e}_f^{k_t}$ ,  $\check{n}_f^{k_t}$  and  $\check{q}_f^{k_t}$ . To obtain a series for log consumption, we use the relationship:

$$c_f^{k_t} = \lambda \bar{q}_f^{k_{t-1}} + (\gamma + \gamma_n) \bar{e}_f^{k_{t-1}} + (\rho + \rho_e) \bar{n}_f^{k_{t-1}} + \check{e}_f^{k_t} + \check{n}_f^{k_t} + \check{q}_f^{k_t},$$

for  $t \geq 1$ . Having recovered the (log) series for the permanent components of earnings, other income, and consumption, we calculate their long-run variances and report them in column 3 of Table 7.

**Importance of Intergenerational Persistence for Long-Run Inequality.** To illustrate the quantitative importance of intergenerational elasticities in the long-run, we re-estimate the baseline model using a constrained version of the GMM estimator where we hold constant the earnings persistence  $\gamma$  at pre-determined values. By exogenously setting larger or smaller values of  $\gamma$ , we can assess whether, and how much, steady-state inequality might deviate from its initial value. Table 18 shows that for counterfactually high values of  $\gamma$ , earnings inequality in the children generation (column 4) can be substantially different from long-run model outcomes (column 5). Moreover, a trade-off between inter-generational persistence,  $\gamma$  (column 1) and idiosyncratic heterogeneity,  $\sigma_{\check{e}^k}^2$

<sup>25</sup>Since we restrict the age range between 30 and 40 years, we re-estimate the baseline model on a smaller sample. The estimates are reported in column 1 of Tables 41 and 42. The VAR is simulated over 100,000 generations.

Table 18: The Importance of Parents: Varying Persistence  $\gamma$ 

$\gamma$	$\widehat{\sigma_{\epsilon^k}^2}$	$\widehat{Var}(\bar{e}^p)$	$\widehat{Var}(\bar{e}^k)$	$\widehat{Var}(e^*)$	$\frac{\gamma^2 \widehat{Var}(\bar{e}^p)}{\widehat{Var}(\bar{e}^k)}$
(1)	(2)	(3)	(4)	(5)	(6)
0.10	0.258	0.185	0.260	0.262	0.9%
<b>0.19</b>	<b>0.253</b>	<b>0.183</b>	<b>0.260</b>	<b>0.265</b>	<b>2.7%</b>
0.30	0.244	0.176	0.260	0.270	6.3%
0.40	0.233	0.166	0.260	0.280	10.4%
0.50	0.221	0.153	0.260	0.298	14.9%
0.60	0.209	0.140	0.260	0.330	19.6%
0.70	0.197	0.128	0.260	0.392	24.2%
0.80	0.186	0.116	0.260	0.526	28.6%
0.90	0.175	0.104	0.260	0.955	32.7%

**Note:** Bold values refer to a specification with  $\gamma$  unconstrained and estimated as part of the optimization. The age range for both children and parents is between 30 and 40 years. Estimation is based on 404 unique parent-child pairs.

(column 2) is evident when explaining the total child variance (column 4).<sup>26</sup>

Despite a falling variance for idiosyncratic innovations,  $\sigma_{\epsilon^k}^2$ , steady-state inequality in column 5 increases with the magnitude of  $\gamma$ . Thus, the cross-generational persistence, rather than the innovations variance, emerges as the key determinant of long-run inequality and as the main reason for the similarity of  $\text{Var}(\bar{e}^k)$  and  $\text{Var}(e^*)$ .<sup>27</sup>

These results emphasize that, without any increases in the underlying dispersion of idiosyncratic innovations, one would have to assume implausibly large values of the intergenerational pass-through to induce significantly higher long-run inequality. It follows that intergenerational persistence dictates the proportional impact of parental heterogeneity on inequality. Further evidence of this is in the last column of Table 18, which documents how changes in  $\gamma$  lead to significant variation in the contribution of parental factors to cross-sectional earnings inequality. A larger  $\gamma$  amplifies the contribution of family background: the parental contribution to inequality swings widely, between 1% and 12% (for values of  $\gamma$  between 0.1 and 0.4) even when steady-state earnings

<sup>26</sup>When intergenerational persistence  $\gamma$  is set to a higher value, the GMM estimator mechanically delivers a lower variance of idiosyncratic heterogeneity (e.g., for earnings, lower  $\sigma_{\epsilon^k}^2$ ) since observed cross-sectional inequality among children remains unchanged.

<sup>27</sup>A striking feature of the GMM estimates in Table 18 is that the child variance remains constant and matches exactly the empirical value. In contrast, the observed parental variance is 0.183 and is not matched by specifications where  $\gamma$  is exogenously fixed. To understand this, consider that the moment estimator has to satisfy equation (14), which implies a direct trade-off between  $\gamma$  and  $\text{Var}(\bar{e}^p)$ . Thus, increasing  $\gamma$  tends to decrease  $\text{Var}(\bar{e}^p)$ . On the other hand, whatever the values for  $\gamma$  and  $\text{Var}(\bar{e}^p)$ , the observed value of  $\text{Var}(\bar{e}^k)$  is always matched exactly by choosing the free parameter  $\sigma_{\epsilon^k}^2$ , which does not enter any other moment condition.

dispersion  $\widehat{Var}(e^*)$  barely changes.

It is interesting to contrast the values in column 6 of Table 18 with baseline estimates of the importance of parental factors in Table 4, where the age range was not restricted. Restricting the age range over which parents' income is measured implies that the importance of family background declines from about 8% to 4% of total variation: that is, roughly half of the parental impact on inequality among children accrues by the time parents reach age 40.

A final caveat for these results is that inference about the evolution of inequality is based on stationary parameter estimates. For this reason in Appendix C.5 we consider the implications of changes in structural parameter estimates on inequality going forward and we explore how inequality evolves over subsequent generations (parent, child, grandchild) while converging to its steady-state level.

**Deriving the Transitional Path of Inequality.** What degree of persistence would generate, all else equal, growing dispersion across generations? To answer this question, one needs to derive a threshold value of persistence as a function of the inequality in that generation. In order to get a closed form expression for these threshold values of persistence, we shut down the cross-persistence terms, that is, restrict  $\gamma_n = \rho_e = 0$ . With these parameter restrictions, earnings in the  $t^{th}$  generation of kids of the same family is given by:

$$e^{kt} = \gamma^t \bar{e}^p + \sum_{j=1}^t \gamma^{t-j} \check{e}^{kt}$$

Since  $\gamma \in (0, 1)$ , there exists a long run stationary distribution for earnings. Assuming  $\text{Var}(\check{e}^{kt}) = \sigma_{\check{e}^k}^2 \forall t$  and  $\text{Cov}(\check{e}^{kt}, \check{e}^{k_{t'}}) = 0 \forall t \neq t'$ , the variance of the stationary distribution of  $e$ , denoted by  $\text{Var}(e^*)$ , is

$$\text{Var}(e^*) = \lim_{t \rightarrow \infty} \left[ \gamma^{2t} \sigma_{\bar{e}^p}^2 + \sum_{j=1}^t \gamma^{2(t-j)} \sigma_{\check{e}^k}^2 \right] = \frac{\sigma_{\check{e}^k}^2}{1 - \gamma^2} \quad (\text{C.1})$$

Similarly, one can derive the stationary variances for other income and consumption as,

$$\text{Var}(n^*) = \frac{\sigma_{\check{n}^k}^2}{1 - \rho^2} \quad (\text{C.2})$$

$$\text{Var}(c^*) = \frac{\sigma_{\check{q}^k}^2}{1 - \lambda^2} + \frac{\sigma_{\check{e}^k}^2}{1 - \gamma^2} + \frac{\sigma_{\check{n}^k}^2}{1 - \rho^2} + \frac{2\sigma_{\check{e}^k, \check{n}^k}}{1 - \gamma\rho} + \frac{2\sigma_{\check{n}^k, \check{q}^k}}{1 - \lambda\rho} + \frac{2\sigma_{\check{e}^k, \check{q}^k}}{1 - \lambda\gamma}. \quad (\text{C.3})$$

Plugging in estimated values for the parameters in equations (C.1) through (C.3),<sup>28</sup> one can

---

<sup>28</sup>Since we restrict the parameters  $\gamma_n = \rho_e = 0$ , we need to re-estimate our baseline model with this additional

Table 19: Intergenerational Elasticities

	Parameters	Estimates (1)
Head Earnings	$\gamma$	0.280 (0.041)
Other Income	$\rho$	0.021 (0.047)
Consumption Shifters	$\lambda$	0.006 (0.051)
<i>No. of Parent-Child Pairs</i>	<i>N</i>	404

**Note:** Bootstrap standard errors (100 repetitions) in parentheses. Parental and child ages vary between 30 and 40. Parameters  $\gamma_n$  and  $\rho_e$  are set to zero. Average parental age is 37 years, while average age of children is 35. Food expenditures are used as a measure of consumption. Estimates use cross-sectional data variation net of cohort and year effects.

identify the threshold values of the persistence parameters beyond which there will be rising inequality. Using equation (C.1), we identify the threshold value of  $\gamma$  above which the variance of earnings would grow from the value estimated in the parents' generation: this is the value of  $\gamma$  such that  $\text{Var}(e^*) \geq \text{Var}(e^p)$ . This threshold value of  $\gamma$  is given by  $\gamma^p \equiv \sqrt{1 - \frac{\sigma_{e^k}^2}{\text{Var}(e^p)}}$ . Any  $\gamma$  larger than  $\gamma^p$  implies growing earnings variance. Based on the parameter estimates in Tables 19 and 20,  $\sigma_{e^k}^2 = 0.246 > \text{Var}(e^p) = 0.183$ , making  $\gamma^p$  an imaginary number. This essentially implies that any non-negative value of  $\gamma$  would result in increasing earnings inequality from the level in the parents' generation. Since our estimate of the current value of  $\gamma$  ( $= 0.279$ ) is positive, the model implies that the earnings variance should become larger in the next generation  $k_1$ . In fact, earnings variance in the child generation,  $\text{Var}(e^{k_1}) = 0.261$  is larger than in the parents' one,  $\text{Var}(e^p) = 0.183$ .

Starting from the children generation, and using equation (C.1) again, we can find the threshold value of  $\gamma$  above which the earnings variance after the child generation would be growing; that is,

$$\gamma^{k_1} \equiv \sqrt{1 - \frac{\sigma_{e^k}^2}{\text{Var}(e^{k_1})}} = \sqrt{1 - \frac{0.246}{0.261}} = 0.24.$$

This is plotted as the dashed vertical line in Figure 5. Any value of  $\gamma$  to the right of that vertical line implies growing earnings variance. Since our estimate of  $\gamma$  ( $= 0.279$ ) lies to the right of the new threshold  $\gamma^{k_1}$ , the threshold corresponding to the generation of grandchildren  $k_2$  (denoted by the

---

restriction. Additionally, we restrict the age range between 30 and 40 years for both parents and kids, in order to facilitate comparison of inequality across different generations in the same age range. These estimates are reported in Tables 19 and 20.

Table 20: Idiosyncratic Variances &amp; Covariances

	Parameters	Estimates (1)
<b><u>Parental Variances</u></b>		
Permanent Head Earnings	$\sigma_{\bar{e}p}^2$	. 0.183 (0.015)
Permanent Other Income	$\sigma_{\bar{n}p}^2$	0.876 (0.113)
Permanent Consumption Shifters	$\sigma_{\bar{q}p}^2$	0.955 (0.113)
<b><u>Child Idiosyncratic Variances</u></b>		
Permanent Head Earnings	$\sigma_{\bar{e}k}^2$	. 0.246 (0.017)
Permanent Other Income	$\sigma_{\bar{n}k}^2$	0.631 (0.058)
Permanent Consumption Shifters	$\sigma_{\bar{q}k}^2$	0.853 (0.072)
<b><u>Parental Covariances</u></b>		
Consumption Shifters & Head Earnings	$\sigma_{\bar{e}p, \bar{q}p}$	. -0.122 (0.030)
Consumption Shifters & Other Income	$\sigma_{\bar{n}p, \bar{q}p}$	-0.840 (0.110)
Head Earnings and Other Income	$\sigma_{\bar{e}p, \bar{n}p}$	-0.000 (0.025)
<b><u>Child Idiosyncratic Covariances</u></b>		
Consumption Shifters & Head Earnings	$\sigma_{\bar{e}k, \bar{q}k}$	. -0.248 (0.025)
Consumption Shifters & Other Income	$\sigma_{\bar{n}k, \bar{q}k}$	-0.623 (0.063)
Head Earnings & Other Income	$\sigma_{\bar{e}k, \bar{n}k}$	0.057 (0.023)
<i>No. of Parent-Child Pairs</i>	<i>N</i>	404

**Note:** Bootstrap standard errors (100 repetitions) in parentheses. This table uses the same sample and model specification as Table 19.

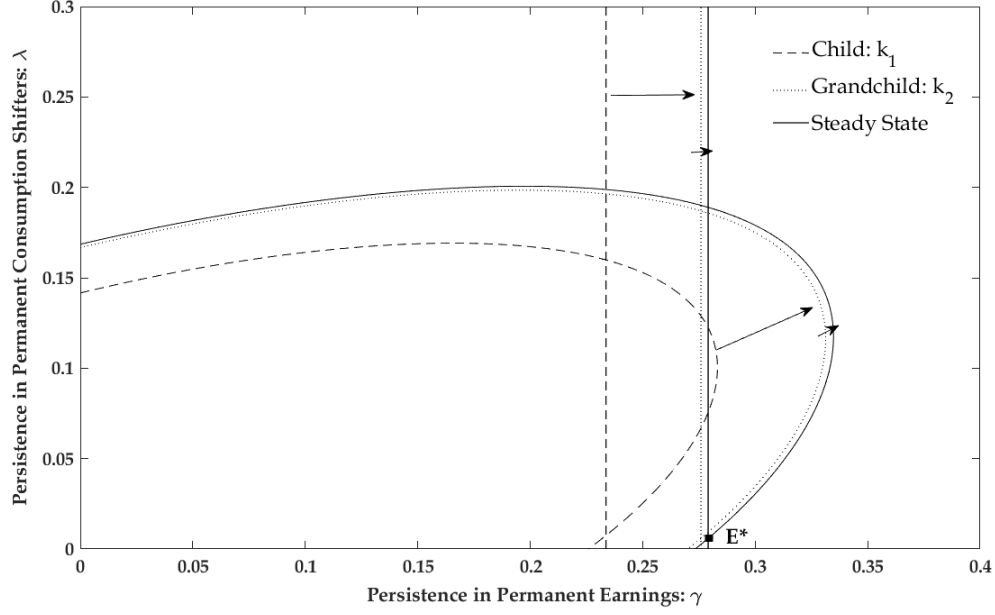


Figure 5: Implication of  $\gamma$  and  $\lambda$  for Long Run Earnings & Consumption Inequality

dotted vertical line in Figure 5) will lie further to the right of  $\gamma^{k_1}$ ; one can repeat these calculations over and over again.<sup>29</sup> Eventually, the economy settles down at the stationary distribution of earnings where the threshold is defined as

$$\gamma^* \equiv \sqrt{1 - \frac{\sigma_{e^k}^2}{\text{Var}(e^*)}} = 0.279,$$

which is the estimated level of  $\gamma$ . We can perform a similar exercise for the evolution of the variance of consumption using equation (C.3). Instead of a single persistence parameter  $\gamma$ , as in the case of earnings, the variance of consumption is a function of three persistence parameters:  $\gamma$ ,  $\rho$  and  $\lambda$ . To make interpretation easier, we hold  $\rho$  constant at its estimated value and study the thresholds of  $\gamma$  and  $\lambda$  that imply increasing or decreasing consumption variance. Equation (C.3) shows that  $\text{Var}(c^*)$  is a non-linear function of  $\gamma$  and  $\lambda$ . First we ask what combinations of  $\gamma$  and  $\lambda$  imply that the variance of consumption is increasing across subsequent generations. For that we would like to plot the threshold value,

$$\text{Var}(c^g) = \frac{\sigma_{\check{q}^k}^2}{1 - \lambda^2} + \frac{\sigma_{\check{e}^k}^2}{1 - \gamma^2} + \frac{\sigma_{\check{n}^k}^2}{1 - \rho^2} + \frac{2\sigma_{\check{e}^k, \check{n}^k}}{1 - \gamma\rho} + \frac{2\sigma_{\check{n}^k, \check{q}^k}}{1 - \lambda\rho} + \frac{2\sigma_{\check{e}^k, \check{q}^k}}{1 - \lambda\gamma},$$

for each generation  $g = \{p, k_1, k_2, \dots\}$  as a function of  $\gamma$  and  $\lambda$ , holding all other parameters constant.

<sup>29</sup>We find  $\gamma^{k_2} = 0.276$ , which is larger than  $\gamma^{k_1}$  but still slightly smaller than 0.279.

However, there is no combination of  $\gamma$  and  $\lambda$  in the economically meaningful range  $[0, 1]$  that satisfies the threshold value equation for  $\text{Var}(c^p)$ . Therefore, any point in the  $(\gamma, \lambda) \in [0, 1]^2$  space will imply rising consumption inequality from the parents' generation. This finding is corroborated by the fact that  $\text{Var}(c^{k_1}) = 0.117 > \text{Var}(c^p) = 0.09$ .

Next, we plot the threshold starting from the children's generation, denoted by the dashed ellipse in Figure 5. Since the estimated point, labelled  $E^*$ , with values  $(\gamma, \lambda) = (0.28, 0.01)$ , lies outside this ellipse, the grandchildren's generation should have a larger consumption variance than the children's generation. Indeed, plotting the corresponding threshold for the grandchild generation (denoted by the dotted ellipse in Figure 5), we find that it lies outside that for the children with  $\text{Var}(c^{k_2}) = 0.124 > \text{Var}(c^{k_1}) = 0.117$ . These dynamics are replicated across generations until the economy settles at the stationary distribution of consumption which gives rise to the solid elliptical threshold of  $\gamma$  and  $\lambda$  in Figure 5.<sup>30</sup>

While the analysis above shows how the estimates of current parameter values help make sense of the evolution of earnings and consumption variances across generations, these hypothetical dynamics are specific to the parameter estimates we feed into the model, which are in turn determined by the raw data moments that we currently observe. For example, the dynamics of increasing earnings variance are contingent on whether our raw data imply  $\text{Var}(e^p) < \text{Var}(e^k)$ . As an example of an alternative scenario, we use the estimates in column (2) of Tables 12 and 43 which does not restrict the age to be between 30 and 40 years, but keeps the  $\gamma_n = \rho_e = 0$  restriction. Relaxing our age restriction implies  $\text{Var}(e^p) > \text{Var}(e^k)$ , so that the thresholds of  $\gamma$  approach the long run threshold from the right, rather than from the left as in Figure 5, suggesting decreasing earnings variance across generations. Similarly, the dynamics of consumption and other income inequality in the long run are also dictated by the empirically observed moments.

**Relaxing Age Restriction.** We replicate the above analysis of inequality evolution using a parametrization of the model based on a sample without age restrictions. This means that the relevant parameter estimates are obtained from column (2) of Tables 12 and 43.

The threshold value of  $\gamma$  beyond which the earnings inequality is increasing in the parents' generation is given by

$$\gamma^p \equiv \sqrt{1 - \frac{\sigma_{e^k}^2}{\text{Var}(e^p)}} = 0.506,$$

and is shown as the dot-dashed vertical line in Figure 6. Since the estimate of the current value of  $\gamma$  ( $= 0.340$ ) lies to the left of that line, the model implies that the earnings variance should become smaller in the next generation  $k_1$ . We corroborate this using equation (C.1) again to find the threshold value of  $\gamma$  above which the earnings variance in the child generation should be growing.

---

<sup>30</sup>The stationary locus for earnings (the solid vertical line) and that of consumption (the solid ellipse) intersect at two points. One of those points, denoted by  $E^*$ , corresponds to the GMM point estimate of  $\gamma$  and  $\lambda$ . The other intersection point cannot be an equilibrium of the model because the stationary locus for other income (not plotted here) passes only through  $E^*$ .

We find

$$\gamma^{k_1} \equiv \sqrt{1 - \frac{\sigma_{\epsilon^k}^2}{\text{Var}(e^{k_1})}} = 0.367,$$

which is less than  $\gamma^p$ . Once again the estimated value of  $\gamma = 0.340$  lies to the left of this new threshold  $\gamma^{k_1}$ , and so the threshold corresponding to the generation of grandchildren  $k_2$  will lie further to the left of  $\gamma^{k_1}$ , and so on. Eventually, the economy settles down at the stationary distribution of earnings where the threshold is defined as  $\gamma^* \equiv \sqrt{1 - \frac{\sigma_{\epsilon^k}^2}{\text{Var}(e^*)}} = 0.340$ , which is the estimated level of  $\gamma$ . We again perform a similar exercise for the consumption variance using

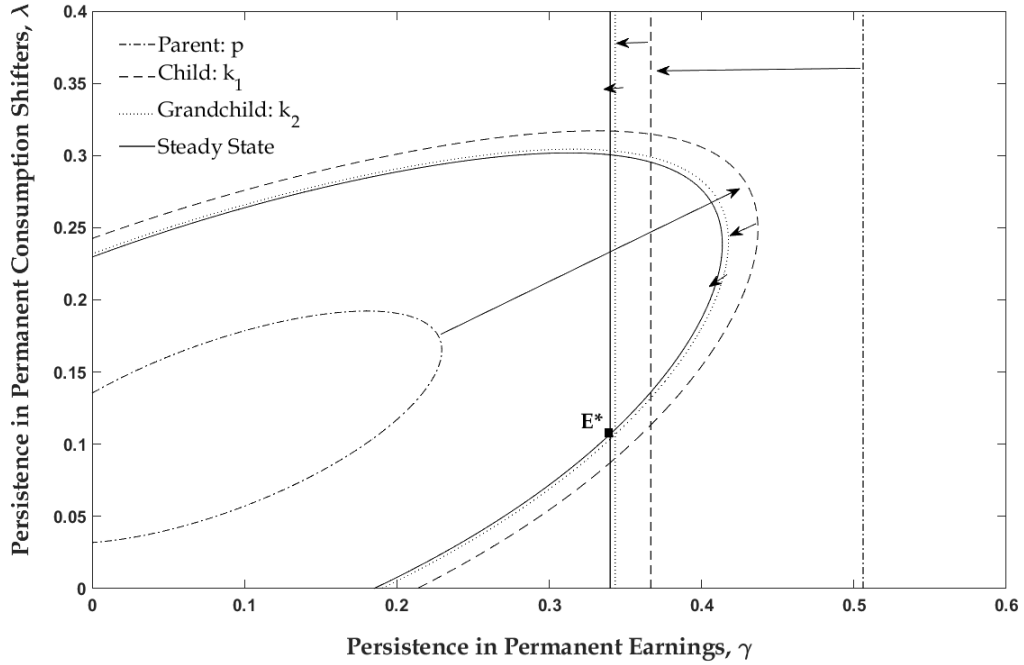


Figure 6: Implication of  $\gamma$  and  $\lambda$  for Long Run Earnings & Consumption Inequality

equation (C.3). The variance of consumption is a function of three persistence parameters:  $\gamma$ ,  $\rho$  and  $\lambda$ . We hold  $\rho$  constant at its estimated value and study the thresholds of  $\gamma$  and  $\lambda$  that imply increasing or decreasing consumption variance. First we ask what combinations of  $\gamma$  and  $\lambda$  imply that the variance of consumption is increasing across generations. For that we plot the threshold value

$$\text{Var}(c^p) = \frac{\sigma_{\psi^k}^2}{1 - \lambda^2} + \frac{\sigma_{\epsilon^k}^2}{1 - \gamma^2} + \frac{\sigma_{\tilde{n}^k}^2}{1 - \rho^2} + \frac{2\sigma_{\epsilon^k, \tilde{n}^k}}{1 - \gamma\rho} + \frac{2\sigma_{\tilde{n}^k, \tilde{q}^k}}{1 - \lambda\rho} + \frac{2\sigma_{\epsilon^k, \tilde{q}^k}}{1 - \lambda\gamma},$$

as a function of  $\gamma$  and  $\lambda$ . This is shown as the dot-dashed ellipse in Figure 6. Any point inside that ellipse implies the variance of consumption for the child generation is less than their parents. Since the estimated point, labelled  $E^*$ , with values  $(\gamma, \lambda) = (0.340, 0.107)$ , lies outside this ellipse, the children's generation should have a larger consumption variance than the parental generation.

Indeed, plotting the corresponding threshold for the child generation, (denoted by the outermost dashed ellipse in Figure 6), we find that it lies outside that for the parents with  $\text{Var}(c^{k_1}) = 0.114 > \text{Var}(c^p) = 0.096$ . However, our estimate values of  $(\gamma, \lambda) = (0.340, 0.107)$  lie inside the ellipse for the child generation. This means that the generation of grandchildren  $k_2$  should exhibit lower consumption variance than the child generation  $k_1$ , and therefore should have a threshold ellipse which lies inside that for the child generation. These dynamics are replicated across generations until the economy settles at the stationary distribution of consumption which gives rise to the solid black elliptical threshold of  $\gamma$  and  $\lambda$  in Figure 6.

## D Appendix to Section 5

### D.1 Role of Marital Selection

In this Appendix section we report estimates for intergenerational elasticities and second moments of individual fixed effects under different definitions of the *other income* variable as below.

**Model A: Baseline Model.** In this specification, we define *other income* as the sum of wife earnings and total transfer income of the head and his wife.

**Model B: Wife Earnings.** In this specification, we measure *other income* as only wife earnings.

**Model C: Three Income Processes.** In this specification, we consider three separate income processes for both the parents and adult kids, namely, head earnings, wife earnings and transfer income. Since such a specification will already increase the number of parameters to be estimated, we abstract away from the panel dimension of the outcome variables to limit the number of parameters from blowing up. Below we present the details of such a specification using time-averaged variables. The parental fixed effects for the three income sources are denoted by  $\bar{e}_f^p$  for head earnings,  $\bar{w}_f^p$  for wife earnings and  $\bar{\pi}_f^p$  for transfer income. Then, the parental consumption fixed effect is given by  $\bar{c}_f^p = \bar{q}_f^p + \bar{e}_f^p + \bar{w}_f^p + \bar{\pi}_f^p$ . The corresponding fixed effects for the adult children are given by the following four equations:

$$\begin{aligned}
\bar{e}_f^k &= (\gamma + \lambda_e) \bar{e}_f^p + (\rho_e + \lambda_e) \bar{w}_f^p + (\varrho_e + \lambda_e) \bar{\pi}_f^p + \lambda_e \bar{q}_f^p + \check{e}_f^k \\
\bar{w}_f^k &= (\gamma_w + \lambda_w) \bar{e}_f^p + (\rho + \lambda_w) \bar{w}_f^p + (\varrho_w + \lambda_w) \bar{\pi}_f^p + \lambda_w \bar{q}_f^p + \check{w}_f^k \\
\bar{\pi}_f^k &= (\gamma_\pi + \lambda_\pi) \bar{e}_f^p + (\rho_\pi + \lambda_\pi) \bar{w}_f^p + (\varrho + \lambda_\pi) \bar{\pi}_f^p + \lambda_\pi \bar{q}_f^p + \check{\pi}_f^k \\
\bar{c}_f^k &= (\lambda + \lambda_e + \lambda_w + \lambda_\pi) \bar{q}_f^p + (\gamma + \lambda_e + \gamma_w + \lambda_w + \gamma_\pi + \lambda_\pi) \bar{e}_f^p + \check{q}_f^k + \check{e}_f^k + \check{w}_f^k + \check{\pi}_f^k \\
&\quad + (\rho_e + \lambda_e + \rho + \lambda_w + \rho_\pi + \lambda_\pi) \bar{w}_f^p + (\varrho_e + \lambda_e + \varrho_w + \lambda_w + \varrho + \lambda_\pi) \bar{\pi}_f^p
\end{aligned}$$

Note that we allow for cross-effects of different sources of income across generations as well as optimal parental transfers (that are proportional to parental consumption level) having an impact on child earnings, his wife's earnings and his consumption level. There are 33 parameters to be identified and estimated — these are the 13 intergenerational persistence parameters -  $\gamma, \gamma_w, \gamma_\pi, \rho, \rho_e, \rho_\pi, \varrho, \varrho_e, \varrho_w, \lambda, \lambda_e, \lambda_w, \lambda_\pi$ ; the 4 variances of parental permanent income and consumption -  $\sigma_{\bar{e}^p}^2, \sigma_{\bar{w}^p}^2, \sigma_{\bar{\pi}^p}^2, \sigma_{\bar{q}^p}^2$ ; the 4 variances of child idiosyncratic permanent income and consumption -  $\sigma_{\check{e}^k}^2, \sigma_{\check{w}^k}^2, \sigma_{\check{\pi}^k}^2, \sigma_{\check{q}^k}^2$ ; the 6 covariances among parental permanent income and consumption components -  $\sigma_{\bar{e}^p, \bar{\pi}^p}, \sigma_{\bar{e}^p, \bar{q}^p}, \sigma_{\bar{w}^p, \bar{\pi}^p}, \sigma_{\bar{w}^p, \bar{q}^p}, \sigma_{\bar{\pi}^p, \bar{q}^p}$ ; and the 6 covariances among child idiosyncratic components of

income and consumption -  $\sigma_{\bar{e}^k, \bar{w}^k}$ ,  $\sigma_{\bar{e}^k, \bar{\pi}^k}$ ,  $\sigma_{\bar{e}^k, \bar{q}^k}$ ,  $\sigma_{\bar{w}^k, \bar{\pi}^k}$ ,  $\sigma_{\bar{w}^k, \bar{q}^k}$ ,  $\sigma_{\bar{\pi}^k, \bar{q}^k}$ . Below we present the moment conditions and the identification argument.

### Parental Variance

$$Var(\bar{e}_f^p) = \sigma_{\bar{e}^p}^2 \quad (D.1)$$

$$Var(\bar{w}_f^p) = \sigma_{\bar{w}^p}^2 \quad (D.2)$$

$$Var(\bar{\pi}_f^p) = \sigma_{\bar{\pi}^p}^2 \quad (D.3)$$

$$Var(\bar{c}_f^p) = \sigma_{\bar{q}^p}^2 + \sigma_{\bar{e}^p}^2 + \sigma_{\bar{w}^p}^2 + \sigma_{\bar{\pi}^p}^2 + 2(\sigma_{\bar{e}^p, \bar{w}^p} + \sigma_{\bar{e}^p, \bar{\pi}^p} + \sigma_{\bar{e}^p, \bar{q}^p} + \sigma_{\bar{w}^p, \bar{\pi}^p} + \sigma_{\bar{w}^p, \bar{q}^p} + \sigma_{\bar{\pi}^p, \bar{q}^p}) \quad (D.4)$$

### Parental Covariance

$$Cov(\bar{e}_f^p, \bar{w}_f^p) = \sigma_{\bar{e}^p, \bar{w}^p} \quad (D.5)$$

$$Cov(\bar{e}_f^p, \bar{\pi}_f^p) = \sigma_{\bar{e}^p, \bar{\pi}^p} \quad (D.6)$$

$$Cov(\bar{e}_f^p, \bar{c}_f^p) = \sigma_{\bar{e}^p}^2 + \sigma_{\bar{e}^p, \bar{w}^p} + \sigma_{\bar{e}^p, \bar{\pi}^p} + \sigma_{\bar{e}^p, \bar{q}^p} \quad (D.7)$$

$$Cov(\bar{w}_f^p, \bar{\pi}_f^p) = \sigma_{\bar{w}^p, \bar{\pi}^p} \quad (D.8)$$

$$Cov(\bar{w}_f^p, \bar{c}_f^p) = \sigma_{\bar{w}^p}^2 + \sigma_{\bar{e}^p, \bar{w}^p} + \sigma_{\bar{w}^p, \bar{\pi}^p} + \sigma_{\bar{w}^p, \bar{q}^p} \quad (D.9)$$

$$Cov(\bar{\pi}_f^p, \bar{c}_f^p) = \sigma_{\bar{\pi}^p}^2 + \sigma_{\bar{e}^p, \bar{\pi}^p} + \sigma_{\bar{w}^p, \bar{\pi}^p} + \sigma_{\bar{\pi}^p, \bar{q}^p} \quad (D.10)$$

### Child Variance

$$\begin{aligned} Var(\bar{e}_f^k) &= (\gamma + \lambda_e)^2 \sigma_{\bar{e}^p}^2 + (\rho_e + \lambda_e)^2 \sigma_{\bar{w}^p}^2 + (\varrho_e + \lambda_e)^2 \sigma_{\bar{\pi}^p}^2 + \lambda_e^2 \sigma_{\bar{q}^p}^2 + \sigma_{\bar{e}^k}^2 \\ &+ 2(\gamma + \lambda_e)[(\rho_e + \lambda_e) \sigma_{\bar{e}^p, \bar{w}^p} + (\varrho_e + \lambda_e) \sigma_{\bar{e}^p, \bar{\pi}^p} + \lambda_e \sigma_{\bar{e}^p, \bar{q}^p}] \\ &+ 2(\rho_e + \lambda_e)[(\varrho_e + \lambda_e) \sigma_{\bar{w}^p, \bar{\pi}^p} + \lambda_e \sigma_{\bar{w}^p, \bar{q}^p}] + 2\lambda_e(\varrho_e + \lambda_e) \sigma_{\bar{\pi}^p, \bar{q}^p} \end{aligned} \quad (D.11)$$

$$\begin{aligned} Var(\bar{w}_f^k) &= (\gamma_w + \lambda_w)^2 \sigma_{\bar{e}^p}^2 + (\rho + \lambda_w)^2 \sigma_{\bar{w}^p}^2 + (\varrho_w + \lambda_w)^2 \sigma_{\bar{\pi}^p}^2 + \lambda_w^2 \sigma_{\bar{q}^p}^2 + \sigma_{\bar{w}^k}^2 \\ &+ 2(\gamma_w + \lambda_w)[(\rho + \lambda_w) \sigma_{\bar{e}^p, \bar{w}^p} + (\varrho_w + \lambda_w) \sigma_{\bar{e}^p, \bar{\pi}^p} + \lambda_w \sigma_{\bar{e}^p, \bar{q}^p}] \\ &+ 2(\rho + \lambda_w)[(\varrho_w + \lambda_w) \sigma_{\bar{w}^p, \bar{\pi}^p} + \lambda_w \sigma_{\bar{w}^p, \bar{q}^p}] + 2\lambda_w(\varrho_w + \lambda_w) \sigma_{\bar{\pi}^p, \bar{q}^p} \end{aligned} \quad (D.12)$$

$$\begin{aligned} Var(\bar{\pi}_f^p) &= (\gamma_\pi + \lambda_\pi)^2 \sigma_{\bar{e}^p}^2 + (\rho_\pi + \lambda_\pi)^2 \sigma_{\bar{w}^p}^2 + (\varrho + \lambda_\pi)^2 \sigma_{\bar{\pi}^p}^2 + \lambda_\pi^2 \sigma_{\bar{q}^p}^2 + \sigma_{\bar{\pi}^k}^2 \\ &+ 2(\gamma_\pi + \lambda_\pi)[(\rho_\pi + \lambda_\pi) \sigma_{\bar{e}^p, \bar{w}^p} + (\varrho + \lambda_\pi) \sigma_{\bar{e}^p, \bar{\pi}^p} + \lambda_\pi \sigma_{\bar{e}^p, \bar{q}^p}] \\ &+ 2(\rho_\pi + \lambda_\pi)[(\varrho + \lambda_\pi) \sigma_{\bar{w}^p, \bar{\pi}^p} + \lambda_\pi \sigma_{\bar{w}^p, \bar{q}^p}] + 2\lambda_\pi(\varrho + \lambda_\pi) \sigma_{\bar{\pi}^p, \bar{q}^p} \end{aligned} \quad (D.13)$$

$$\begin{aligned}
Var(\bar{c}_f^k) = & (\lambda + \lambda_e + \lambda_w + \lambda_\pi)^2 \sigma_{\bar{q}^p}^2 + (\gamma + \lambda_e + \gamma_w + \lambda_w + \gamma_\pi + \lambda_\pi)^2 \sigma_{\bar{e}^p}^2 + \sigma_{\check{q}^k}^2 + \sigma_{\check{e}^k}^2 + \sigma_{\check{w}^k}^2 + \sigma_{\check{\pi}^k}^2 \\
& + (\rho_e + \lambda_e + \rho + \lambda_w + \rho_\pi + \lambda_\pi)^2 \sigma_{\bar{w}^p}^2 + (\varrho_e + \lambda_e + \varrho_w + \lambda_w + \varrho + \lambda_\pi)^2 \sigma_{\bar{\pi}^p}^2 \\
& + 2[(\gamma + \lambda_e + \gamma_w + \lambda_w + \gamma_\pi + \lambda_\pi)(\rho_e + \lambda_e + \rho + \lambda_w + \rho_\pi + \lambda_\pi) \sigma_{\bar{e}^p, \bar{w}^p} + \sigma_{\check{e}^k, \check{w}^k}] \\
& + 2[(\gamma + \lambda_e + \gamma_w + \lambda_w + \gamma_\pi + \lambda_\pi)(\varrho_e + \lambda_e + \varrho_w + \lambda_w + \varrho + \lambda_\pi) \sigma_{\bar{e}^p, \bar{\pi}^p} + \sigma_{\check{e}^k, \check{\pi}^k}] \\
& + 2[(\gamma + \lambda_e + \gamma_w + \lambda_w + \gamma_\pi + \lambda_\pi)(\lambda + \lambda_e + \lambda_w + \lambda_\pi) \sigma_{\bar{e}^p, \bar{q}^p} + \sigma_{\check{e}^k, \check{q}^k}] \\
& + 2[(\rho_e + \lambda_e + \rho + \lambda_w + \rho_\pi + \lambda_\pi)(\varrho_e + \lambda_e + \varrho_w + \lambda_w + \varrho + \lambda_\pi) \sigma_{\bar{w}^p, \bar{\pi}^p} + \sigma_{\check{w}^k, \check{\pi}^k}] \\
& + 2[(\rho_e + \lambda_e + \rho + \lambda_w + \rho_\pi + \lambda_\pi)(\lambda + \lambda_e + \lambda_w + \lambda_\pi) \sigma_{\bar{w}^p, \bar{q}^p} + \sigma_{\check{w}^k, \check{q}^k}] \\
& + 2[(\varrho_e + \lambda_e + \varrho_w + \lambda_w + \varrho + \lambda_\pi)(\lambda + \lambda_e + \lambda_w + \lambda_\pi) \sigma_{\bar{\pi}^p, \bar{q}^p} + \sigma_{\check{\pi}^k, \check{q}^k}] \tag{D.14}
\end{aligned}$$

### Child Covariance

$$\begin{aligned}
Cov(\bar{e}_f^k, \bar{w}_f^k) = & (\gamma + \lambda_e)(\gamma_w + \lambda_w) \sigma_{\bar{e}^p}^2 + (\rho_e + \lambda_e)(\rho + \lambda_w) \sigma_{\bar{w}^p}^2 + (\varrho_e + \lambda_e)(\varrho_w + \lambda_w) \sigma_{\bar{\pi}^p}^2 + \lambda_e \lambda_w \sigma_{\bar{q}^p}^2 \\
& + \sigma_{\check{e}^k, \check{w}^k} + [(\gamma + \lambda_e)(\rho + \lambda_w) + (\rho_e + \lambda_e)(\gamma_w + \lambda_w)] \sigma_{\bar{e}^p, \bar{w}^p} \\
& + [(\gamma + \lambda_e)(\varrho_w + \lambda_w) + (\varrho_e + \lambda_e)(\gamma_w + \lambda_w)] \sigma_{\bar{e}^p, \bar{\pi}^p} \\
& + [\lambda_w(\gamma + \lambda_e) + \lambda_e(\gamma_w + \lambda_w)] \sigma_{\bar{e}^p, \bar{q}^p} \\
& + [(\rho_e + \lambda_e)(\varrho_w + \lambda_w) + (\varrho_e + \lambda_e)(\rho + \lambda_w)] \sigma_{\bar{w}^p, \bar{\pi}^p} \\
& + [\lambda_w(\rho_e + \lambda_e) + \lambda_e(\rho + \lambda_w)] \sigma_{\bar{w}^p, \bar{q}^p} + [\lambda_w(\varrho_e + \lambda_e) + \lambda_e(\varrho_w + \lambda_w)] \sigma_{\bar{\pi}^p, \bar{q}^p} \tag{D.15}
\end{aligned}$$

$$\begin{aligned}
Cov(\bar{e}_f^k, \bar{\pi}_f^k) = & (\gamma + \lambda_e)(\gamma_\pi + \lambda_\pi) \sigma_{\bar{e}^p}^2 + (\rho_e + \lambda_e)(\rho_\pi + \lambda_\pi) \sigma_{\bar{w}^p}^2 + (\varrho_e + \lambda_e)(\varrho + \lambda_\pi) \sigma_{\bar{\pi}^p}^2 + \lambda_e \lambda_\pi \sigma_{\bar{q}^p}^2 \\
& + \sigma_{\check{e}^k, \check{\pi}^k} + [(\gamma + \lambda_e)(\rho_\pi + \lambda_\pi) + (\varrho_e + \lambda_e)(\gamma_\pi + \lambda_\pi)] \sigma_{\bar{e}^p, \bar{w}^p} \\
& + [(\gamma + \lambda_e)(\varrho + \lambda_\pi) + (\varrho_e + \lambda_e)(\gamma_\pi + \lambda_\pi)] \sigma_{\bar{e}^p, \bar{\pi}^p} \\
& + [\lambda_\pi(\gamma + \lambda_e) + \lambda_e(\gamma_\pi + \lambda_\pi)] \sigma_{\bar{e}^p, \bar{q}^p} \\
& + [(\rho_e + \lambda_e)(\varrho + \lambda_\pi) + (\varrho_e + \lambda_e)(\rho_\pi + \lambda_\pi)] \sigma_{\bar{w}^p, \bar{\pi}^p} \\
& + [\lambda_\pi(\rho_e + \lambda_e) + \lambda_e(\rho_\pi + \lambda_\pi)] \sigma_{\bar{w}^p, \bar{q}^p} + [\lambda_\pi(\varrho_e + \lambda_e) + \lambda_e(\varrho + \lambda_\pi)] \sigma_{\bar{\pi}^p, \bar{q}^p} \tag{D.16}
\end{aligned}$$

$$\begin{aligned}
Cov(\bar{e}_f^k, \bar{c}_f^k) = & (\gamma + \lambda_e)(\gamma + \lambda_e + \gamma_w + \lambda_w + \gamma_\pi + \lambda_\pi) \sigma_{\bar{e}^p}^2 \\
& + (\rho_e + \lambda_e)(\rho_e + \lambda_e + \rho + \lambda_w + \rho_\pi + \lambda_\pi) \sigma_{\bar{w}^p}^2 \\
& + (\varrho_e + \lambda_e)(\varrho_e + \lambda_e + \varrho_w + \lambda_w + \varrho + \lambda_\pi) \sigma_{\bar{\pi}^p}^2 + \lambda_e(\lambda + \lambda_e + \lambda_w + \lambda_\pi) \sigma_{\bar{q}^p}^2 \\
& + \sigma_{\check{e}^k, \check{q}^k} + \sigma_{\check{e}^k, \check{w}^k} + \sigma_{\check{e}^k, \check{\pi}^k} + \sigma_{\check{e}^k}^2 \\
& + [(\gamma + \lambda_e)(\rho_e + \lambda_e + \rho + \lambda_w + \rho_\pi + \lambda_\pi) + (\rho_e + \lambda_e)(\gamma + \lambda_e + \gamma_w + \lambda_w + \gamma_\pi + \lambda_\pi)] \sigma_{\bar{e}^p, \bar{w}^p} \\
& + [(\gamma + \lambda_e)(\varrho_e + \lambda_e + \varrho_w + \lambda_w + \varrho + \lambda_\pi) + (\varrho_e + \lambda_e)(\gamma + \lambda_e + \gamma_w + \lambda_w + \gamma_\pi + \lambda_\pi)] \sigma_{\bar{e}^p, \bar{\pi}^p} \\
& + [(\gamma + \lambda_e)(\lambda + \lambda_e + \lambda_w + \lambda_\pi) + \lambda_e(\gamma + \lambda_e + \gamma_w + \lambda_w + \gamma_\pi + \lambda_\pi)] \sigma_{\bar{e}^p, \bar{q}^p} \\
& + [(\rho_e + \lambda_e)(\varrho_e + \lambda_e + \varrho_w + \lambda_w + \varrho + \lambda_\pi) + (\varrho_e + \lambda_e)(\rho_e + \lambda_e + \rho + \lambda_w + \rho_\pi + \lambda_\pi)] \sigma_{\bar{w}^p, \bar{\pi}^p} \\
& + [(\rho_e + \lambda_e)(\lambda + \lambda_e + \lambda_w + \lambda_\pi) + \lambda_e(\rho_e + \lambda_e + \rho + \lambda_w + \rho_\pi + \lambda_\pi)] \sigma_{\bar{w}^p, \bar{q}^p} \\
& + [(\varrho_e + \lambda_e)(\lambda + \lambda_e + \lambda_w + \lambda_\pi) + \lambda_e(\varrho_e + \lambda_e + \varrho_w + \lambda_w + \varrho + \lambda_\pi)] \sigma_{\bar{\pi}^p, \bar{q}^p} \tag{D.17}
\end{aligned}$$

$$\begin{aligned}
Cov(\bar{w}_f^k, \bar{\pi}_f^k) &= (\gamma_w + \lambda_w)(\gamma_\pi + \lambda_\pi)\sigma_{\bar{e}^p}^2 + (\rho + \gamma_w)(\rho_\pi + \lambda_\pi)\sigma_{\bar{w}^p}^2 + (\varrho_w + \lambda_w)(\varrho + \lambda_\pi)\sigma_{\bar{\pi}^p}^2 + \lambda_w\lambda_\pi\sigma_{\bar{q}^p}^2 \\
&+ \sigma_{\check{w}^k, \check{\pi}^k} + [(\gamma_w + \lambda_w)(\rho_\pi + \lambda_\pi) + (\rho + \lambda_w)(\gamma_\pi + \lambda_\pi)]\sigma_{\bar{e}^p, \bar{w}^p} \\
&+ [(\gamma_w + \lambda_w)(\varrho + \lambda_\pi) + (\gamma_\pi + \lambda_\pi)(\varrho_w + \lambda_w)]\sigma_{\bar{e}^p, \bar{\pi}^p} \\
&+ [\lambda_\pi(\gamma_w + \lambda_w) + \lambda_w(\gamma_\pi + \lambda_\pi)]\sigma_{\bar{e}^p, \bar{q}^p} + [(\rho + \lambda_w)(\varrho + \lambda_\pi) + (\rho_\pi + \lambda_\pi)(\varrho_w + \lambda_w)]\sigma_{\bar{w}^p, \bar{\pi}^p} \\
&+ [\lambda_\pi(\rho + \lambda_w) + \lambda_w(\rho_\pi + \lambda_\pi)]\sigma_{\bar{w}^p, \bar{q}^p} + [\lambda_\pi(\varrho_w + \lambda_w) + \lambda_w(\varrho + \lambda_\pi)]\sigma_{\bar{\pi}^p, \bar{q}^p} \quad (D.18)
\end{aligned}$$

$$\begin{aligned}
Cov(\bar{w}_f^k, \bar{c}_f^k) &= (\gamma_w + \lambda_w)(\gamma + \lambda_e + \gamma_w + \lambda_w + \gamma_\pi + \lambda_\pi)\sigma_{\bar{e}^p}^2 \\
&+ (\rho + \lambda_w)(\rho_e + \lambda_e + \rho + \lambda_w + \rho_\pi + \lambda_\pi)\sigma_{\bar{w}^p}^2 \\
&+ (\varrho_w + \lambda_w)(\varrho_e + \lambda_e + \varrho_w + \lambda_w + \varrho + \lambda_\pi)\sigma_{\bar{\pi}^p}^2 + \lambda_w(\lambda + \lambda_e + \lambda_w + \lambda_\pi)\sigma_{\bar{q}^p}^2 \\
&+ \sigma_{\check{w}^k, \check{q}^k} + \sigma_{\check{e}^k, \check{w}^k} + \sigma_{\check{w}^k, \check{\pi}^k} + \sigma_{\check{w}^k}^2 \\
&+ [(\gamma_w + \lambda_w)(\rho_e + \lambda_e + \rho + \lambda_w + \rho_\pi + \lambda_\pi) + (\rho + \lambda_w)(\gamma + \lambda_e + \gamma_w + \lambda_w + \gamma_\pi + \lambda_\pi)]\sigma_{\bar{e}^p, \bar{w}^p} \\
&+ [(\gamma_w + \lambda_w)(\varrho_e + \lambda_e + \varrho_w + \lambda_w + \varrho + \lambda_\pi) + (\varrho_w + \lambda_w)(\gamma + \lambda_e + \gamma_w + \lambda_w + \gamma_\pi + \lambda_\pi)]\sigma_{\bar{e}^p, \bar{\pi}^p} \\
&+ [(\gamma_w + \lambda_w)(\lambda + \lambda_e + \lambda_w + \lambda_\pi) + \lambda_w(\gamma + \lambda_e + \gamma_w + \lambda_w + \gamma_\pi + \lambda_\pi)]\sigma_{\bar{e}^p, \bar{q}^p} \\
&+ [(\rho + \lambda_w)(\varrho_e + \lambda_e + \varrho_w + \lambda_w + \varrho + \lambda_\pi) + (\varrho_w + \lambda_w)(\rho_e + \lambda_e + \rho + \lambda_w + \rho_\pi + \lambda_\pi)]\sigma_{\bar{w}^p, \bar{\pi}^p} \\
&+ [(\rho + \lambda_w)(\lambda + \lambda_e + \lambda_w + \lambda_\pi) + \lambda_w(\rho_e + \lambda_e + \rho + \lambda_w + \rho_\pi + \lambda_\pi)]\sigma_{\bar{w}^p, \bar{q}^p} \\
&+ [(\varrho_w + \lambda_w)(\lambda + \lambda_e + \lambda_w + \lambda_\pi) + \lambda_w(\varrho_e + \lambda_e + \varrho_w + \lambda_w + \varrho + \lambda_\pi)]\sigma_{\bar{\pi}^p, \bar{q}^p} \quad (D.19)
\end{aligned}$$

$$\begin{aligned}
Cov(\bar{\pi}_f^k, \bar{c}_f^k) &= (\gamma_\pi + \lambda_\pi)(\gamma + \lambda_e + \gamma_w + \lambda_w + \gamma_\pi + \lambda_\pi)\sigma_{\bar{e}^p}^2 \\
&+ (\rho_\pi + \lambda_\pi)(\rho_e + \lambda_e + \rho + \lambda_w + \rho_\pi + \lambda_\pi)\sigma_{\bar{w}^p}^2 \\
&+ (\varrho + \lambda_\pi)(\varrho_e + \lambda_e + \varrho_w + \lambda_w + \varrho + \lambda_\pi)\sigma_{\bar{\pi}^p}^2 + \lambda_\pi(\lambda + \lambda_e + \lambda_w + \lambda_\pi)\sigma_{\bar{q}^p}^2 \\
&+ \sigma_{\check{\pi}^k, \check{q}^k} + \sigma_{\check{e}^k, \check{\pi}^k} + \sigma_{\check{w}^k, \check{\pi}^k} + \sigma_{\check{\pi}^k}^2 \\
&+ [(\gamma_\pi + \lambda_\pi)(\rho_e + \lambda_e + \rho + \lambda_w + \rho_\pi + \lambda_\pi) + (\rho_\pi + \lambda_\pi)(\gamma + \lambda_e + \gamma_w + \lambda_w + \gamma_\pi + \lambda_\pi)]\sigma_{\bar{e}^p, \bar{w}^p} \\
&+ [(\gamma_\pi + \lambda_\pi)(\varrho_e + \lambda_e + \varrho_w + \lambda_w + \varrho + \lambda_\pi) + (\varrho + \lambda_\pi)(\gamma + \lambda_e + \gamma_w + \lambda_w + \gamma_\pi + \lambda_\pi)]\sigma_{\bar{e}^p, \bar{\pi}^p} \\
&+ [(\gamma_\pi + \lambda_\pi)(\lambda + \lambda_e + \lambda_w + \lambda_\pi) + \lambda_\pi(\gamma + \lambda_e + \gamma_w + \lambda_w + \gamma_\pi + \lambda_\pi)]\sigma_{\bar{e}^p, \bar{q}^p} \\
&+ [(\rho_\pi + \lambda_\pi)(\varrho_e + \lambda_e + \varrho_w + \lambda_w + \varrho + \lambda_\pi) + (\varrho + \lambda_\pi)(\rho_e + \lambda_e + \rho + \lambda_w + \rho_\pi + \lambda_\pi)]\sigma_{\bar{w}^p, \bar{\pi}^p} \\
&+ [(\rho_\pi + \lambda_\pi)(\lambda + \lambda_e + \lambda_w + \lambda_\pi) + \lambda_\pi(\rho_e + \lambda_e + \rho + \lambda_w + \rho_\pi + \lambda_\pi)]\sigma_{\bar{w}^p, \bar{q}^p} \\
&+ [(\varrho + \lambda_\pi)(\lambda + \lambda_e + \lambda_w + \lambda_\pi) + \lambda_\pi(\varrho_e + \lambda_e + \varrho_w + \lambda_w + \varrho + \lambda_\pi)]\sigma_{\bar{\pi}^p, \bar{q}^p} \quad (D.20)
\end{aligned}$$

## Cross-Generation Covariance

$$Cov(\bar{e}_f^p, \bar{e}_f^k) = (\gamma + \lambda_e)\sigma_{\bar{e}^p}^2 + (\rho_e + \lambda_e)\sigma_{\bar{e}^p, \bar{w}^p} + (\varrho_e + \lambda_e)\sigma_{\bar{e}^p, \bar{\pi}^p} + \lambda_e\sigma_{\bar{e}^p, \bar{q}^p} \quad (D.21)$$

$$Cov(\bar{e}_f^p, \bar{w}_f^k) = (\gamma_w + \lambda_w)\sigma_{\bar{e}^p}^2 + (\rho + \lambda_w)\sigma_{\bar{e}^p, \bar{w}^p} + (\varrho_w + \lambda_w)\sigma_{\bar{e}^p, \bar{\pi}^p} + \lambda_w\sigma_{\bar{e}^p, \bar{q}^p} \quad (D.22)$$

$$Cov(\bar{e}_f^p, \bar{\pi}_f^k) = (\gamma_\pi + \lambda_\pi)\sigma_{\bar{e}^p}^2 + (\rho_\pi + \lambda_\pi)\sigma_{\bar{e}^p, \bar{w}^p} + (\varrho + \lambda_\pi)\sigma_{\bar{e}^p, \bar{\pi}^p} + \lambda_\pi\sigma_{\bar{e}^p, \bar{q}^p} \quad (D.23)$$

$$\begin{aligned}
Cov(\bar{e}_f^p, \bar{c}_f^k) &= (\gamma + \lambda_e + \gamma_w + \lambda_w + \gamma_\pi + \lambda_\pi)\sigma_{\bar{e}^p}^2 + (\rho_e + \lambda_e + \rho + \lambda_w + \rho_\pi + \lambda_\pi)\sigma_{\bar{e}^p, \bar{w}^p} \\
&+ (\varrho_e + \lambda_e + \varrho_w + \lambda_w + \varrho + \lambda_\pi)\sigma_{\bar{e}^p, \bar{\pi}^p} + (\lambda + \lambda_e + \lambda_w + \lambda_\pi)\sigma_{\bar{e}^p, \bar{q}^p} \quad (D.24)
\end{aligned}$$

$$Cov(\bar{w}_f^p, \bar{e}_f^k) = (\gamma + \lambda_e) \sigma_{\bar{e}^p, \bar{w}^p} + (\rho_e + \lambda_e) \sigma_{\bar{w}^p}^2 + (\varrho_e + \lambda_e) \sigma_{\bar{w}^p, \bar{\pi}^p} + \lambda_e \sigma_{\bar{w}^p, \bar{q}^p} \quad (D.25)$$

$$Cov(\bar{w}_f^p, \bar{w}_f^k) = (\gamma_w + \lambda_w) \sigma_{\bar{e}^p, \bar{w}^p} + (\rho + \lambda_w) \sigma_{\bar{w}^p}^2 + (\varrho_w + \lambda_w) \sigma_{\bar{w}^p, \bar{\pi}^p} + \lambda_w \sigma_{\bar{w}^p, \bar{q}^p} \quad (D.26)$$

$$Cov(\bar{w}_f^p, \bar{\pi}_f^k) = (\gamma_\pi + \lambda_\pi) \sigma_{\bar{e}^p, \bar{w}^p} + (\rho_\pi + \lambda_\pi) \sigma_{\bar{w}^p}^2 + (\varrho + \lambda_\pi) \sigma_{\bar{w}^p, \bar{\pi}^p} + \lambda_\pi \sigma_{\bar{w}^p, \bar{q}^p} \quad (D.27)$$

$$Cov(\bar{w}_f^p, \bar{c}_f^k) = (\gamma + \lambda_e + \gamma_w + \lambda_w + \gamma_\pi + \lambda_\pi) \sigma_{\bar{e}^p, \bar{w}^p} + (\rho_e + \lambda_e + \rho + \lambda_w + \rho_\pi + \lambda_\pi) \sigma_{\bar{w}^p}^2 \\ + (\varrho_e + \lambda_e + \varrho_w + \lambda_w + \varrho + \lambda_\pi) \sigma_{\bar{w}^p, \bar{\pi}^p} + (\lambda + \lambda_e + \lambda_w + \lambda_\pi) \sigma_{\bar{w}^p, \bar{q}^p} \quad (D.28)$$

$$Cov(\bar{\pi}_f^p, \bar{e}_f^k) = (\gamma + \lambda_e) \sigma_{\bar{e}^p, \bar{\pi}^p} + (\rho_e + \lambda_e) \sigma_{\bar{w}^p, \bar{\pi}^p} + (\varrho_e + \lambda_e) \sigma_{\bar{\pi}^p}^2 + \lambda_e \sigma_{\bar{\pi}^p, \bar{q}^p} \quad (D.29)$$

$$Cov(\bar{\pi}_f^p, \bar{w}_f^k) = (\gamma_w + \lambda_w) \sigma_{\bar{e}^p, \bar{\pi}^p} + (\rho + \lambda_w) \sigma_{\bar{w}^p, \bar{\pi}^p} + (\varrho_w + \lambda_w) \sigma_{\bar{\pi}^p}^2 + \lambda_w \sigma_{\bar{\pi}^p, \bar{q}^p} \quad (D.30)$$

$$Cov(\bar{\pi}_f^p, \bar{\pi}_f^k) = (\gamma_\pi + \lambda_\pi) \sigma_{\bar{e}^p, \bar{\pi}^p} + (\rho_\pi + \lambda_\pi) \sigma_{\bar{w}^p, \bar{\pi}^p} + (\varrho + \lambda_\pi) \sigma_{\bar{\pi}^p}^2 + \lambda_\pi \sigma_{\bar{\pi}^p, \bar{q}^p} \quad (D.31)$$

$$Cov(\bar{\pi}_f^p, \bar{c}_f^k) = (\gamma + \lambda_e + \gamma_w + \lambda_w + \gamma_\pi + \lambda_\pi) \sigma_{\bar{e}^p, \bar{\pi}^p} + (\rho_e + \lambda_e + \rho + \lambda_w + \rho_\pi + \lambda_\pi) \sigma_{\bar{w}^p, \bar{\pi}^p} \\ + (\varrho_e + \lambda_e + \varrho_w + \lambda_w + \varrho + \lambda_\pi) \sigma_{\bar{\pi}^p}^2 + (\lambda + \lambda_e + \lambda_w + \lambda_\pi) \sigma_{\bar{\pi}^p, \bar{q}^p} \quad (D.32)$$

$$Cov(\bar{c}_f^p, \bar{e}_f^k) = (\gamma + \lambda_e) \sigma_{\bar{e}^p}^2 + (\rho_e + \lambda_e) \sigma_{\bar{w}^p}^2 + (\varrho_e + \lambda_e) \sigma_{\bar{\pi}^p}^2 + \lambda_e \sigma_{\bar{q}^p}^2 \\ + (\gamma + \rho_e + 2\lambda_e) \sigma_{\bar{e}^p, \bar{w}^p} + (\gamma + \varrho_e + 2\lambda_e) \sigma_{\bar{e}^p, \bar{\pi}^p} + (\gamma + 2\lambda_e) \sigma_{\bar{e}^p, \bar{q}^p} \\ + (\rho_e + \varrho_e + 2\lambda_e) \sigma_{\bar{w}^p, \bar{\pi}^p} + (\rho_e + 2\lambda_e) \sigma_{\bar{w}^p, \bar{q}^p} + (\varrho_e + 2\lambda_e) \sigma_{\bar{\pi}^p, \bar{q}^p} \quad (D.33)$$

$$Cov(\bar{c}_f^p, \bar{w}_f^k) = (\gamma_w + \lambda_w) \sigma_{\bar{e}^p}^2 + (\rho + \lambda_w) \sigma_{\bar{w}^p}^2 + (\varrho_w + \lambda_w) \sigma_{\bar{\pi}^p}^2 + \lambda_w \sigma_{\bar{q}^p}^2 \\ + (\gamma_w + \rho + 2\lambda_w) \sigma_{\bar{e}^p, \bar{w}^p} + (\gamma_w + \varrho_w + 2\lambda_w) \sigma_{\bar{e}^p, \bar{\pi}^p} + (\gamma_w + 2\lambda_w) \sigma_{\bar{e}^p, \bar{q}^p} \\ + (\rho + \varrho_w + 2\lambda_w) \sigma_{\bar{w}^p, \bar{\pi}^p} + (\rho + 2\lambda_w) \sigma_{\bar{w}^p, \bar{q}^p} + (\varrho_w + 2\lambda_w) \sigma_{\bar{\pi}^p, \bar{q}^p} \quad (D.34)$$

$$Cov(\bar{c}_f^p, \bar{\pi}_f^k) = (\gamma_\pi + \lambda_\pi) \sigma_{\bar{e}^p}^2 + (\rho_\pi + \lambda_\pi) \sigma_{\bar{w}^p}^2 + (\varrho + \lambda_\pi) \sigma_{\bar{\pi}^p}^2 + \lambda_\pi \sigma_{\bar{q}^p}^2 \\ + (\gamma_\pi + \rho_\pi + 2\lambda_\pi) \sigma_{\bar{e}^p, \bar{w}^p} + (\gamma_\pi + \varrho + 2\lambda_\pi) \sigma_{\bar{e}^p, \bar{\pi}^p} + (\gamma_\pi + 2\lambda_\pi) \sigma_{\bar{e}^p, \bar{q}^p} \\ + (\rho_\pi + \varrho + 2\lambda_\pi) \sigma_{\bar{w}^p, \bar{\pi}^p} + (\rho_\pi + 2\lambda_\pi) \sigma_{\bar{w}^p, \bar{q}^p} + (\varrho + 2\lambda_\pi) \sigma_{\bar{\pi}^p, \bar{q}^p} \quad (D.35)$$

$$Cov(\bar{c}_f^p, \bar{c}_f^k) = (\gamma + \lambda_e + \gamma_w + \lambda_w + \gamma_\pi + \lambda_\pi) \sigma_{\bar{e}^p}^2 + (\rho_e + \lambda_e + \rho + \lambda_w + \rho_\pi + \lambda_\pi) \sigma_{\bar{w}^p}^2 \\ + (\varrho_e + \lambda_e + \varrho_w + \lambda_w + \varrho + \lambda_\pi) \sigma_{\bar{\pi}^p}^2 + (\lambda + \lambda_e + \lambda_w + \lambda_\pi) \sigma_{\bar{q}^p}^2 \\ + [\gamma + \gamma_w + \gamma_\pi + \rho_e + \rho + \rho_\pi + 2(\lambda_e + \lambda_w + \lambda_\pi)] \sigma_{\bar{e}^p, \bar{w}^p} \\ + [\gamma + \gamma_w + \gamma_\pi + \varrho_e + \varrho_w + \varrho + 2(\lambda_e + \lambda_w + \lambda_\pi)] \sigma_{\bar{e}^p, \bar{\pi}^p} \\ + [\gamma + \gamma_w + \gamma_\pi + \lambda + 2(\lambda_e + \lambda_w + \lambda_\pi)] \sigma_{\bar{e}^p, \bar{q}^p} \\ + [\rho_e + \rho + \rho_\pi + \varrho_e + \varrho_w + \varrho + 2(\lambda_e + \lambda_w + \lambda_\pi)] \sigma_{\bar{w}^p, \bar{\pi}^p} \\ + [\rho_e + \rho + \rho_\pi + \lambda + 2(\lambda_e + \lambda_w + \lambda_\pi)] \sigma_{\bar{w}^p, \bar{q}^p} \\ + [\varrho_e + \varrho_w + \varrho + \lambda + 2(\lambda_e + \lambda_w + \lambda_\pi)] \sigma_{\bar{\pi}^p, \bar{q}^p} \quad (D.36)$$

There are 36 moment conditions, (D.1) through (D.36), to identify 33 parameters. One can immediately identify the parental parameters,  $\sigma_{\bar{e}^p}^2$ ,  $\sigma_{\bar{w}^p}^2$ ,  $\sigma_{\bar{\pi}^p}^2$ ,  $\sigma_{\bar{e}^p, \bar{w}^p}$ ,  $\sigma_{\bar{e}^p, \bar{\pi}^p}$  and  $\sigma_{\bar{w}^p, \bar{\pi}^p}$  from the moments (D.1), (D.2), (D.3), (D.5), (D.6) and (D.8) respectively. This makes the identification of  $\sigma_{\bar{e}^p, \bar{q}^p}$ ,  $\sigma_{\bar{w}^p, \bar{q}^p}$  and  $\sigma_{\bar{\pi}^p, \bar{q}^p}$  immediately possible from equations (D.7), (D.9) and (D.10) respectively. This leaves  $\sigma_{\bar{q}^p}^2$  to be identified from (D.4). This concludes the identification of the 10 parental variance-covariance parameters. Next, we focus on the identification of the 13 intergenerational

persistence parameters using equations (D.21) through (D.36). First, we notice that (D.21), (D.25), (D.29) and (D.33) are 4 equations in 4 unknowns -  $(\gamma + \lambda_e)$ ,  $(\rho_e + \lambda_e)$ ,  $(\varrho_e + \lambda_e)$  and  $\lambda_e$ . Thus, these equations can be simulatenously used to identify the parameters  $\gamma$ ,  $\rho_e$ ,  $\varrho_e$  and  $\lambda_e$ . A similar argument can be used to identify  $\rho$ ,  $\gamma_w$ ,  $\varrho_w$  and  $\lambda_w$  from equations (D.22), (D.26), (D.30) and (D.34) jointly. The parameters  $\varrho$ ,  $\gamma_\pi$ ,  $\rho_\pi$  and  $\lambda_\pi$  are also identified by simultaneously considering the 4 equations (D.23), (D.27), (D.31) and (D.35). This leaves  $\lambda$  to be identified from equation (D.24).

Table 21: Intergenerational Elasticities

Variables	Parameters	Model B (1)	Model C (3)
Head Earnings: $\bar{e}_f^p$ on $\bar{e}_f^k$	$\gamma$	0.275 (0.029)	0.196 (0.040)
$\bar{e}_f^p$ on $\bar{w}_f^k$	$\gamma_w$	0.232 (0.043)	0.147 (0.042)
$\bar{e}_f^p$ on $\bar{\pi}_f^k$	$\gamma_\pi$	-	0.065 (0.077)
Wife Earnings: $\bar{w}_f^p$ on $\bar{w}_f^k$	$\rho$	0.142 (0.040)	0.035 (0.044)
$\bar{w}_f^p$ on $\bar{e}_f^k$	$\rho_e$	0.147 (0.032)	0.051 (0.038)
$\bar{w}_f^p$ on $\bar{\pi}_f^k$	$\rho_\pi$	-	0.035 (0.071)
Transfer Income: $\bar{\pi}_f^p$ on $\bar{\pi}_f^k$	$\varrho$	-	0.036 (0.053)
$\bar{\pi}_f^p$ on $\bar{e}_f^k$	$\varrho_e$	-	-0.001 (0.019)
$\bar{\pi}_f^p$ on $\bar{w}_f^k$	$\varrho_w$	-	0.055 (0.021)
Consumption Shifters: $\bar{q}_f^p$ on $\bar{q}_f^k$	$\lambda$	0.374 (0.060)	0.084 (0.054)
<i>No. of Parent-Child Pairs</i>	<i>N</i>	459	459

**Note:** Bootstrap standard errors (100 repetitions) in parentheses. All columns use data that is purged of year and birth-cohort effects. Baseline model with 459 parent-child pairs yields the following estimates:  $\gamma = 0.253(0.032)$ ,  $\rho = 0.094(0.045)$ ,  $\gamma_n = 0.185(0.045)$ ,  $\rho_e = 0.086(0.028)$  and  $\lambda = 0.216(0.060)$ .

Finally,  $\sigma_{\bar{e}^k}^2$ ,  $\sigma_{\bar{w}^k}^2$ ,  $\sigma_{\bar{\pi}^k}^2$ ,  $\sigma_{\bar{e}^k, \bar{w}^k}$ ,  $\sigma_{\bar{e}^k, \bar{\pi}^k}$  and  $\sigma_{\bar{w}^k, \bar{\pi}^k}$  can be identified from (D.11), (D.12), (D.13), (D.15), (D.16) and (D.18) respectively. This identifies  $\sigma_{\bar{e}^k, \bar{q}^k}$ ,  $\sigma_{\bar{w}^k, \bar{q}^k}$ ,  $\sigma_{\bar{\pi}^k, \bar{q}^k}$  and  $\sigma_{\bar{q}^k}^2$  from (D.17), (D.19), (D.20) and (D.14) respectively.

Table 22: Variances &amp; Covariances

Variables	Parameters	Model B (1)	Model C (3)
<b><u>Parental Variances</u></b>			
Permanent Head Earnings	$\sigma_{\bar{e}P}^2$	0.296 (0.032)	0.293 (0.026)
Permanent Wife Earnings	$\sigma_{\bar{w}P}^2$	0.294 (0.022)	0.301 (0.019)
Permanent Transfer Income	$\sigma_{\bar{\pi}P}^2$	-	1.300 (0.136)
Permanent Consumption Shifters	$\sigma_{\bar{q}P}^2$	0.501 (0.046)	1.973 (0.165)
<b><u>Child Idiosyncratic Variances</u></b>			
Permanent Head Earnings	$\sigma_{\bar{e}k}^2$	0.197 (0.014)	0.218 (0.012)
Permanent Wife Earnings	$\sigma_{\bar{w}k}^2$	0.297 (0.021)	0.311 (0.021)
Permanent Transfer Income	$\sigma_{\bar{\pi}k}^2$	-	1.067 (0.087)
Permanent Consumption Shifters	$\sigma_{\bar{q}k}^2$	0.463 (0.029)	1.828 (0.124)
<b><u>Parental Covariances</u></b>			
Head Earnings & Wife Earnings	$\sigma_{\bar{e}P, \bar{w}P}$	0.063 (0.015)	0.067 (0.015)
Head Earnings & Transfer Income	$\sigma_{\bar{e}P, \bar{\pi}P}$	-	0.043 (0.036)
Head Earnings & Consumption-Shifters	$\sigma_{\bar{e}P, \bar{q}P}$	-0.258 (0.030)	-0.298 (0.049)
Wife Earnings & Transfer Income	$\sigma_{\bar{w}P, \bar{\pi}P}$	-	0.066 (0.033)
Wife Earnings & Consumption-Shifters	$\sigma_{\bar{w}P, \bar{q}P}$	-0.302 (0.031)	-0.389 (0.046)
Transfer Income & Consumption-Shifters	$\sigma_{\bar{\pi}P, \bar{q}P}$	-	-1.369 (0.141)
<b><u>Child Idiosyncratic Covariances</u></b>			
Head Earnings & Wife Earnings	$\sigma_{\bar{e}k, \bar{w}k}$	0.057 (0.012)	0.076 (0.011)
Head Earnings & Transfer Income	$\sigma_{\bar{e}k, \bar{\pi}k}$	-	0.061 (0.026)
Head Earnings & Consumption-Shifters	$\sigma_{\bar{e}k, \bar{q}k}$	-0.201 (0.016)	-0.304 (0.033)
Wife Earnings & Transfer Income	$\sigma_{\bar{w}k, \bar{\pi}k}$	-	0.098 (0.030)
Wife Earnings & Consumption-Shifters	$\sigma_{\bar{w}k, \bar{q}k}$	-0.291 (0.021)	-0.423 (0.035)
Transfer Income & Consumption-Shifters	$\sigma_{\bar{\pi}k, \bar{q}k}$	-	-1.183 (0.098)
<i>No. of Parent-Child Pairs</i>	<i>N</i>	459	459

**Note:** See Table 21 for details. Parameter estimates for baseline model using 459 parent-child pairs are as follows:  $\sigma_{\bar{e}P}^2 = 0.296(0.027)$ ,  $\sigma_{\bar{\pi}P}^2 = 0.457(0.032)$ ,  $\sigma_{\bar{q}P}^2 = 0.646(0.043)$ ,  $\sigma_{\bar{e}k}^2 = 0.207(0.014)$ ,  $\sigma_{\bar{\pi}k}^2 = 0.442(0.038)$ ,  $\sigma_{\bar{q}k}^2 = 0.594(0.043)$ ,  $\sigma_{\bar{e}P, \bar{\pi}P} = 0.049(0.016)$ ,  $\sigma_{\bar{e}P, \bar{q}P} = -0.244(0.026)$ ,  $\sigma_{\bar{\pi}P, \bar{q}P} = -0.455(0.034)$ ,  $\sigma_{\bar{e}k, \bar{\pi}k} = 0.050(0.015)$ ,  $\sigma_{\bar{e}k, \bar{q}k} = -0.207(0.020)$ ,  $\sigma_{\bar{\pi}k, \bar{q}k} = -0.423(0.038)$ .

## D.2 Liquidity Constraints

### D.2.1 High Consumption Growth

We classify a household as constrained in year  $t$  if the growth rate in food expenditure for that household between years  $t$  and  $t+2$  is greater than 25%. We can extend our definition of constrained observations as follows: we can additionally label an observation constrained in year  $t$  if the growth rate in food expenditure between years  $t-2$  and  $t$  is less than -25% (i.e., a decrease of more than 25%). We estimate our baseline model by excluding the ‘constrained’ observations from both generations according to the two alternative definitions.

Table 23: Estimates of Intergenerational Elasticity

Variables	Parameters	Baseline (1)	Exclude High Growth (2)	Exclude High & Low Growth (3)
Head Earnings	$\gamma$	0.229 (0.028)	0.230 (0.026)	0.233 (0.028)
Other Income	$\rho$	0.099 (0.027)	0.089 (0.032)	0.074 (0.031)
$\bar{e}_f^p$ on $\bar{n}_f^k$	$\gamma_n$	0.208 (0.035)	0.204 (0.034)	0.182 (0.039)
$\bar{n}_f^p$ on $\bar{e}_f^k$	$\rho_e$	0.055 (0.019)	0.058 (0.016)	0.062 (0.018)
Consumption Shifters	$\lambda$	0.153 (0.037)	0.146 (0.038)	0.130 (0.036)
<i>No. of Parent-Child Pairs</i>	$N$	761	757	756

**Note:** Bootstrap standard errors (100 repetitions) in parentheses. *Baseline* refers to data of 761 parent-child pairs for which no observation has been dropped because of too high or too low food consumption growth in any year. *Exclude High Growth* refers to the sample of parent-child pairs for whom observations for certain years were dropped if the growth in food consumption was higher than 25% over the next 2 years. *Exclude High & Low Growth* refers to the sample of parent-child pairs for whom observations for certain years were dropped if the growth in food consumption was higher than 25% over the next 2 years or the growth was lower than -25% from the previous 2 years. Dropping observations for those years in which the household is identified to be constrained may or may not lead to dropping the parent-child pair depending on if there is still any observation left for both the parent and the child.

While we find that excluding the potentially constrained observations reduces the intergenerational persistence and the role of parents in explaining inequality in the child generation as the theory predicts, the differences with the baseline results are quite small and not statistically significant.

Table 24: Parental Importance for Child Inequality

Variables	Baseline (1)	Exclude High Growth (2)	Exclude High & Low Growth (3)
Head Earnings	7.9%	7.9%	7.7%
Other Income	4.4%	4.0%	2.8%
Consumption	30.1%	29.6%	27.0%

**Note:** Results are based on parameter estimates from Table 23 and variance-covariance parameter estimates not shown here.

### D.2.2 High Consumption Volatility Relative to Income Volatility over the Life-Cycle

For each generation we drop the top decile of individuals based on the ratio of variance of food expenditure to the variance of head earnings over the life-cycle. The idea is that high volatility of consumption relative to that of income is indicative of lack of effective consumption smoothing, and such households are more likely to be liquidity constrained. However, as we see in Tables 25 and 26, dropping such households makes no statistically significant change to the intergenerational persistence parameters or to the role of parents in determining inequality in the children's generation.

Table 25: Estimates of Intergenerational Elasticity

Variables	Parameters	Baseline Sample (1)	Restricted Sample (2)
Head Earnings	$\gamma$	0.229 (0.028)	0.239 (0.028)
Other Income	$\rho$	0.099 (0.027)	0.087 (0.033)
$\bar{e}_f^p$ on $\bar{n}_f^k$	$\gamma_n$	0.208 (0.035)	0.193 (0.037)
$\bar{n}_f^p$ on $\bar{e}_f^k$	$\rho_e$	0.055 (0.019)	0.069 (0.022)
Consumption Shifters	$\lambda$	0.153 (0.037)	0.172 (0.045)
No. of Parent-Child Pairs	$N$	761	576

**Note:** Bootstrap standard errors (100 repetitions) in parentheses. *Baseline Sample* refers to data of 761 parent-child pairs that is purged of year and birth cohort effects. *Restricted Sample* refers to the sample of 576 parent-child pairs who are in the bottom 90% of the baseline sample in either generation in terms of the ratio of variance of food consumption to variance of head earnings over the lifetime.

Table 26: Parental Importance for Child Inequality

Variables	Baseline Sample	Restricted Sample
	(1)	(2)
Head Earnings	7.9%	9.2%
Other Income	4.4%	3.8%
Consumption	30.1%	29.5%

**Note:** Results are based on parameter estimates from Table 25 and variance-covariance parameter estimates not shown here.

### D.2.3 Young Parents

Table 27: Estimates: Intergenerational Elasticities

Parameters	$Parent Age^k < 35$	$Parent Age^k < 30$	$Parent Age^k < 25$	$Parent Age^k < 20$	$Parent Age^k < 15$
	(1)	(2)	(3)	(4)	(5)
$\gamma$	0.258 (0.039)	0.255 (0.036)	0.229 (0.033)	0.247 (0.044)	0.167 (0.038)
$\rho$	0.125 (0.046)	0.126 (0.038)	0.118 (0.033)	0.100 (0.036)	0.068 (0.038)
$\gamma_n$	0.183 (0.054)	0.190 (0.044)	0.226 (0.055)	0.207 (0.049)	0.217 (0.059)
$\rho_e$	0.073 (0.022)	0.074 (0.023)	0.070 (0.021)	0.062 (0.018)	0.025 (0.021)
$\lambda$	0.203 (0.055)	0.203 (0.044)	0.194 (0.042)	0.174 (0.044)	0.102 (0.054)
$\lambda_e$	0.048 (0.07)	0.036 (0.073)	0.079 (0.068)	0.043 (0.069)	0.132 (0.055)
$\lambda_n$	0.072 (0.089)	0.068 (0.079)	0.045 (0.091)	0.068 (0.086)	0.080 (0.07)
$N$	573	573	573	573	573

**Note:** Bootstrap standard errors (100 repetitions) in parentheses. All child variables are averages above age 25 years of the child. Each column (1) through (5) corresponds to the period over which the averages for the parental variables are calculated. Food expenditure is used as a proxy measure of consumption, and the sum of wife earnings and transfer income is used as the measure of *other income*. All columns use cross-sectional data variation, net of cohort and year effects. The results are robust to using only wife earnings as the measure of *other income*.

In Table 27, we show that the intergenerational persistence parameters are comparable no matter at what age of the children we take the averages of the parental variables. The idea is that if there are considerable binding credit constraints when the parents are younger and their children are still living with them, then the intergenerational persistence would be higher for that time-period than

in the later stages of parental life when these constraints are generally relaxed. However, we do not find any evidence of decreasing parental importance as we keep studying progressively older parents (see Table 28).

Table 28: Importance of Young Parental Heterogeneity for Child Inequality

Variables	$Parent Age^k < 35$ (1)	$Parent Age^k < 30$ (2)	$Parent Age^k < 25$ (3)	$Parent Age^k < 20$ (4)	$Parent Age^k < 15$ (5)
Head Earnings	9.9	9.5	8.3	8.1	4.6
Other Income	4.7	4.9	5.1	4.3	3.5
Consumption	30.6	30.0	31.6	32.9	33.7

**Note:** All numbers are percentages and are based on parameter estimates in Table 27 and the corresponding variance-covariance parameter estimates (not shown here).

### D.3 Optimal Parental Transfers

The optimization problem of the parent is given by:

$$\begin{aligned}
& \max_{\{C_{f,s}^p, \mathcal{T}_{f,s}\}_{s=t}^T} \mathbb{E}_t \sum_{j=0}^{T-t} \beta^j \left[ \frac{(C_{f,t+j}^p)^{1-\sigma}}{1-\sigma} + \mu_1 \cdot \frac{\mathcal{T}_{f,t+j}^{1-\mu_2}}{1-\mu_2} \right] \\
& s.t. \\
& A_{f,t+1}^p = (1+r) (A_{f,t}^p + E_{f,t}^p + N_{f,t}^p - C_{f,t}^p - \mathcal{T}_{f,t}),
\end{aligned} \tag{D.37}$$

where  $\mathcal{T}_{f,t}$  is the expenditure by the parent on the child at time  $t$  in the form of human capital investment and/or inter-vivos transfers.

The first order conditions obtained by optimizing with respect to consumption  $C_{f,t}^p$ , one-period ahead resource  $A_{f,t}^p$ , and child expenditure  $\mathcal{T}_{f,t}$  are as follows:

$$(C_{f,t}^p)^{-\sigma} = \mathbb{L}_t^p (1+r) \tag{D.38}$$

$$\mathbb{L}_t^p = \beta (1+r) \mathbb{E}_t (\mathbb{L}_{t+1}^p) \tag{D.39}$$

$$\mu_1 \cdot \mathcal{T}_{f,t}^{-\mu_2} = \mathbb{L}_t^p (1+r) \tag{D.40}$$

where  $\mathbb{L}_t^p$  is the Lagrange multiplier of the parent's period- $t$  budget constraint. Combining equations (D.38) and (D.39) yields the usual consumption Euler equation:

$$(C_{f,t}^p)^{-\sigma} = \beta (1+r) \mathbb{E}_t \left[ (C_{f,t+1}^p)^{-\sigma} \right] \tag{D.41}$$

Combining the first order conditions (D.38) and (D.40), we get the following intra-temporal opti-

mality condition in logarithms:

$$\begin{aligned}\ln(\mathcal{T}_{f,t}) \equiv \tau_{f,t} &= \frac{\ln(\mu_1)}{\mu_2} + \frac{\sigma}{\mu_2} \cdot \mathcal{C}_{f,t}^p \\ \implies \bar{\tau}_f &= \frac{\ln(\mu_1)}{\mu_2} + \frac{\sigma}{\mu_2} \cdot \bar{\mathcal{C}}_f^p\end{aligned}\tag{D.42}$$

We assume that the child's human capital,  $H_f^k$  is partly determined by the parental expenditure on the child and partly by his own ability to convert that parental expenditure into human capital,  $\Gamma_f^k$ . In particular, we assume a human capital production function:  $H_f^k = \Gamma_f^k \cdot \left( \prod_{t=G_{25}^p}^{G_{65}^p} \mathcal{T}_{f,t} \right)^{\frac{\eta_1}{G_{65}^p - G_{25}^p}}$  with a returns to scale of  $\eta_1 > 0$  in the geometric mean of per-period parental expenditure  $\mathcal{T}_{f,t}$  on the child between parental ages of 25 and 65 years (i.e.,  $G_{25}^p$  through  $G_{65}^p$ ). Taking logarithm of the human capital production function, we can express the child's human capital in terms of the average parental log-consumption:

$$\begin{aligned}h_f^k \equiv \ln(H_f^k) &= \ln(\Gamma_f^k) + \frac{\eta_1}{G_{65}^p - G_{25}^p} \cdot \sum_{t=G_{25}^p}^{G_{65}^p} \ln(\mathcal{T}_{f,t}) \\ &= \ln(\Gamma_f^k) + \frac{\eta_1}{G_{65}^p - G_{25}^p} \cdot \sum_{t=G_{25}^p}^{G_{65}^p} \frac{\ln(\mu_1) + \sigma \cdot \mathcal{C}_{f,t}^p}{\mu_2} \\ &= \ln(\Gamma_f^k) + \frac{\eta_1 \ln(\mu_1)}{\mu_2} + \left( \frac{\eta_1 \sigma}{\mu_2} \right) \cdot \bar{\mathcal{C}}_f^p\end{aligned}\tag{D.43}$$

Next, we make the following two assumptions —

- (i) Earnings fixed effect of the child is a linear deterministic function of his human capital in logarithms, that is,  $\bar{e}_f^k = \ln(w) + \eta_2 \cdot h_f^k$ , where  $w$  is the labour market return to human capital averaged over the life-cycle of an individual, and the parameter  $\eta_2$  denotes the returns to scale of human capital in the earnings function. This functional form is similar to the one assumed in [Becker et al. \(2018\)](#) for the relationship between earnings and human capital.
- (ii) The child's ability  $\Gamma_f^k$  to convert parental expenditure on the child  $\mathcal{T}_{f,t}$  into human capital  $H_f^k$ , the so-called 'smartness' or 'efficiency' of the child,  $\Gamma_f^k$  is partly determined by parental earnings and other income. In particular, we assume,  $\ln(\Gamma_f^k) = \gamma^h \bar{e}_f^p + \rho_e^h \bar{n}_f^p + \check{h}_f^k$ , where  $\check{h}_f^k$  is the idiosyncratic smartness of the child that is not related to family background.

Combining the assumptions above, we get

$$\begin{aligned}\bar{e}_f^k &= \ln(w) + \eta_2 \left[ \gamma^h \bar{e}_f^p + \rho_e^h \bar{n}_f^p + \check{h}_f^k + \frac{\eta_1 \ln(\mu_1)}{\mu_2} + \left( \frac{\eta_1 \sigma}{\mu_2} \right) \bar{c}_f^p \right] \\ \Rightarrow \bar{e}_f^k &= \left[ \ln(w) + \frac{\eta_1 \eta_2 \ln(\mu_1)}{\mu_2} \right] + \gamma \bar{e}_f^p + \rho_e \bar{n}_f^p + \lambda_e \bar{c}_f^p + \check{e}_f^k\end{aligned}\quad (\text{D.44})$$

where  $\gamma = \gamma^h \eta_2$ ,  $\rho_e \equiv \rho_e^h \eta_2$ ,  $\lambda_e \equiv \frac{\eta_1 \eta_2 \sigma}{\mu_2}$ , and  $\check{e}_f^k \equiv \check{h}_f^k \eta_2$ . In the empirical implementation we de-mean all the log variables, and hence the constant term  $\left[ \ln(w) + \frac{\eta_1 \eta_2 \ln(\mu_1)}{\mu_2} \right]$  will drop out from equation (D.44) to yield equation (D.45):

$$\bar{e}_f^k = \gamma \bar{e}_f^p + \rho_e \bar{n}_f^p + \lambda_e \bar{c}_f^p + \check{e}_f^k \quad (\text{D.45})$$

that is, the fixed effect of child earnings depends linearly on the parental fixed effects in earnings, other income and consumption, and on his own idiosyncratic fixed effect (in logs).

Parental expenditure on the child can take the form of inter-vivos transfers, which directly affects the transfer income component of other income of the adult child: such parental expenditure is also proportional to parental consumption (in logs) as in equation (D.42). Moreover, child's other income can be influenced by his wife's earnings, which in turn can depend not only the parental income processes of the child but also on the inter-vivos transfers. Therefore, one can write an other income process for the adult child that is similar to his earnings process in equation (D.45), where the other income fixed effect of the child depends linearly on the fixed effects of the two income sources and consumption in the previous generation and his own idiosyncratic fixed effect, that is,

$$\bar{n}_f^k = \rho \bar{n}_f^p + \gamma_n \bar{e}_f^p + \lambda_n \bar{c}_f^p + \check{n}_f^k \quad (\text{D.46})$$

The model presented above has 6 equations summarizing the earnings, other income and consumption processes for parents and their adult children. With 6 equations, the set of variance-covariance moment conditions that can be used to estimate the parameters of the model are the same as in the baseline case. Thus, there are 21 moment conditions (see below), when we use time-averaged data, for identifying 19 parameters (two more than our baseline case because of the additional effects of parental consumption on child earnings and other income through  $\lambda_e$  and  $\lambda_n$ ). If either one of  $\lambda_e$  and  $\lambda_n$  is estimated to be significantly different from zero, it can serve as an evidence for the presence of paternalistic motives in the U.S. data.

## Parental Variance

$$\text{Var}(\bar{e}_f^p) = \sigma_{\bar{e}^p}^2 \quad (\text{D.47})$$

$$\text{Var}(\bar{n}_f^p) = \sigma_{\bar{n}^p}^2 \quad (\text{D.48})$$

$$\text{Var}(\bar{c}_f^p) = \sigma_{\bar{q}^p}^2 + \sigma_{\bar{e}^p}^2 + \sigma_{\bar{n}^p}^2 + 2(\sigma_{\bar{e}^p, \bar{q}^p} + \sigma_{\bar{n}^p, \bar{q}^p} + \sigma_{\bar{e}^p, \bar{n}^p}) \quad (\text{D.49})$$

## Parental Covariance

$$\text{Cov}(\bar{e}_f^p, \bar{n}_f^p) = \sigma_{\bar{e}^p, \bar{n}^p} \quad (\text{D.50})$$

$$\text{Cov}(\bar{e}_f^p, \bar{c}_f^p) = \sigma_{\bar{e}^p}^2 + \sigma_{\bar{e}^p, \bar{q}^p} + \sigma_{\bar{e}^p, \bar{n}^p} \quad (\text{D.51})$$

$$\text{Cov}(\bar{n}_f^p, \bar{c}_f^p) = \sigma_{\bar{n}^p}^2 + \sigma_{\bar{n}^p, \bar{q}^p} + \sigma_{\bar{e}^p, \bar{n}^p} \quad (\text{D.52})$$

## Child Variance

$$\begin{aligned} \text{Var}(\bar{e}_f^k) = & (\gamma + \lambda_e)^2 \sigma_{\bar{e}^p}^2 + (\rho_e + \lambda_e)^2 \sigma_{\bar{n}^p}^2 + \lambda_e^2 \sigma_{\bar{q}^p}^2 + \sigma_{\bar{e}^k}^2 \\ & + 2[(\gamma + \lambda_e)(\rho_e + \lambda_e) \sigma_{\bar{e}^p, \bar{n}^p} + \lambda_e(\gamma + \lambda_e) \sigma_{\bar{e}^p, \bar{q}^p} + \lambda_e(\rho_e + \lambda_e) \sigma_{\bar{n}^p, \bar{q}^p}] \end{aligned} \quad (\text{D.53})$$

$$\begin{aligned} \text{Var}(\bar{n}_f^k) = & (\gamma_n + \lambda_n)^2 \sigma_{\bar{e}^p}^2 + (\rho + \lambda_n)^2 \sigma_{\bar{n}^p}^2 + \lambda_n^2 \sigma_{\bar{q}^p}^2 + \sigma_{\bar{n}^k}^2 \\ & + 2[(\gamma_n + \lambda_n)(\rho + \lambda_n) \sigma_{\bar{e}^p, \bar{n}^p} + \lambda_n(\gamma_n + \lambda_n) \sigma_{\bar{e}^p, \bar{q}^p} + \lambda_n(\rho + \lambda_n) \sigma_{\bar{n}^p, \bar{q}^p}] \end{aligned} \quad (\text{D.54})$$

$$\begin{aligned} \text{Var}(\bar{c}_f^k) = & (\lambda + \lambda_e + \lambda_n)^2 \sigma_{\bar{q}^p}^2 + (\gamma + \gamma_n + \lambda_e + \lambda_n)^2 \sigma_{\bar{e}^p}^2 + (\rho + \rho_e + \lambda_e + \lambda_n)^2 \sigma_{\bar{n}^p}^2 \\ & + 2(\gamma + \gamma_n + \lambda_e + \lambda_n)(\lambda + \lambda_e + \lambda_n) \sigma_{\bar{e}^p, \bar{q}^p} \\ & + 2(\rho + \rho_e + \lambda_e + \lambda_n)(\lambda + \lambda_e + \lambda_n) \sigma_{\bar{n}^p, \bar{q}^p} \\ & + 2(\rho + \rho_e + \lambda_e + \lambda_n)(\gamma + \gamma_n + \lambda_e + \lambda_n) \sigma_{\bar{e}^p, \bar{n}^p} \\ & + \sigma_{\bar{q}^k}^2 + \sigma_{\bar{e}^k}^2 + \sigma_{\bar{n}^k}^2 + 2[\sigma_{\bar{e}^k, \bar{q}^k} + \sigma_{\bar{n}^k, \bar{q}^k} + \sigma_{\bar{e}^k, \bar{n}^k}] \end{aligned} \quad (\text{D.55})$$

## Child Covariance

$$\begin{aligned} \text{Cov}(\bar{e}_f^k, \bar{n}_f^k) = & (\gamma + \lambda_e)(\gamma_n + \lambda_n) \sigma_{\bar{e}^p}^2 + (\rho + \lambda_n)(\rho_e + \lambda_e) \sigma_{\bar{n}^p}^2 + \lambda_e \lambda_n \sigma_{\bar{q}^p}^2 + \sigma_{\bar{e}^k, \bar{n}^k} \\ & + [(\rho + \lambda_n)(\gamma + \lambda_e) + (\rho_e + \lambda_n)(\gamma_n + \lambda_n)] \sigma_{\bar{e}^p, \bar{n}^p} \\ & + [\lambda_n(\gamma + \lambda_e) + \lambda_e(\lambda + \lambda_n)] \sigma_{\bar{e}^p, \bar{q}^p} + [\lambda_n(\rho_e + \lambda_e) + \lambda_e(\rho + \lambda_n)] \sigma_{\bar{n}^p, \bar{q}^p} \end{aligned} \quad (\text{D.56})$$

$$\begin{aligned}
\text{Cov}(\bar{e}_f^k, \bar{c}_f^k) &= (\gamma + \lambda_e)(\gamma + \gamma_n + \lambda_e + \lambda_n) \sigma_{\bar{e}^p}^2 + (\rho_e + \lambda_e)(\rho + \rho_e + \lambda_e + \lambda_n) \sigma_{\bar{n}^p}^2 \\
&+ \lambda_e(\lambda + \lambda_e + \lambda_n) \sigma_{\bar{q}^p}^2 + \sigma_{\bar{e}^k}^2 + \sigma_{\bar{e}^k, \bar{n}^k} + \sigma_{\bar{e}^k, \bar{q}^k} \\
&+ [(\gamma + \lambda_e)(\lambda + \lambda_e + \lambda_n) + \lambda_e(\gamma + \gamma_n + \lambda_e + \lambda_n)] \sigma_{\bar{e}^p, \bar{q}^p} \\
&+ [(\rho_e + \lambda_e)(\lambda + \lambda_e + \lambda_n) + \lambda_e(\rho + \rho_e + \lambda_e + \lambda_n)] \sigma_{\bar{n}^p, \bar{q}^p} \\
&+ [(\gamma + \lambda_e)(\rho + \rho_e + \lambda_e + \lambda_n) + (\rho_e + \lambda_n)(\gamma + \gamma_n + \lambda_e + \lambda_n)] \sigma_{\bar{e}^p, \bar{n}^p} \quad (\text{D.57})
\end{aligned}$$

$$\begin{aligned}
\text{Cov}(\bar{n}_f^k, \bar{c}_f^k) &= (\gamma_n + \lambda_n)(\gamma + \gamma_n + \lambda_e + \lambda_n) \sigma_{\bar{e}^p}^2 + (\rho + \lambda_n)(\rho + \rho_e + \lambda_e + \lambda_n) \sigma_{\bar{n}^p}^2 \\
&+ \lambda_n(\lambda + \lambda_e + \lambda_n) \sigma_{\bar{q}^p}^2 + \sigma_{\bar{n}^k}^2 + \sigma_{\bar{e}^k, \bar{n}^k} + \sigma_{\bar{n}^k, \bar{q}^k} \\
&+ [(\gamma_n + \lambda_n)(\lambda + \lambda_e + \lambda_n) + \lambda_n(\gamma + \gamma_n + \lambda_e + \lambda_n)] \sigma_{\bar{e}^p, \bar{q}^p} \\
&+ [(\rho + \lambda_n)(\lambda + \lambda_e + \lambda_n) + \lambda_n(\rho + \rho_e + \lambda_e + \lambda_n)] \sigma_{\bar{n}^p, \bar{q}^p} \\
&+ [(\gamma_n + \lambda_n)(\rho + \rho_e + \lambda_e + \lambda_n) + (\rho + \lambda_n)(\gamma + \gamma_n + \lambda_e + \lambda_n)] \sigma_{\bar{e}^p, \bar{n}^p} \quad (\text{D.58})
\end{aligned}$$

### Cross-generation Covariance

$$\begin{aligned}
\text{Cov}(\bar{e}_f^p, \bar{c}_f^k) &= (\gamma + \gamma_n + \lambda_e + \lambda_n) \sigma_{\bar{e}^p}^2 \\
&+ (\lambda + \lambda_e + \lambda_n) \sigma_{\bar{e}^p, \bar{q}^p} + (\rho + \rho_e + \lambda_e + \lambda_n) \sigma_{\bar{e}^p, \bar{n}^p} \quad (\text{D.59})
\end{aligned}$$

$$\begin{aligned}
\text{Cov}(\bar{n}_f^p, \bar{c}_f^k) &= (\rho + \rho_e + \lambda_e + \lambda_n) \sigma_{\bar{n}^p}^2 \\
&+ (\lambda + \lambda_e + \lambda_n) \sigma_{\bar{n}^p, \bar{q}^p} + (\gamma + \gamma_n + \lambda_e + \lambda_n) \sigma_{\bar{e}^p, \bar{n}^p} \quad (\text{D.60})
\end{aligned}$$

$$\begin{aligned}
\text{Cov}(\bar{c}_f^p, \bar{e}_f^k) &= (\gamma + \lambda_e)(\sigma_{\bar{e}^p}^2 + \sigma_{\bar{e}^p, \bar{q}^p} + \sigma_{\bar{e}^p, \bar{n}^p}) + (\rho_e + \lambda_e)(\sigma_{\bar{n}^p}^2 + \sigma_{\bar{n}^p, \bar{q}^p} + \sigma_{\bar{e}^p, \bar{n}^p}) \\
&+ \lambda_e(\sigma_{\bar{q}^p}^2 + \sigma_{\bar{e}^p, \bar{q}^p} + \sigma_{\bar{n}^p, \bar{q}^p}) \quad (\text{D.61})
\end{aligned}$$

$$\begin{aligned}
\text{Cov}(\bar{c}_f^p, \bar{n}_f^k) &= (\gamma_n + \lambda_n)(\sigma_{\bar{e}^p}^2 + \sigma_{\bar{e}^p, \bar{q}^p} + \sigma_{\bar{e}^p, \bar{n}^p}) + (\rho + \lambda_n)(\sigma_{\bar{n}^p}^2 + \sigma_{\bar{n}^p, \bar{q}^p} + \sigma_{\bar{e}^p, \bar{n}^p}) \\
&+ \lambda_n(\sigma_{\bar{q}^p}^2 + \sigma_{\bar{e}^p, \bar{q}^p} + \sigma_{\bar{n}^p, \bar{q}^p}) \quad (\text{D.62})
\end{aligned}$$

$$\text{Cov}(\bar{e}_f^p, \bar{e}_f^k) = (\gamma + \lambda_e) \sigma_{\bar{e}^p}^2 + (\rho_e + \lambda_e) \sigma_{\bar{e}^p, \bar{n}^p} + \lambda_e \sigma_{\bar{e}^p, \bar{q}^p} \quad (\text{D.63})$$

$$\text{Cov}(\bar{n}_f^p, \bar{n}_f^k) = (\rho + \lambda_n) \sigma_{\bar{n}^p}^2 + (\gamma_n + \lambda_n) \sigma_{\bar{e}^p, \bar{n}^p} + \lambda_n \sigma_{\bar{n}^p, \bar{q}^p} \quad (\text{D.64})$$

$$\text{Cov}(\bar{e}_f^p, \bar{n}_f^k) = (\rho + \lambda_n) \sigma_{\bar{e}^p, \bar{n}^p} + (\lambda + \lambda_n) \sigma_{\bar{e}^p}^2 + \lambda_n \sigma_{\bar{e}^p, \bar{q}^p} \quad (\text{D.65})$$

$$\text{Cov}(\bar{n}_f^p, \bar{e}_f^k) = (\gamma + \lambda_e) \sigma_{\bar{e}^p, \bar{n}^p} + (\rho_e + \lambda_e) \sigma_{\bar{n}^p}^2 + \lambda_e \sigma_{\bar{n}^p, \bar{q}^p} \quad (\text{D.66})$$

$$\begin{aligned}
\text{Cov}(\bar{c}_f^p, \bar{c}_f^k) &= (\lambda + \lambda_e + \lambda_n)(\sigma_{\bar{q}^p}^2 + \sigma_{\bar{e}^p, \bar{q}^p} + \sigma_{\bar{n}^p, \bar{q}^p}) \\
&+ (\gamma + \gamma_n + \lambda_e + \lambda_n)(\sigma_{\bar{e}^p}^2 + \sigma_{\bar{e}^p, \bar{q}^p} + \sigma_{\bar{e}^p, \bar{n}^p}) \\
&+ (\rho + \rho_e + \lambda_e + \lambda_n)(\sigma_{\bar{n}^p}^2 + \sigma_{\bar{n}^p, \bar{q}^p} + \sigma_{\bar{e}^p, \bar{n}^p}) \quad (\text{D.67})
\end{aligned}$$

The parameters  $\sigma_{\bar{e}^p}^2$ ,  $\sigma_{\bar{n}^p}^2$  and  $\sigma_{\bar{e}^p, \bar{n}^p}$  are directly identified from equations (D.47), (D.48) and (D.50) respectively. Consequently,  $\sigma_{\bar{e}^p, \bar{q}^p}$  and  $\sigma_{\bar{n}^p, \bar{q}^p}$  are identified from (D.51) and (D.52) respectively, which leaves the last parental variance parameter  $\sigma_{\bar{q}^p}^2$  to be identified from (D.49). Consider-

ing equations (D.61), (D.63) and (D.66) together, we notice that these are 3 equations in 3 unknown parameter combinations —  $(\gamma + \lambda_e)$ ,  $(\rho_e + \lambda_e)$  and  $\lambda_e$ , because the rest of the parameters in these equations have already been identified above from the parental moment conditions. Therefore, these equations can be used to simultaneously identify  $\gamma$ ,  $\rho_e$  and  $\lambda_e$ . Similarly, equations (D.62), (D.64) and (D.65) can be used to identify  $\rho$ ,  $\gamma_n$  and  $\lambda_n$  simultaneously. The remaining inter-generational persistence parameter,  $\lambda$  is then identified from equation (D.59). Turning to the identification of the child parameters next, we notice that  $\sigma_{\tilde{e}^k}^2$ ,  $\sigma_{\tilde{n}^k}^2$  and  $\sigma_{\tilde{e}^k, \tilde{n}^k}$  can now be identified from equations (D.53), (D.54) and (D.56) respectively. Finally, we note that equations (D.55), (D.57) and (D.58) can be simultaneously used to identify the remaining three idiosyncratic child parameters —  $\sigma_{\tilde{q}^k}^2$ ,  $\sigma_{\tilde{e}^k, \tilde{q}^k}$  and  $\sigma_{\tilde{n}^k, \tilde{q}^k}$ .

Table 29: Intergenerational Elasticities (Optimal Parental Transfers)

Variables	Parameters	Baseline	Observable
		(1)	(2)
Head Earnings	$\gamma$	0.208 (0.035)	0.309 (0.026)
Other Income	$\rho$	0.094 (0.028)	0.221 (0.048)
$\bar{e}_f^p$ on $\bar{n}_f^k$	$\gamma_n$	0.175 (0.040)	0.208 (0.034)
$\bar{n}_f^p$ on $\bar{e}_f^k$	$\rho_e$	0.052 (0.018)	0.095 (0.033)
Consumption Shifters	$\lambda$	0.151 (0.033)	0.448 (0.047)
Parental Transfers $\left(\bar{e}_f^p\right)$ on $\bar{e}_f^k$	$\lambda_e$	0.060 (0.065)	0.100 (0.052)
Parental Transfers $\left(\bar{e}_f^p\right)$ on $\bar{n}_f^k$	$\lambda_n$	0.091 (0.066)	0.172 (0.079)
<i>No. of Parent-Child Pairs</i>	<i>N</i>	761	761

**Note:** Bootstrap standard errors (100 repetitions) in parentheses. *Baseline* refers to data that is purged of year and birth-cohort effects. These data are then regressed on various observable controls (viz., dummies for family size, state of residence, number of children, employment status, race and education). *Observable* refers to the fitted values from this regression. The average age for parents in the sample is 47 years; that of children is 37 years. The *Other Income* variable is measured as the sum of wife earnings and total transfer income.

The intergenerational persistence parameters are reported in Table 29, while the variance-covariance parameters are shown in Table 30. Table 9 reports the importance of parents in determining the cross-sectional heterogeneity in the children's generation. We find that all the estimates are very close to those obtained from the model in Section 2, where we did not allow the parents to optimize over child transfers. The new parameters,  $\lambda_e$  and  $\lambda_n$ , which capture the direct impact of parental transfers on the earnings and other income of the children are estimated to be close to zero, thereby validating the choice of the original model in Section 2.

Table 30: Variance-Covariance of Idiosyncratic Components (Optimal Parental Transfers)

	Parameters	Baseline (1)	Observable (2)
<b><u>Parental Variances</u></b>			
Permanent Head Earnings	$\sigma_{\bar{e}^p}^2$	0.297 (0.021)	0.095 (0.005)
Permanent Other Income	$\sigma_{\bar{n}^p}^2$	0.805 (0.065)	0.085 (0.008)
Permanent Consumption Shifters	$\sigma_{\bar{q}^p}^2$	1.036 (0.073)	0.197 (0.018)
<b><u>Child Idiosyncratic Variances</u></b>			
Permanent Head Earnings	$\sigma_{\bar{e}^k}^2$	0.229 (0.015)	0.041 (0.002)
Permanent Other Income	$\sigma_{\bar{n}^k}^2$	0.511 (0.037)	0.062 (0.004)
Permanent Consumption Shifters	$\sigma_{\bar{q}^k}^2$	0.734 (0.052)	0.106 (0.006)
<b><u>Parental Covariances</u></b>			
Consumption Shifters & Head Earnings	$\sigma_{\bar{e}^p, \bar{q}^p}$	-0.274 (0.023)	-0.121 (0.008)
Consumption Shifters & Other Income	$\sigma_{\bar{n}^p, \bar{q}^p}$	-0.817 (0.067)	-0.116 (0.012)
Head Earnings and Other Income	$\sigma_{\bar{e}^p, \bar{n}^p}$	0.070 (0.016)	0.060 (0.006)
<b><u>Child Idiosyncratic Covariances</u></b>			
Consumption Shifters & Head Earnings	$\sigma_{\bar{e}^k, \bar{q}^k}$	-0.250 (0.023)	-0.059 (0.003)
Consumption Shifters & Other Income	$\sigma_{\bar{n}^k, \bar{q}^k}$	-0.525 (0.040)	-0.070 (0.004)
Head Earnings & Other Income	$\sigma_{\bar{e}^k, \bar{n}^k}$	0.076 (0.015)	0.031 (0.002)
<i>No. of Parent-Child Pairs</i>	<i>N</i>	761	761

**Note:** See notes to Table 29.

## E Appendix to Section 6

### E.1 Panel Variation with Persistent and Transitory Shocks

The model is summarized by the following 6 equations.

$$e_{f,t}^p = \bar{e}_f^p + \mathcal{E}_{f,t}^p + \varepsilon_{f,t}^p \quad (\text{E.1})$$

$$\text{where } \mathcal{E}_{f,t}^p = \alpha_e^p \mathcal{E}_{f,t-1}^p + \epsilon_{f,t}^p \text{ with } \epsilon_{f,t}^p \stackrel{i.i.d.}{\sim} N(0, \sigma_{\epsilon^p}^2) \text{ and } \varepsilon_{f,t}^p \stackrel{i.i.d.}{\sim} N(0, \sigma_{\varepsilon^p}^2)$$

$$n_{f,t}^p = \bar{n}_f^p + \Theta_{f,t}^p + \vartheta_{f,t}^p \quad (\text{E.2})$$

$$\text{where } \Theta_{f,t}^p = \alpha_n^p \Theta_{f,t-1}^p + \theta_{f,t}^p \text{ with } \theta_{f,t}^p \stackrel{i.i.d.}{\sim} N(0, \sigma_{\theta^p}^2) \text{ and } \vartheta_{f,t}^p \stackrel{i.i.d.}{\sim} N(0, \sigma_{\vartheta^p}^2) \quad (\text{E.3})$$

$$c_{f,t}^p = \bar{q}_f^p + \bar{e}_f^p + \bar{n}_f^p + \Phi_{f,t}^p + \varphi_{f,t}^p + \frac{r\mathcal{E}_{f,t}^p}{1+r-\alpha_e^p} + \frac{r\Theta_{f,t}^p}{1+r-\alpha_n^p} + \frac{r}{1+r} (\varepsilon_{f,t}^p + \vartheta_{f,t}^p) \quad (\text{E.4})$$

$$\text{where } \Phi_{f,t}^p = \alpha_q^p \Phi_{f,t-1}^p + \phi_{f,t}^p \text{ with } \phi_{f,t}^p \stackrel{i.i.d.}{\sim} N(0, \sigma_{\phi^p}^2) \text{ and } \varphi_{f,t}^p \stackrel{i.i.d.}{\sim} N(0, \sigma_{\varphi^p}^2)$$

$$e_{f,t}^k = (\gamma + \lambda_e) \bar{e}_f^p + (\rho_e + \lambda_e) \bar{n}_f^p + \lambda_e \bar{q}_f^p + \check{e}_f^k + \mathcal{E}_{f,t}^k + \varepsilon_{f,t}^k \quad (\text{E.5})$$

$$\text{where } \mathcal{E}_{f,t}^k = \alpha_e^k \mathcal{E}_{f,t-1}^k + \epsilon_{f,t}^k \text{ with } \epsilon_{f,t}^k \stackrel{i.i.d.}{\sim} N(0, \sigma_{\epsilon^k}^2) \text{ and } \varepsilon_{f,t}^k \stackrel{i.i.d.}{\sim} N(0, \sigma_{\varepsilon^k}^2)$$

$$n_{f,t}^k = (\rho + \lambda_n) \bar{n}_f^p + (\gamma_n + \lambda_n) \bar{e}_f^p + \lambda_n \bar{q}_f^p + \check{n}_f^k + \Theta_{f,t}^k + \vartheta_{f,t}^k \quad (\text{E.6})$$

$$\text{where } \Theta_{f,t}^k = \alpha_n^k \Theta_{f,t-1}^k + \theta_{f,t}^k \text{ with } \theta_{f,t}^k \stackrel{i.i.d.}{\sim} N(0, \sigma_{\theta^k}^2) \text{ and } \vartheta_{f,t}^k \stackrel{i.i.d.}{\sim} N(0, \sigma_{\vartheta^k}^2)$$

$$\begin{aligned} c_{f,t}^k &= (\lambda + \lambda_e + \lambda_n) \bar{q}_f^p + (\gamma + \gamma_n + \lambda_e + \lambda_n) \bar{e}_f^p + (\rho + \rho_e + \lambda_e + \lambda_n) \bar{n}_f^p + \check{q}_f^k + \check{e}_f^k + \check{n}_f^k \\ &+ \Phi_{f,t}^k + \varphi_{f,t}^k + \frac{r\mathcal{E}_{f,t}^k}{1+r-\alpha_e^k} + \frac{r\Theta_{f,t}^k}{1+r-\alpha_n^k} + \frac{r}{1+r} (\varepsilon_{f,t}^k + \vartheta_{f,t}^k) \end{aligned} \quad (\text{E.7})$$

$$\text{where } \Phi_{f,t}^k = \alpha_q^k \Phi_{f,t-1}^k + \phi_{f,t}^k \text{ with } \phi_{f,t}^k \stackrel{i.i.d.}{\sim} N(0, \sigma_{\phi^k}^2) \text{ and } \varphi_{f,t}^k \stackrel{i.i.d.}{\sim} N(0, \sigma_{\varphi^k}^2)$$

To account for the biennial nature of the PSID data from 1998 onwards, we take the one-period lead/lag of the variables to be a two-year lead/lag in the data. We assume that the innovations to the autoregressive persistent shocks have zero mean and are correlated within a generation contemporaneously but uncorrelated across generations.

## Parental Variance

$$\text{Var}(e_{f,t}^p) = \sigma_{\bar{e}^p}^2 + \frac{\sigma_{\epsilon^p}^2}{1 - (\alpha_e^p)^2} + \sigma_{\epsilon^p}^2 \quad (\text{E.8})$$

$$\text{Var}(n_{f,t}^p) = \sigma_{\bar{n}^p}^2 + \frac{\sigma_{\theta^p}^2}{1 - (\alpha_n^p)^2} + \sigma_{\vartheta^p}^2 \quad (\text{E.9})$$

$$\begin{aligned} \text{Var}(c_{f,t}^p) &= \sigma_{\bar{q}^p}^2 + \sigma_{\bar{e}^p}^2 + \sigma_{\bar{n}^p}^2 + 2(\sigma_{\bar{e}^p, \bar{q}^p} + \sigma_{\bar{n}^p, \bar{q}^p} + \sigma_{\bar{e}^p, \bar{n}^p}) + \sigma_{\varphi^p}^2 \\ &+ \frac{2r\sigma_{\epsilon^p, \phi^p}}{(1+r-\alpha_e^p)(1-\alpha_e^p\alpha_q^p)} + \frac{2r\sigma_{\theta^p, \phi^p}}{(1+r-\alpha_n^p)(1-\alpha_n^p\alpha_q^p)} + \frac{\sigma_{\phi^p}^2}{1 - (\alpha_q^p)^2} \\ &+ \left(\frac{r}{1+r}\right)^2 (\sigma_{\epsilon^p}^2 + \sigma_{\vartheta^p}^2) + \left(\frac{r}{1+r-\alpha_e^p}\right)^2 \frac{\sigma_{\epsilon^p}^2}{1 - (\alpha_e^p)^2} \\ &+ \left(\frac{r}{1+r-\alpha_n^p}\right)^2 \frac{\sigma_{\theta^p}^2}{1 - (\alpha_n^p)^2} + \left[\frac{2r^2}{(1+r-\alpha_e^p)(1+r-\alpha_n^p)}\right] \frac{\sigma_{\epsilon^p, \theta^p}}{1 - \alpha_e^p\alpha_n^p} \end{aligned} \quad (\text{E.10})$$

## Child Variance

$$\begin{aligned} \text{Var}(e_{f,t}^k) &= (\gamma + \lambda_e)^2 \sigma_{\bar{e}^p}^2 + (\rho_e + \lambda_e)^2 \sigma_{\bar{n}^p}^2 + \lambda_e^2 \sigma_{\bar{q}^p}^2 + \sigma_{\epsilon^k}^2 + \frac{\sigma_{\epsilon^k}^2}{1 - (\alpha_e^k)^2} + \sigma_{\epsilon^k}^2 \\ &+ 2[(\gamma + \lambda_e)(\rho_e + \lambda_e)\sigma_{\bar{e}^p, \bar{n}^p} + \lambda_e(\gamma + \lambda_e)\sigma_{\bar{e}^p, \bar{q}^p} + \lambda_e(\rho_e + \lambda_e)\sigma_{\bar{n}^p, \bar{q}^p}] \end{aligned} \quad (\text{E.11})$$

$$\begin{aligned} \text{Var}(n_{f,t}^k) &= (\gamma_n + \lambda_n)^2 \sigma_{\bar{e}^p}^2 + (\rho + \lambda_n)^2 \sigma_{\bar{n}^p}^2 + \lambda_n^2 \sigma_{\bar{q}^p}^2 + \sigma_{\tilde{n}^k}^2 + \frac{\sigma_{\theta^k}^2}{1 - (\alpha_n^k)^2} + \sigma_{\vartheta^k}^2 \\ &+ 2[(\gamma_n + \lambda_n)(\rho + \lambda_n)\sigma_{\bar{e}^p, \bar{n}^p} + \lambda_n(\gamma_n + \lambda_n)\sigma_{\bar{e}^p, \bar{q}^p} + \lambda_n(\rho + \lambda_n)\sigma_{\bar{n}^p, \bar{q}^p}] \end{aligned} \quad (\text{E.12})$$

$$\begin{aligned} \text{Var}(c_{f,t}^k) &= (\lambda + \lambda_e + \lambda_n)^2 \sigma_{\bar{q}^p}^2 + (\gamma + \gamma_n + \lambda_e + \lambda_n)^2 \sigma_{\bar{e}^p}^2 + (\rho + \rho_e + \lambda_e + \lambda_n)^2 \sigma_{\bar{n}^p}^2 \\ &+ 2(\gamma + \gamma_n + \lambda_e + \lambda_n)(\lambda + \lambda_e + \lambda_n)\sigma_{\bar{e}^p, \bar{q}^p} + 2(\rho + \rho_e + \lambda_e + \lambda_n)(\lambda + \lambda_e + \lambda_n)\sigma_{\bar{n}^p, \bar{q}^p} \\ &+ 2(\rho + \rho_e + \lambda_e + \lambda_n)(\gamma + \gamma_n + \lambda_e + \lambda_n)\sigma_{\bar{e}^p, \bar{n}^p} \\ &+ \sigma_{\tilde{q}^k}^2 + \sigma_{\tilde{\epsilon}^k}^2 + \sigma_{\tilde{n}^k}^2 + 2[\sigma_{\tilde{\epsilon}^k, \tilde{n}^k} + \sigma_{\tilde{\epsilon}^k, \tilde{q}^k} + \sigma_{\tilde{n}^k, \tilde{q}^k}] + \sigma_{\varphi^k}^2 \\ &+ \frac{2r\sigma_{\epsilon^k, \phi^k}}{(1+r-\alpha_e^k)(1-\alpha_e^k\alpha_q^k)} + \frac{2r\sigma_{\theta^k, \phi^k}}{(1+r-\alpha_n^k)(1-\alpha_n^k\alpha_q^k)} + \frac{\sigma_{\phi^k}^2}{1 - (\alpha_q^k)^2} \\ &+ \left(\frac{r}{1+r}\right)^2 (\sigma_{\epsilon^k}^2 + \sigma_{\vartheta^k}^2) + \left(\frac{r}{1+r-\alpha_e^k}\right)^2 \frac{\sigma_{\epsilon^k}^2}{1 - (\alpha_e^k)^2} \\ &+ \left(\frac{r}{1+r-\alpha_n^k}\right)^2 \frac{\sigma_{\theta^k}^2}{1 - (\alpha_n^k)^2} + \left[\frac{2r^2}{(1+r-\alpha_e^k)(1+r-\alpha_n^k)}\right] \frac{\sigma_{\epsilon^k, \theta^k}}{1 - \alpha_e^k\alpha_n^k} \end{aligned} \quad (\text{E.13})$$

## Contemporaneous Parental Covariance

$$Cov(e_{f,t}^p, n_{f,t}^p) = \sigma_{\bar{e}^p, \bar{n}^p} + \frac{\sigma_{\epsilon^p, \theta^p}}{1 - \alpha_e^p \alpha_n^p} \quad (\text{E.14})$$

$$\begin{aligned} Cov(e_{ft}^p, c_{ft}^p) &= \sigma_{\bar{e}^p}^2 + \sigma_{\bar{e}^p, \bar{q}^p} + \sigma_{\bar{e}^p, \bar{n}^p} + \left( \frac{r}{1 + r - \alpha_e^p} \right) \frac{\sigma_{\epsilon^p}^2}{1 - (\alpha_e^p)^2} \\ &+ \left( \frac{r}{1 + r - \alpha_n^p} \right) \frac{\sigma_{\epsilon^p, \theta^p}}{1 - \alpha_e^p \alpha_n^p} + \frac{\sigma_{\epsilon^p, \phi^p}}{1 - \alpha_e^p \alpha_q^p} + \frac{r}{1 + r} \sigma_{\epsilon^p}^2 \end{aligned} \quad (\text{E.15})$$

$$\begin{aligned} Cov(n_{f,t}^p, c_{f,t}^p) &= \sigma_{\bar{n}^p}^2 + \sigma_{\bar{n}^p, \bar{q}^p} + \sigma_{\bar{e}^p, \bar{n}^p} + \left( \frac{r}{1 + r - \alpha_n^p} \right) \frac{\sigma_{\theta^p}^2}{1 - (\alpha_n^p)^2} \\ &+ \left( \frac{r}{1 + r - \alpha_e^p} \right) \frac{\sigma_{\epsilon^p, \theta^p}}{1 - \alpha_e^p \alpha_n^p} + \frac{\sigma_{\theta^p, \phi^p}}{1 - \alpha_n^p \alpha_q^p} + \frac{r}{1 + r} \sigma_{\vartheta^p}^2 \end{aligned} \quad (\text{E.16})$$

## Contemporaneous Child Covariance

$$\begin{aligned} Cov(e_{f,t}^k, n_{f,t}^k) &= (\gamma + \lambda_e)(\gamma_n + \lambda_n) \sigma_{\bar{e}^p}^2 + (\rho + \lambda_n)(\rho_e + \lambda_e) \sigma_{\bar{n}^p}^2 + \lambda_e \lambda_n \sigma_{\bar{q}^p}^2 + \sigma_{\check{\epsilon}^k, \check{n}^k} + \frac{\sigma_{\epsilon^k, \theta^k}}{1 - \alpha_e^k \alpha_n^k} \\ &+ [(\rho + \lambda_n)(\gamma + \lambda_e) + (\rho_e + \lambda_e)(\gamma_n + \lambda_n)] \sigma_{\bar{e}^p, \bar{n}^p} \\ &+ [\lambda_n(\gamma + \lambda_e) + \lambda_e(\gamma_n + \lambda_n)] \sigma_{\bar{e}^p, \bar{q}^p} + [\lambda_n(\rho_e + \lambda_e) + \lambda_e(\rho + \lambda_n)] \sigma_{\bar{n}^p, \bar{q}^p} \end{aligned} \quad (\text{E.17})$$

$$\begin{aligned} Cov(e_{f,t}^k, c_{f,t}^k) &= (\gamma + \lambda_e)(\gamma + \gamma_n + \lambda_e + \lambda_n) \sigma_{\bar{e}^p}^2 + (\rho_e + \lambda_e)(\rho + \rho_e + \lambda_e + \lambda_n) \sigma_{\bar{n}^p}^2 + \sigma_{\check{\epsilon}^k}^2 + \sigma_{\check{\epsilon}^k, \check{n}^k} + \sigma_{\check{\epsilon}^k, \check{q}^k} \\ &+ \lambda_e(\lambda + \lambda_e + \lambda_n) \sigma_{\bar{q}^p}^2 + [(\gamma + \lambda_e)(\lambda + \lambda_e + \lambda_n) + \lambda_e(\gamma + \gamma_n + \lambda_e + \lambda_n)] \sigma_{\bar{e}^p, \bar{q}^p} \\ &+ [(\rho_e + \lambda_e)(\lambda + \lambda_e + \lambda_n) + \lambda_e(\rho + \rho_e + \lambda_e + \lambda_n)] \sigma_{\bar{n}^p, \bar{q}^p} \\ &+ [(\gamma + \lambda_e)(\rho + \rho_e + \lambda_e + \lambda_n) + (\rho_e + \lambda_e)(\gamma + \gamma_n + \lambda_e + \lambda_n)] \sigma_{\bar{e}^p, \bar{n}^p} \\ &+ \left( \frac{r}{1 + r - \alpha_e^k} \right) \frac{\sigma_{\epsilon^k}^2}{1 - (\alpha_e^k)^2} + \left( \frac{r}{1 + r - \alpha_n^k} \right) \frac{\sigma_{\epsilon^k, \theta^k}}{1 - \alpha_e^k \alpha_n^k} + \frac{\sigma_{\epsilon^k, \phi^k}}{1 - \alpha_e^k \alpha_q^k} + \frac{r}{1 + r} \sigma_{\epsilon^k}^2 \end{aligned} \quad (\text{E.18})$$

$$\begin{aligned} Cov(n_{f,t}^k, c_{f,t}^k) &= (\gamma_n + \lambda_n)(\gamma + \gamma_n + \lambda_e + \lambda_n) \sigma_{\bar{e}^p}^2 + (\rho + \lambda_n)(\rho + \rho_e + \lambda_e + \lambda_n) \sigma_{\bar{n}^p}^2 + \sigma_{\check{n}^k}^2 + \sigma_{\check{\epsilon}^k, \check{n}^k} + \sigma_{\check{n}^k, \check{q}^k} \\ &+ \lambda_n(\lambda + \lambda_e + \lambda_n) \sigma_{\bar{q}^p}^2 + [(\gamma_n + \lambda_n)(\lambda + \lambda_e + \lambda_n) + \lambda_n(\gamma + \gamma_n + \lambda_e + \lambda_n)] \sigma_{\bar{e}^p, \bar{q}^p} \\ &+ [(\rho + \lambda_n)(\lambda + \lambda_e + \lambda_n) + \lambda_n(\rho + \rho_e + \lambda_e + \lambda_n)] \sigma_{\bar{n}^p, \bar{q}^p} \\ &+ [(\gamma_n + \lambda_n)(\rho + \rho_e + \lambda_e + \lambda_n) + (\rho + \lambda_n)(\gamma + \gamma_n + \lambda_e + \lambda_n)] \sigma_{\bar{e}^p, \bar{n}^p} \\ &+ \left( \frac{r}{1 + r - \alpha_n^k} \right) \frac{\sigma_{\theta^k}^2}{1 - (\alpha_n^k)^2} + \left( \frac{r}{1 + r - \alpha_e^k} \right) \frac{\sigma_{\epsilon^k, \theta^k}}{1 - \alpha_e^k \alpha_n^k} + \frac{\sigma_{\theta^k, \phi^k}}{1 - \alpha_n^k \alpha_q^k} + \frac{r}{1 + r} \sigma_{\vartheta^k}^2 \end{aligned} \quad (\text{E.19})$$

## Cross-Generation Covariance

$$\begin{aligned} \text{Cov}(e_{f,t}^p, c_{f,t}^k) &= (\gamma + \gamma_n + \lambda_e + \lambda_n) \sigma_{\bar{e}^p}^2 \\ &+ (\lambda + \lambda_e + \lambda_n) \sigma_{\bar{e}^p, \bar{q}^p} + (\rho + \rho_e + \lambda_e + \lambda_n) \sigma_{\bar{e}^p, \bar{n}^p} \end{aligned} \quad (\text{E.20})$$

$$\begin{aligned} \text{Cov}(n_{f,t}^p, c_{f,t}^k) &= (\rho + \rho_e + \lambda_e + \lambda_n) \sigma_{\bar{n}^p}^2 \\ &+ (\lambda + \lambda_e + \lambda_n) \sigma_{\bar{n}^p, \bar{q}^p} + (\gamma + \gamma_n + \lambda_e + \lambda_n) \sigma_{\bar{e}^p, \bar{n}^p} \end{aligned} \quad (\text{E.21})$$

$$\begin{aligned} \text{Cov}(c_{f,t}^p, e_{f,t}^k) &= (\gamma + \lambda_e) (\sigma_{\bar{e}^p}^2 + \sigma_{\bar{e}^p, \bar{q}^p} + \sigma_{\bar{e}^p, \bar{n}^p}) + (\rho_e + \lambda_e) (\sigma_{\bar{n}^p}^2 + \sigma_{\bar{n}^p, \bar{q}^p} + \sigma_{\bar{e}^p, \bar{n}^p}) \\ &+ \lambda_e (\sigma_{\bar{q}^p}^2 + \sigma_{\bar{e}^p, \bar{q}^p} + \sigma_{\bar{n}^p, \bar{q}^p}) \end{aligned} \quad (\text{E.22})$$

$$\begin{aligned} \text{Cov}(c_{f,t}^p, n_{f,t}^k) &= (\gamma_n + \lambda_n) (\sigma_{\bar{e}^p}^2 + \sigma_{\bar{e}^p, \bar{q}^p} + \sigma_{\bar{e}^p, \bar{n}^p}) + (\rho + \lambda_n) (\sigma_{\bar{n}^p}^2 + \sigma_{\bar{n}^p, \bar{q}^p} + \sigma_{\bar{e}^p, \bar{n}^p}) \\ &+ \lambda_n (\sigma_{\bar{q}^p}^2 + \sigma_{\bar{e}^p, \bar{q}^p} + \sigma_{\bar{n}^p, \bar{q}^p}) \end{aligned} \quad (\text{E.23})$$

$$\text{Cov}(e_{f,t}^p, e_{f,t}^k) = (\gamma + \lambda_e) \sigma_{\bar{e}^p}^2 + (\rho_e + \lambda_e) \sigma_{\bar{e}^p, \bar{n}^p} + \lambda_e \sigma_{\bar{e}^p, \bar{q}^p} \quad (\text{E.24})$$

$$\text{Cov}(n_{f,t}^p, n_{f,t}^k) = (\rho + \lambda_n) \sigma_{\bar{n}^p}^2 + (\gamma_n + \lambda_n) \sigma_{\bar{e}^p, \bar{n}^p} + \lambda_n \sigma_{\bar{n}^p, \bar{q}^p} \quad (\text{E.25})$$

$$\text{Cov}(e_{f,t}^p, n_{f,t}^k) = (\rho + \lambda_n) \sigma_{\bar{e}^p, \bar{n}^p} + (\lambda + \lambda_n) \sigma_{\bar{e}^p}^2 + \lambda_n \sigma_{\bar{e}^p, \bar{q}^p} \quad (\text{E.26})$$

$$\text{Cov}(n_{f,t}^p, e_{f,t}^k) = (\gamma + \lambda_e) \sigma_{\bar{e}^p, \bar{n}^p} + (\rho_e + \lambda_e) \sigma_{\bar{n}^p}^2 + \lambda_e \sigma_{\bar{n}^p, \bar{q}^p} \quad (\text{E.27})$$

$$\begin{aligned} \text{Cov}(c_{f,t}^p, c_{f,t}^k) &= (\lambda + \lambda_e + \lambda_n) (\sigma_{\bar{q}^p}^2 + \sigma_{\bar{e}^p, \bar{q}^p} + \sigma_{\bar{n}^p, \bar{q}^p}) \\ &+ (\gamma + \gamma_n + \lambda_e + \lambda_n) (\sigma_{\bar{e}^p}^2 + \sigma_{\bar{e}^p, \bar{q}^p} + \sigma_{\bar{e}^p, \bar{n}^p}) \\ &+ (\rho + \rho_e + \lambda_e + \lambda_n) (\sigma_{\bar{n}^p}^2 + \sigma_{\bar{n}^p, \bar{q}^p} + \sigma_{\bar{e}^p, \bar{n}^p}) \end{aligned} \quad (\text{E.28})$$

## Non-contemporaneous Covariances (lag 1) for Parent

$$\text{Cov}(e_{f,t}^p, e_{f,t+1}^p) = \sigma_{\bar{e}^p}^2 + \frac{\alpha_e^p \sigma_{\epsilon^p}^2}{1 - (\alpha_e^p)^2} \quad (\text{E.29})$$

$$\text{Cov}(n_{f,t}^p, n_{f,t+1}^p) = \sigma_{\bar{n}^p}^2 + \frac{\alpha_n^p \sigma_{\theta^p}^2}{1 - (\alpha_n^p)^2} \quad (\text{E.30})$$

$$\begin{aligned} \text{Cov}(c_{f,t}^p, c_{f,t+1}^p) &= \sigma_{\bar{q}^p}^2 + \sigma_{\bar{e}^p}^2 + \sigma_{\bar{n}^p}^2 + 2(\sigma_{\bar{e}^p, \bar{q}^p} + \sigma_{\bar{n}^p, \bar{q}^p} + \sigma_{\bar{e}^p, \bar{n}^p}) + \frac{\alpha_q^p \sigma_{\phi^p}^2}{1 - (\alpha_q^p)^2} \\ &+ \left( \frac{r}{1 + r - \alpha_e^p} \right) \frac{(\alpha_e^p + \alpha_q^p) \sigma_{\epsilon^p, \phi^p}}{1 - \alpha_e^p \alpha_q^p} + \left( \frac{r}{1 + r - \alpha_n^p} \right) \frac{(\alpha_n^p + \alpha_q^p) \sigma_{\theta^p, \phi^p}}{1 - \alpha_n^p \alpha_q^p} \\ &+ \left( \frac{r}{1 + r - \alpha_e^p} \right)^2 \frac{\alpha_e^p \sigma_{\epsilon^p}^2}{1 - (\alpha_e^p)^2} + \left( \frac{r}{1 + r - \alpha_n^p} \right)^2 \frac{\alpha_n^p \sigma_{\theta^p}^2}{1 - (\alpha_n^p)^2} \\ &+ \left( \frac{r}{1 + r - \alpha_e^p} \right) \left( \frac{r}{1 + r - \alpha_n^p} \right) \frac{(\alpha_e^p + \alpha_n^p) \sigma_{\epsilon^p, \theta^p}}{1 - \alpha_e^p \alpha_n^p} \end{aligned} \quad (\text{E.31})$$

$$\text{Cov}(e_{f,t}^p, n_{f,t+1}^p) = \sigma_{\bar{e}^p, \bar{n}^p} + \frac{\alpha_n^p \sigma_{\epsilon^p, \theta^p}}{1 - \alpha_e^p \alpha_n^p} \quad (\text{E.32})$$

$$\text{Cov}(n_{f,t}^p, e_{f,t+1}^p) = \sigma_{\bar{e}^p, \bar{n}^p} + \frac{\alpha_e^p \sigma_{\epsilon^p, \theta^p}}{1 - \alpha_e^p \alpha_n^p} \quad (\text{E.33})$$

$$\begin{aligned}
Cov(e_{f,t}^p, c_{f,t+1}^p) &= \sigma_{\bar{e}^p}^2 + \sigma_{\bar{e}^p, \bar{q}^p} + \sigma_{\bar{e}^p, \bar{n}^p} + \frac{\alpha_q^p \sigma_{\epsilon^p, \phi^p}}{1 - \alpha_e^p \alpha_q^p} \\
&+ \left( \frac{r}{1 + r - \alpha_n^p} \right) \frac{\alpha_n^p \sigma_{\epsilon^p, \theta^p}}{1 - \alpha_e^p \alpha_n^p} + \left( \frac{r}{1 + r - \alpha_e^p} \right) \frac{\alpha_e^p \sigma_{\epsilon^p}^2}{1 - (\alpha_e^p)^2}
\end{aligned} \tag{E.34}$$

$$\begin{aligned}
Cov(n_{f,t}^p, c_{f,t+1}^p) &= \sigma_{\bar{n}^p}^2 + \sigma_{\bar{n}^p, \bar{q}^p} + \sigma_{\bar{e}^p, \bar{n}^p} + \frac{\alpha_q^p \sigma_{\theta^p, \phi^p}}{1 - \alpha_n^p \alpha_q^p} \\
&+ \left( \frac{r}{1 + r - \alpha_e^p} \right) \frac{\alpha_e^p \sigma_{\epsilon^p, \theta^p}}{1 - \alpha_e^p \alpha_n^p} + \left( \frac{r}{1 + r - \alpha_n^p} \right) \frac{\alpha_n^p \sigma_{\theta^p}^2}{1 - (\alpha_n^p)^2}
\end{aligned} \tag{E.35}$$

$$\begin{aligned}
Cov(c_{f,t}^p, e_{f,t+1}^p) &= \sigma_{\bar{e}^p}^2 + \sigma_{\bar{e}^p, \bar{q}^p} + \sigma_{\bar{e}^p, \bar{n}^p} + \frac{\alpha_e^p \sigma_{\epsilon^p, \phi^p}}{1 - \alpha_e^p \alpha_q^p} \\
&+ \left( \frac{r}{1 + r - \alpha_n^p} \right) \frac{\alpha_e^p \sigma_{\epsilon^p, \theta^p}}{1 - \alpha_e^p \alpha_n^p} + \left( \frac{r}{1 + r - \alpha_e^p} \right) \frac{\alpha_e^p \sigma_{\epsilon^p}^2}{1 - (\alpha_e^p)^2}
\end{aligned} \tag{E.36}$$

$$\begin{aligned}
Cov(c_{f,t}^p, n_{f,t+1}^p) &= \sigma_{\bar{n}^p}^2 + \sigma_{\bar{q}^p, \bar{n}^p} + \sigma_{\bar{e}^p, \bar{n}^p} + \frac{\alpha_n^p \sigma_{\theta^p, \phi^p}}{1 - \alpha_n^p \alpha_q^p} \\
&+ \left( \frac{r}{1 + r - \alpha_e^p} \right) \frac{\alpha_n^p \sigma_{\epsilon^p, \theta^p}}{1 - \alpha_e^p \alpha_n^p} + \left( \frac{r}{1 + r - \alpha_n^p} \right) \frac{\alpha_n^p \sigma_{\theta^p}^2}{1 - (\alpha_n^p)^2}
\end{aligned} \tag{E.37}$$

### Non-contemporaneous Covariances (lag 1) for Child

$$\begin{aligned}
Cov(e_{f,t}^k, e_{f,t+1}^k) &= (\gamma + \lambda_e)^2 \sigma_{\bar{e}^p}^2 + (\rho_e + \lambda_e)^2 \sigma_{\bar{n}^p}^2 + \lambda_e^2 \sigma_{\bar{q}^p}^2 + \sigma_{\epsilon^k}^2 + \frac{\alpha_e^k \sigma_{\epsilon^k}^2}{1 - (\alpha_e^k)^2} \\
&+ 2\lambda_e [(\gamma + \lambda_e) \sigma_{\bar{e}^p, \bar{q}^p} + (\rho_e + \lambda_e) \sigma_{\bar{n}^p, \bar{q}^p}] \\
&+ 2(\gamma + \lambda_e) (\rho_e + \lambda_e) \sigma_{\bar{e}^p, \bar{n}^p}
\end{aligned} \tag{E.38}$$

$$\begin{aligned}
Cov(n_{f,t}^k, n_{f,t+1}^k) &= (\gamma_n + \lambda_n)^2 \sigma_{\bar{e}^p}^2 + (\rho + \lambda_n)^2 \sigma_{\bar{n}^p}^2 + \lambda_n^2 \sigma_{\bar{q}^p}^2 + \sigma_{\tilde{n}^k}^2 + \frac{\alpha_n^k \sigma_{\theta^k}^2}{1 - (\alpha_n^k)^2} \\
&+ 2\lambda_n [(\gamma_n + \lambda_n) \sigma_{\bar{e}^p, \bar{q}^p} + (\rho + \lambda_n) \sigma_{\bar{n}^p, \bar{q}^p}] \\
&+ 2(\gamma_n + \lambda_n) (\rho + \lambda_n) \sigma_{\bar{e}^p, \bar{n}^p}
\end{aligned} \tag{E.39}$$

$$\begin{aligned}
Cov(e_{f,t}^k, n_{f,t+1}^k) &= (\gamma + \lambda_e) (\gamma_n + \lambda_n) \sigma_{\bar{e}^p}^2 + (\rho + \lambda_n) (\rho_e + \lambda_e) \sigma_{\bar{n}^p}^2 + \lambda_e \lambda_n \sigma_{\bar{q}^p}^2 + \sigma_{\epsilon^k, \tilde{n}^k} + \frac{\alpha_n^k \sigma_{\epsilon^k, \theta^k}}{1 - \alpha_e^k \alpha_n^k} \\
&+ [(\rho + \lambda_n) (\gamma + \lambda_e) + (\rho_e + \lambda_e) (\gamma_n + \lambda_n)] \sigma_{\bar{e}^p, \bar{n}^p} \\
&+ [\lambda_n (\gamma + \lambda_e) + \lambda_e (\gamma_n + \lambda_n)] \sigma_{\bar{e}^p, \bar{q}^p} + [\lambda_n (\rho_e + \lambda_e) + \lambda_e (\rho + \lambda_n)] \sigma_{\bar{n}^p, \bar{q}^p}
\end{aligned} \tag{E.40}$$

$$\begin{aligned}
Cov(n_{f,t}^k, e_{f,t+1}^k) &= (\gamma + \lambda_e) (\gamma_n + \lambda_n) \sigma_{\bar{e}^p}^2 + (\rho + \lambda_n) (\rho_e + \lambda_e) \sigma_{\bar{n}^p}^2 + \lambda_e \lambda_n \sigma_{\bar{q}^p}^2 + \sigma_{\epsilon^k, \tilde{n}^k} + \frac{\alpha_e^k \sigma_{\epsilon^k, \theta^k}}{1 - \alpha_e^k \alpha_n^k} \\
&+ [(\rho + \lambda_n) (\gamma + \lambda_e) + (\rho_e + \lambda_e) (\gamma_n + \lambda_n)] \sigma_{\bar{e}^p, \bar{n}^p} \\
&+ [\lambda_n (\gamma + \lambda_e) + \lambda_e (\gamma_n + \lambda_n)] \sigma_{\bar{e}^p, \bar{q}^p} + [\lambda_n (\rho_e + \lambda_e) + \lambda_e (\rho + \lambda_n)] \sigma_{\bar{n}^p, \bar{q}^p}
\end{aligned} \tag{E.41}$$

$$\begin{aligned}
Cov(c_{f,t}^k, c_{f,t+1}^k) &= (\lambda + \lambda_e + \lambda_n)^2 \sigma_{\bar{q}^p}^2 + (\gamma + \gamma_n + \lambda_e + \lambda_n)^2 \sigma_{\bar{e}^p}^2 + (\rho + \rho_e + \lambda_e + \lambda_n)^2 \sigma_{\bar{n}^p}^2 \\
&+ 2(\gamma + \gamma_n + \lambda_e + \lambda_n)(\lambda + \lambda_e + \lambda_n) \sigma_{\bar{e}^p, \bar{q}^p} \\
&+ 2(\rho + \rho_e + \lambda_e + \lambda_n)(\lambda + \lambda_e + \lambda_n) \sigma_{\bar{n}^p, \bar{q}^p} \\
&+ 2(\rho + \rho_e + \lambda_e + \lambda_n)(\gamma + \gamma_n + \lambda_e + \lambda_n) \sigma_{\bar{e}^p, \bar{n}^p} \\
&+ \sigma_{\bar{q}^k}^2 + \sigma_{\bar{e}^k}^2 + \sigma_{\bar{n}^k}^2 + 2[\sigma_{\bar{e}^k, \bar{n}^k} + \sigma_{\bar{e}^k, \bar{q}^k} + \sigma_{\bar{n}^k, \bar{q}^k}] + \frac{\alpha_q^k \sigma_{\phi^k}^2}{1 - (\alpha_q^k)^2} \\
&+ \left( \frac{r}{1 + r - \alpha_e^k} \right) \frac{(\alpha_e^k + \alpha_q^k) \sigma_{\epsilon^k, \phi^k}}{1 - \alpha_e^k \alpha_q^k} + \left( \frac{r}{1 + r - \alpha_n^k} \right) \frac{(\alpha_n^k + \alpha_q^k) \sigma_{\theta^k, \phi^k}}{1 - \alpha_n^k \alpha_q^k} \\
&+ \left( \frac{r}{1 + r - \alpha_e^k} \right)^2 \frac{\alpha_e^k \sigma_{\epsilon^k}^2}{1 - (\alpha_e^k)^2} + \left( \frac{r}{1 + r - \alpha_n^k} \right)^2 \frac{\alpha_n^k \sigma_{\theta^k}^2}{1 - (\alpha_n^k)^2} \\
&+ \left( \frac{r}{1 + r - \alpha_e^k} \right) \left( \frac{r}{1 + r - \alpha_n^k} \right) \frac{(\alpha_e^k + \alpha_n^k) \sigma_{\epsilon^k, \theta^k}}{1 - \alpha_e^k \alpha_n^k} \tag{E.42}
\end{aligned}$$

$$\begin{aligned}
Cov(e_{f,t}^k, c_{f,t+1}^k) &= (\gamma + \lambda_e)(\gamma + \gamma_n + \lambda_e + \lambda_n) \sigma_{\bar{e}^p}^2 + (\rho_e + \lambda_e)(\rho + \rho_e + \lambda_e + \lambda_n) \sigma_{\bar{n}^p}^2 + \frac{\alpha_q^k \sigma_{\epsilon^k, \phi^k}}{1 - \alpha_e^k \alpha_q^k} \\
&+ \lambda_e(\lambda + \lambda_e + \lambda_n) \sigma_{\bar{q}^p}^2 + \sigma_{\bar{e}^k}^2 + \sigma_{\bar{e}^k, \bar{n}^k} + \sigma_{\bar{e}^k, \bar{q}^k} + \left( \frac{r}{1 + r - \alpha_n^k} \right) \frac{\alpha_n^k \sigma_{\epsilon^k, \theta^k}}{1 - \alpha_e^k \alpha_n^k} \\
&+ [(\gamma + \lambda_e)(\lambda + \lambda_e + \lambda_n) + \lambda_e(\gamma + \gamma_n + \lambda_e + \lambda_n)] \sigma_{\bar{e}^p, \bar{q}^p} + \left( \frac{r}{1 + r - \alpha_e^k} \right) \frac{\alpha_e^k \sigma_{\epsilon^k}^2}{1 - (\alpha_e^k)^2} \\
&+ [(\rho_e + \lambda_e)(\lambda + \lambda_e + \lambda_n) + \lambda_e(\rho + \rho_e + \lambda_e + \lambda_n)] \sigma_{\bar{n}^p, \bar{q}^p} \\
&+ [(\gamma + \lambda_e)(\rho + \rho_e + \lambda_e + \lambda_n) + (\rho_e + \lambda_e)(\gamma + \gamma_n + \lambda_e + \lambda_n)] \sigma_{\bar{e}^p, \bar{n}^p} \tag{E.43}
\end{aligned}$$

$$\begin{aligned}
Cov(n_{f,t}^k, c_{f,t+1}^k) &= (\gamma_n + \lambda_n)(\gamma + \gamma_n + \lambda_e + \lambda_n) \sigma_{\bar{e}^p}^2 + (\rho + \lambda_n)(\rho + \rho_e + \lambda_e + \lambda_n) \sigma_{\bar{n}^p}^2 + \frac{\alpha_q^k \sigma_{\theta^k, \phi^k}}{1 - \alpha_n^k \alpha_q^k} \\
&+ \lambda_n(\lambda + \lambda_e + \lambda_n) \sigma_{\bar{q}^p}^2 + \sigma_{\bar{n}^k}^2 + \sigma_{\bar{e}^k, \bar{n}^k} + \sigma_{\bar{n}^k, \bar{q}^k} + \left( \frac{r}{1 + r - \alpha_e^k} \right) \frac{\alpha_e^k \sigma_{\epsilon^k, \theta^k}}{1 - \alpha_e^k \alpha_n^k} \\
&+ [(\gamma_n + \lambda_n)(\lambda + \lambda_e + \lambda_n) + \lambda_n(\gamma + \gamma_n + \lambda_e + \lambda_n)] \sigma_{\bar{e}^p, \bar{q}^p} + \left( \frac{r}{1 + r - \alpha_n^k} \right) \frac{\alpha_n^k \sigma_{\theta^k}^2}{1 - (\alpha_n^k)^2} \\
&+ [(\rho + \lambda_n)(\lambda + \lambda_e + \lambda_n) + \lambda_n(\rho + \rho_e + \lambda_e + \lambda_n)] \sigma_{\bar{n}^p, \bar{q}^p} \\
&+ [(\gamma_n + \lambda_n)(\rho + \rho_e + \lambda_e + \lambda_n) + (\rho + \lambda_n)(\gamma + \gamma_n + \lambda_e + \lambda_n)] \sigma_{\bar{e}^p, \bar{n}^p} \tag{E.44}
\end{aligned}$$

$$\begin{aligned}
Cov(c_{f,t}^k, e_{f,t+1}^k) &= (\gamma + \lambda_e)(\gamma + \gamma_n + \lambda_e + \lambda_n) \sigma_{\bar{e}^p}^2 + (\rho_e + \lambda_e)(\rho + \rho_e + \lambda_e + \lambda_n) \sigma_{\bar{n}^p}^2 + \frac{\alpha_e^k \sigma_{\epsilon^k, \phi^k}}{1 - \alpha_e^k \alpha_q^k} \\
&+ \lambda_e(\lambda + \lambda_e + \lambda_n) \sigma_{\bar{q}^p}^2 + \sigma_{\bar{e}^k}^2 + \sigma_{\bar{e}^k, \bar{n}^k} + \sigma_{\bar{e}^k, \bar{n}^k} + \left( \frac{r}{1 + r - \alpha_n^k} \right) \frac{\alpha_e^k \sigma_{\epsilon^k, \theta^k}}{1 - \alpha_e^k \alpha_n^k} \\
&+ [(\gamma + \lambda_e)(\lambda + \lambda_e + \lambda_n) + \lambda_e(\gamma + \gamma_n + \lambda_e + \lambda_n)] \sigma_{\bar{e}^p, \bar{q}^p} + \left( \frac{r}{1 + r - \alpha_e^k} \right) \frac{\alpha_e^k \sigma_{\epsilon^k}^2}{1 - (\alpha_e^k)^2} \\
&+ [(\rho_e + \lambda_e)(\lambda + \lambda_e + \lambda_n) + \lambda_e(\rho + \rho_e + \lambda_e + \lambda_n)] \sigma_{\bar{n}^p, \bar{q}^p} \\
&+ [(\gamma + \lambda_e)(\rho + \rho_e + \lambda_e + \lambda_n) + (\rho_e + \lambda_e)(\gamma + \gamma_n + \lambda_e + \lambda_n)] \sigma_{\bar{e}^p, \bar{n}^p} \tag{E.45}
\end{aligned}$$

$$\begin{aligned}
Cov(c_{f,t}^k, n_{f,t+1}^k) &= (\gamma_n + \lambda_n)(\gamma + \gamma_n + \lambda_e + \lambda_n) \sigma_{\bar{e}^p}^2 + (\rho + \lambda_n)(\rho + \rho_e + \lambda_e + \lambda_n) \sigma_{\bar{n}^p}^2 + \frac{\alpha_n^k \sigma_{\theta^k, \phi^k}}{1 - \alpha_n^k \alpha_q^k} \\
&+ \lambda_n(\lambda + \lambda_e + \lambda_n) \sigma_{\bar{q}^p}^2 + \sigma_{\bar{n}^k}^2 + \sigma_{\bar{e}^k, \bar{n}^k} + \sigma_{\bar{n}^k, \bar{q}^k} + \left( \frac{r}{1 + r - \alpha_e^k} \right) \frac{\alpha_n^k \sigma_{\epsilon^k, \theta^k}}{1 - \alpha_e^k \alpha_n^k} \\
&+ [(\gamma_n + \lambda_n)(\lambda + \lambda_e + \lambda_n) + \lambda_n(\gamma + \gamma_n + \lambda_e + \lambda_n)] \sigma_{\bar{e}^p, \bar{q}^p} + \left( \frac{r}{1 + r - \alpha_n^k} \right) \frac{\alpha_n^k \sigma_{\theta^k}^2}{1 - (\alpha_n^k)^2} \\
&+ [(\rho + \lambda_n)(\lambda + \lambda_e + \lambda_n) + \lambda_n(\rho + \rho_e + \lambda_e + \lambda_n)] \sigma_{\bar{n}^p, \bar{q}^p} \\
&+ [(\gamma_n + \lambda_n)(\rho + \rho_e + \lambda_e + \lambda_n) + (\rho + \lambda_n)(\gamma + \gamma_n + \lambda_e + \lambda_n)] \sigma_{\bar{e}^p, \bar{n}^p} \tag{E.46}
\end{aligned}$$

### Non-contemporaneous Covariances (lag 2) for Parent

$$Cov(e_{f,t}^p, e_{f,t+2}^p) = \sigma_{\bar{e}^p}^2 + \frac{(\alpha_e^p)^2 \sigma_{\epsilon^p}^2}{1 - (\alpha_e^p)^2} \tag{E.47}$$

$$Cov(n_{f,t}^p, n_{f,t+2}^p) = \sigma_{\bar{n}^p}^2 + \frac{(\alpha_n^p)^2 \sigma_{\theta^p}^2}{1 - (\alpha_n^p)^2} \tag{E.48}$$

$$\begin{aligned}
Cov(c_{f,t}^p, c_{f,t+2}^p) &= \sigma_{\bar{q}^p}^2 + \sigma_{\bar{e}^p}^2 + \sigma_{\bar{n}^p}^2 + 2(\sigma_{\bar{q}^p, \bar{e}^p} + \sigma_{\bar{q}^p, \bar{n}^p} + \sigma_{\bar{e}^p, \bar{n}^p}) + \frac{(\alpha_q^p)^2 \sigma_{\phi^p}^2}{1 - (\alpha_q^p)^2} \\
&+ \left( \frac{r}{1 + r - \alpha_e^p} \right) \frac{((\alpha_e^p)^2 + (\alpha_q^p)^2) \sigma_{\epsilon^p, \phi^p}}{1 - \alpha_e^p \alpha_q^p} + \left( \frac{r}{1 + r - \alpha_n^p} \right) \frac{((\alpha_n^p)^2 + (\alpha_q^p)^2) \sigma_{\theta^p, \phi^p}}{1 - \alpha_n^p \alpha_q^p} \\
&+ \left( \frac{r}{1 + r - \alpha_e^p} \right)^2 \frac{(\alpha_e^p)^2 \sigma_{\epsilon^p}^2}{1 - (\alpha_e^p)^2} + \left( \frac{r}{1 + r - \alpha_n^p} \right)^2 \frac{(\alpha_n^p)^2 \sigma_{\theta^p}^2}{1 - (\alpha_n^p)^2} \\
&+ \left( \frac{r}{1 + r - \alpha_e^p} \right) \left( \frac{r}{1 + r - \alpha_n^p} \right) \frac{((\alpha_e^p)^2 + (\alpha_n^p)^2) \sigma_{\epsilon^p, \theta^p}}{1 - \alpha_e^p \alpha_n^p} \tag{E.49}
\end{aligned}$$

$$Cov(e_{f,t}^p, n_{f,t+2}^p) = \sigma_{\bar{e}^p, \bar{n}^p} + \frac{(\alpha_n^p)^2 \sigma_{\epsilon^p, \theta^p}}{1 - \alpha_e^p \alpha_n^p} \tag{E.50}$$

$$Cov(n_{f,t}^p, e_{f,t+2}^p) = \sigma_{\bar{e}^p, \bar{n}^p} + \frac{(\alpha_e^p)^2 \sigma_{\epsilon^p, \theta^p}}{1 - \alpha_e^p \alpha_n^p} \tag{E.51}$$

$$\begin{aligned}
Cov(e_{f,t}^p, c_{f,t+2}^p) &= \sigma_{\bar{e}^p}^2 + \sigma_{\bar{e}^p, \bar{q}^p} + \sigma_{\bar{e}^p, \bar{n}^p} + \frac{(\alpha_q^p)^2 \sigma_{\epsilon^p, \phi^p}}{1 - \alpha_e^p \alpha_q^p} \\
&+ \left( \frac{r}{1 + r - \alpha_n^p} \right) \frac{(\alpha_n^p)^2 \sigma_{\epsilon^p, \theta^p}}{1 - \alpha_e^p \alpha_n^p} + \left( \frac{r}{1 + r - \alpha_e^p} \right) \frac{(\alpha_e^p)^2 \sigma_{\epsilon^p}^2}{1 - (\alpha_e^p)^2} \quad (E.52)
\end{aligned}$$

$$\begin{aligned}
Cov(n_{f,t}^p, c_{f,t+2}^p) &= \sigma_{\bar{n}^p}^2 + \sigma_{\bar{n}^p, \bar{q}^p} + \sigma_{\bar{e}^p, \bar{n}^p} + \frac{(\alpha_q^p)^2 \sigma_{\theta^p, \phi^p}}{1 - \alpha_n^p \alpha_q^p} \\
&+ \left( \frac{r}{1 + r - \alpha_e^p} \right) \frac{(\alpha_e^p)^2 \sigma_{\epsilon^p, \theta^p}}{1 - \alpha_e^p \alpha_n^p} + \left( \frac{r}{1 + r - \alpha_n^p} \right) \frac{(\alpha_n^p)^2 \sigma_{\theta^p}^2}{1 - (\alpha_n^p)^2} \quad (E.53)
\end{aligned}$$

$$\begin{aligned}
Cov(c_{f,t}^p, e_{f,t+2}^p) &= \sigma_{\bar{e}^p}^2 + \sigma_{\bar{e}^p, \bar{q}^p} + \sigma_{\bar{e}^p, \bar{n}^p} + \frac{(\alpha_e^p)^2 \sigma_{\epsilon^p, \phi^p}}{1 - \alpha_e^p \alpha_q^p} \\
&+ \left( \frac{r}{1 + r - \alpha_n^p} \right) \frac{(\alpha_e^p)^2 \sigma_{\epsilon^p, \theta^p}}{1 - \alpha_e^p \alpha_n^p} + \left( \frac{r}{1 + r - \alpha_e^p} \right) \frac{(\alpha_e^p)^2 \sigma_{\epsilon^p}^2}{1 - (\alpha_e^p)^2} \quad (E.54)
\end{aligned}$$

$$\begin{aligned}
Cov(c_{f,t}^p, n_{f,t+2}^p) &= \sigma_{\bar{n}^p}^2 + \sigma_{\bar{q}^p, \bar{n}^p} + \sigma_{\bar{e}^p, \bar{n}^p} + \frac{(\alpha_n^p)^2 \sigma_{\theta^p, \phi^p}}{1 - \alpha_n^p \alpha_q^p} \\
&+ \left( \frac{r}{1 + r - \alpha_e^p} \right) \frac{(\alpha_n^p)^2 \sigma_{\epsilon^p, \theta^p}}{1 - \alpha_e^p \alpha_n^p} + \left( \frac{r}{1 + r - \alpha_n^p} \right) \frac{(\alpha_n^p)^2 \sigma_{\theta^p}^2}{1 - (\alpha_n^p)^2} \quad (E.55)
\end{aligned}$$

### Non-contemporaneous Covariances (lag 2) for Child

$$\begin{aligned}
Cov(e_{f,t}^k, e_{f,t+2}^k) &= (\gamma + \lambda_e)^2 \sigma_{\bar{e}^p}^2 + (\rho_e + \lambda_e)^2 \sigma_{\bar{n}^p}^2 + \lambda_e^2 \sigma_{\bar{q}^p}^2 + \sigma_{\epsilon^k}^2 + \frac{(\alpha_e^k)^2 \sigma_{\epsilon^k}^2}{1 - (\alpha_e^k)^2} \\
&+ 2\lambda_e [(\gamma + \lambda_e) \sigma_{\bar{e}^p, \bar{q}^p} + (\rho_e + \lambda_e) \sigma_{\bar{n}^p, \bar{q}^p}] \\
&+ 2(\gamma + \lambda_e)(\rho_e + \lambda_e) \sigma_{\bar{e}^p, \bar{n}^p} \quad (E.56)
\end{aligned}$$

$$\begin{aligned}
Cov(n_{f,t}^k, n_{f,t+2}^k) &= (\gamma_n + \lambda_n)^2 \sigma_{\bar{e}^p}^2 + (\rho + \lambda_n)^2 \sigma_{\bar{n}^p}^2 + \lambda_n^2 \sigma_{\bar{q}^p}^2 + \sigma_{\tilde{n}^k}^2 + \frac{(\alpha_n^k)^2 \sigma_{\theta^k}^2}{1 - (\alpha_n^k)^2} \\
&+ 2\lambda_n [(\gamma_n + \lambda_n) \sigma_{\bar{e}^p, \bar{q}^p} + (\rho + \lambda_n) \sigma_{\bar{n}^p, \bar{q}^p}] \\
&+ 2(\gamma_n + \lambda_n)(\rho + \lambda_n) \sigma_{\bar{e}^p, \bar{n}^p} \quad (E.57)
\end{aligned}$$

$$\begin{aligned}
Cov(e_{f,t}^k, n_{f,t+2}^k) &= (\gamma + \lambda_e)(\gamma_n + \lambda_n) \sigma_{\bar{e}^p}^2 + (\rho + \lambda_n)(\rho_e + \lambda_e) \sigma_{\bar{n}^p}^2 + \lambda_e \lambda_n \sigma_{\bar{q}^p}^2 + \sigma_{\epsilon^k, \tilde{n}^k} + \frac{(\alpha_n^k)^2 \sigma_{\epsilon^k, \theta^k}}{1 - \alpha_e^k \alpha_n^k} \\
&+ [(\rho + \lambda_n)(\gamma + \lambda_e) + (\rho_e + \lambda_e)(\gamma_n + \lambda_n)] \sigma_{\bar{e}^p, \bar{n}^p} \\
&+ [\lambda_n(\gamma + \lambda_e) + \lambda_e(\gamma_n + \lambda_n)] \sigma_{\bar{e}^p, \bar{q}^p} + [\lambda_n(\rho_e + \lambda_e) + \lambda_e(\rho + \lambda_n)] \sigma_{\bar{n}^p, \bar{q}^p} \quad (E.58)
\end{aligned}$$

$$\begin{aligned}
Cov(n_{f,t}^k, e_{f,t+2}^k) &= (\gamma + \lambda_e)(\gamma_n + \lambda_n) \sigma_{\bar{e}^p}^2 + (\rho + \lambda_n)(\rho_e + \lambda_e) \sigma_{\bar{n}^p}^2 + \lambda_e \lambda_n \sigma_{\bar{q}^p}^2 + \sigma_{\epsilon^k, \tilde{n}^k} + \frac{(\alpha_e^k)^2 \sigma_{\epsilon^k, \theta^k}}{1 - \alpha_e^k \alpha_n^k} \\
&+ [(\rho + \lambda_n)(\gamma + \lambda_e) + (\rho_e + \lambda_e)(\gamma_n + \lambda_n)] \sigma_{\bar{e}^p, \bar{n}^p} \\
&+ [\lambda_n(\gamma + \lambda_e) + \lambda_e(\gamma_n + \lambda_n)] \sigma_{\bar{e}^p, \bar{q}^p} + [\lambda_n(\rho_e + \lambda_e) + \lambda_e(\rho + \lambda_n)] \sigma_{\bar{n}^p, \bar{q}^p} \quad (E.59)
\end{aligned}$$

$$\begin{aligned}
Cov(c_{f,t}^k, c_{f,t+2}^k) &= (\lambda + \lambda_e + \lambda_n)^2 \sigma_{\bar{q}^p}^2 + (\gamma + \gamma_n + \lambda_e + \lambda_n)^2 \sigma_{\bar{e}^p}^2 + (\rho + \rho_e + \lambda_e + \lambda_n)^2 \sigma_{\bar{n}^p}^2 \\
&+ 2(\gamma + \gamma_n + \lambda_e + \lambda_n)(\lambda + \lambda_e + \lambda_n) \sigma_{\bar{e}^p, \bar{q}^p} \\
&+ 2(\rho + \rho_e + \lambda_e + \lambda_n)(\lambda + \lambda_e + \lambda_n) \sigma_{\bar{n}^p, \bar{q}^p} \\
&+ 2(\rho + \rho_e + \lambda_e + \lambda_n)(\gamma + \gamma_n + \lambda_e + \lambda_n) \sigma_{\bar{e}^p, \bar{n}^p} \\
&+ \sigma_{\bar{q}^k}^2 + \sigma_{\bar{e}^k}^2 + \sigma_{\bar{n}^k}^2 + 2[\sigma_{\bar{e}^k, \bar{n}^k} + \sigma_{\bar{e}^k, \bar{q}^k} + \sigma_{\bar{n}^k, \bar{q}^k}] + \frac{(\alpha_q^k)^2 \sigma_{\phi^k}^2}{1 - (\alpha_q^k)^2} \\
&+ \left( \frac{r}{1 + r - \alpha_e^k} \right) \frac{((\alpha_e^k)^2 + (\alpha_q^k)^2) \sigma_{\epsilon^k, \phi^k}}{1 - \alpha_e^k \alpha_q^k} + \left( \frac{r}{1 + r - \alpha_n^k} \right) \frac{((\alpha_n^k)^2 + (\alpha_q^k)^2) \sigma_{\theta^k, \phi^k}}{1 - \alpha_n^k \alpha_q^k} \\
&+ \left( \frac{r}{1 + r - \alpha_e^k} \right)^2 \frac{(\alpha_e^k)^2 \sigma_{\epsilon^k}^2}{1 - (\alpha_e^k)^2} + \left( \frac{r}{1 + r - \alpha_n^k} \right)^2 \frac{(\alpha_n^k)^2 \sigma_{\theta^k}^2}{1 - (\alpha_n^k)^2} \\
&+ \left( \frac{r}{1 + r - \alpha_e^k} \right) \left( \frac{r}{1 + r - \alpha_n^k} \right) \frac{((\alpha_e^k)^2 + (\alpha_n^k)^2) \sigma_{\epsilon^k, \theta^k}}{1 - \alpha_e^k \alpha_n^k} \tag{E.60}
\end{aligned}$$

$$\begin{aligned}
Cov(e_{f,t}^k, c_{f,t+2}^k) &= (\gamma + \lambda_e)(\gamma + \gamma_n + \lambda_e + \lambda_n) \sigma_{\bar{e}^p}^2 + (\rho_e + \lambda_e)(\rho + \rho_e + \lambda_e + \lambda_n) \sigma_{\bar{n}^p}^2 + \frac{(\alpha_q^k)^2 \sigma_{\epsilon^k, \phi^k}}{1 - \alpha_e^k \alpha_q^k} \\
&+ \lambda_e(\lambda + \lambda_e + \lambda_n) \sigma_{\bar{q}^p}^2 + \sigma_{\bar{e}^k}^2 + \sigma_{\bar{e}^k, \bar{n}^k} + \sigma_{\bar{e}^k, \bar{q}^k} + \left( \frac{r}{1 + r - \alpha_n^k} \right) \frac{(\alpha_n^k)^2 \sigma_{\epsilon^k, \theta^k}}{1 - \alpha_e^k \alpha_n^k} \\
&+ [(\gamma + \lambda_e)(\lambda + \lambda_e + \lambda_n) + \lambda_e(\gamma + \gamma_n + \lambda_e + \lambda_n)] \sigma_{\bar{e}^p, \bar{q}^p} + \left( \frac{r}{1 + r - \alpha_e^k} \right) \frac{(\alpha_e^k)^2 \sigma_{\epsilon^k}^2}{1 - (\alpha_e^k)^2} \\
&+ [(\rho_e + \lambda_e)(\lambda + \lambda_e + \lambda_n) + \lambda_e(\rho + \rho_e + \lambda_e + \lambda_n)] \sigma_{\bar{n}^p, \bar{q}^p} \\
&+ [(\gamma + \lambda_e)(\rho + \rho_e + \lambda_e + \lambda_n) + (\rho_e + \lambda_e)(\gamma + \gamma_n + \lambda_e + \lambda_n)] \sigma_{\bar{e}^p, \bar{n}^p} \tag{E.61}
\end{aligned}$$

$$\begin{aligned}
Cov(n_{f,t}^k, c_{f,t+2}^k) &= (\gamma_n + \lambda_n)(\gamma + \gamma_n + \lambda_e + \lambda_n) \sigma_{\bar{e}^p}^2 + (\rho + \lambda_n)(\rho + \rho_e + \lambda_e + \lambda_n) \sigma_{\bar{n}^p}^2 + \frac{(\alpha_q^k)^2 \sigma_{\theta^k, \phi^k}}{1 - \alpha_n^k \alpha_q^k} \\
&+ \lambda_n(\lambda + \lambda_e + \lambda_n) \sigma_{\bar{q}^p}^2 + \sigma_{\bar{n}^k}^2 + \sigma_{\bar{e}^k, \bar{n}^k} + \sigma_{\bar{n}^k, \bar{q}^k} + \left( \frac{r}{1 + r - \alpha_e^k} \right) \frac{(\alpha_e^k)^2 \sigma_{\epsilon^k, \theta^k}}{1 - \alpha_e^k \alpha_n^k} \\
&+ [(\gamma_n + \lambda_n)(\lambda + \lambda_e + \lambda_n) + \lambda_n(\gamma + \gamma_n + \lambda_e + \lambda_n)] \sigma_{\bar{e}^p, \bar{q}^p} + \left( \frac{r}{1 + r - \alpha_n^k} \right) \frac{(\alpha_n^k)^2 \sigma_{\theta^k}^2}{1 - (\alpha_n^k)^2} \\
&+ [(\rho + \lambda_n)(\lambda + \lambda_e + \lambda_n) + \lambda_n(\rho + \rho_e + \lambda_e + \lambda_n)] \sigma_{\bar{n}^p, \bar{q}^p} \\
&+ [(\gamma_n + \lambda_n)(\rho + \rho_e + \lambda_e + \lambda_n) + (\rho + \lambda_n)(\gamma + \gamma_n + \lambda_e + \lambda_n)] \sigma_{\bar{e}^p, \bar{n}^p} \tag{E.62}
\end{aligned}$$

$$\begin{aligned}
Cov(c_{f,t}^k, e_{f,t+2}^k) &= (\gamma + \lambda_e)(\gamma + \gamma_n + \lambda_e + \lambda_n) \sigma_{\bar{e}^p}^2 + (\rho_e + \lambda_e)(\rho + \rho_e + \lambda_e + \lambda_n) \sigma_{\bar{n}^p}^2 + \frac{(\alpha_e^k)^2 \sigma_{\epsilon^k, \phi^k}}{1 - \alpha_e^k \alpha_q^k} \\
&+ \lambda_e(\lambda + \lambda_e + \lambda_n) \sigma_{\bar{q}^p}^2 + \sigma_{\bar{\epsilon}^k}^2 + \sigma_{\bar{\epsilon}^k, \bar{n}^k} + \sigma_{\bar{\epsilon}^k, \bar{q}^k} + \left( \frac{r}{1 + r - \alpha_n^k} \right) \frac{(\alpha_e^k)^2 \sigma_{\xi^k, \eta^k}}{1 - \alpha_e^k \alpha_n^k} \\
&+ [(\gamma + \lambda_e)(\lambda + \lambda_e + \lambda_n) + \lambda_e(\gamma + \lambda + \lambda_e + \lambda_n)] \sigma_{\bar{e}^p, \bar{q}^p} + \left( \frac{r}{1 + r - \alpha_e^p} \right) \frac{(\alpha_e^k)^2 \sigma_{\epsilon^k}^2}{1 - (\alpha_e^k)^2} \\
&+ [(\rho_e + \lambda_e)(\lambda + \lambda_e + \lambda_n) + \lambda_e(\rho + \rho_e + \lambda_e + \lambda_n)] \sigma_{\bar{n}^p, \bar{q}^p} \\
&+ [(\gamma + \lambda_e)(\rho + \rho_e + \lambda_e + \lambda_n) + (\rho_e + \lambda_e)(\gamma + \gamma_n + \lambda_e + \lambda_n)] \sigma_{\bar{e}^p, \bar{n}^p} \quad (E.63)
\end{aligned}$$

$$\begin{aligned}
Cov(c_{f,t}^k, n_{f,t+2}^k) &= (\gamma_n + \lambda_n)(\gamma + \gamma_n + \lambda_e + \lambda_n) \sigma_{\bar{e}^p}^2 + (\rho + \lambda_n)(\rho + \rho_e + \lambda_e + \lambda_n) \sigma_{\bar{n}^p}^2 + \frac{(\alpha_n^k)^2 \sigma_{\theta^k, \phi^k}}{1 - \alpha_n^k \alpha_q^k} \\
&+ \lambda_n(\lambda + \lambda_e + \lambda_n) \sigma_{\bar{q}^p}^2 + \sigma_{\bar{n}^k}^2 + \sigma_{\bar{\epsilon}^k, \bar{n}^k} + \sigma_{\bar{n}^k, \bar{q}^k} + \left( \frac{r}{1 + r - \alpha_e^k} \right) \frac{(\alpha_n^k)^2 \sigma_{\epsilon^k, \theta^k}}{1 - \alpha_e^k \alpha_n^k} \\
&+ [(\lambda + \lambda_n)(\lambda + \lambda_e + \lambda_n) + \lambda_n(\gamma + \gamma_n + \lambda_e + \lambda_n)] \sigma_{\bar{e}^p, \bar{q}^p} + \left( \frac{r}{1 + r - \alpha_n^k} \right) \frac{(\alpha_n^k)^2 \sigma_{\theta^k}^2}{1 - (\alpha_n^k)^2} \\
&+ [(\rho + \lambda_n)(\lambda + \lambda_e + \lambda_n) + \lambda_n(\rho + \rho_e + \lambda_e + \lambda_n)] \sigma_{\bar{n}^p, \bar{q}^p} \\
&+ [(\gamma_n + \lambda_n)(\rho + \rho_e + \lambda_e + \lambda_n) + (\rho + \lambda_n)(\gamma + \gamma_n + \lambda_e + \lambda_n)] \sigma_{\bar{e}^p, \bar{n}^p} \quad (E.64)
\end{aligned}$$

### Non-contemporaneous Covariances (lag 3) for Parent

$$Cov(e_{f,t}^p, e_{f,t+3}^p) = \sigma_{\bar{e}^p}^2 + \frac{(\alpha_e^p)^3 \sigma_{\epsilon^p}^2}{1 - (\alpha_e^p)^2} \quad (E.65)$$

$$Cov(n_{f,t}^p, n_{f,t+6}^p) = \sigma_{\bar{n}^p}^2 + \frac{(\alpha_n^p)^3 \sigma_{\theta^p}^2}{1 - (\alpha_n^p)^2} \quad (E.66)$$

$$\begin{aligned}
Cov(c_{f,t}^p, c_{f,t+3}^p) &= \sigma_{\bar{q}^p}^2 + \sigma_{\bar{e}^p}^2 + \sigma_{\bar{n}^p}^2 + 2(\sigma_{\bar{e}^p, \bar{q}^p} + \sigma_{\bar{n}^p, \bar{q}^p} + \sigma_{\bar{e}^p, \bar{n}^p}) + \frac{(\alpha_q^p)^3 \sigma_{\phi^p}^2}{1 - (\alpha_q^p)^2} \\
&+ \left( \frac{r}{1 + r - \alpha_e^p} \right) \frac{((\alpha_e^p)^3 + (\alpha_q^p)^3) \sigma_{\epsilon^p, \phi^p}}{1 - \alpha_e^p \alpha_q^p} + \left( \frac{r}{1 + r - \alpha_n^p} \right) \frac{((\alpha_n^p)^3 + (\alpha_q^p)^3) \sigma_{\theta^p, \phi^p}}{1 - \alpha_n^p \alpha_q^p} \\
&+ \left( \frac{r}{1 + r - \alpha_e^p} \right)^2 \frac{(\alpha_e^p)^3 \sigma_{\epsilon^p}^2}{1 - (\alpha_e^p)^2} + \left( \frac{r}{1 + r - \alpha_n^p} \right)^2 \frac{(\alpha_n^p)^3 \sigma_{\theta^p}^2}{1 - (\alpha_n^p)^2} \\
&+ \left( \frac{r}{1 + r - \alpha_e^p} \right) \left( \frac{r}{1 + r - \alpha_n^p} \right) \frac{((\alpha_e^p)^3 + (\alpha_n^p)^3) \sigma_{\epsilon^p, \theta^p}}{1 - \alpha_e^p \alpha_n^p} \quad (E.67)
\end{aligned}$$

$$Cov(e_{f,t}^p, n_{f,t+3}^p) = \sigma_{\bar{e}^p, \bar{n}^p} + \frac{(\alpha_n^p)^3 \sigma_{\epsilon^p, \theta^p}}{1 - \alpha_e^p \alpha_n^p} \quad (E.68)$$

$$Cov(n_{f,t}^p, e_{f,t+3}^p) = \sigma_{\bar{e}^p, \bar{n}^p} + \frac{(\alpha_e^p)^3 \sigma_{\epsilon^p, \theta^p}}{1 - \alpha_e^p \alpha_n^p} \quad (E.69)$$

$$\begin{aligned}
Cov(e_{f,t}^p, c_{f,t+6}^p) &= \sigma_{\bar{e}^p}^2 + \sigma_{\bar{e}^p, \bar{q}^p} + \sigma_{\bar{e}^p, \bar{n}^p} + \frac{(\alpha_q^p)^3 \sigma_{\epsilon^p, \phi^p}}{1 - \alpha_e^p \alpha_q^p} \\
&+ \left( \frac{r}{1 + r - \alpha_n^p} \right) \frac{(\alpha_n^p)^3 \sigma_{\epsilon^p, \theta^p}}{1 - \alpha_e^p \alpha_n^p} + \left( \frac{r}{1 + r - \alpha_e^p} \right) \frac{(\alpha_e^p)^3 \sigma_{\epsilon^p}^2}{1 - (\alpha_e^p)^2} \quad (E.70)
\end{aligned}$$

$$\begin{aligned}
Cov(n_{f,t}^p, c_{f,t+3}^p) &= \sigma_{\bar{n}^p}^2 + \sigma_{\bar{n}^p, \bar{q}^p} + \sigma_{\bar{e}^p, \bar{n}^p} + \frac{(\alpha_q^p)^3 \sigma_{\theta^p, \phi^p}}{1 - \alpha_n^p \alpha_q^p} \\
&+ \left( \frac{r}{1 + r - \alpha_e^p} \right) \frac{(\alpha_e^p)^3 \sigma_{\epsilon^p, \theta^p}}{1 - \alpha_e^p \alpha_n^p} + \left( \frac{r}{1 + r - \alpha_n^p} \right) \frac{(\alpha_n^p)^3 \sigma_{\theta^p}^2}{1 - (\alpha_n^p)^2} \quad (E.71)
\end{aligned}$$

$$\begin{aligned}
Cov(c_{f,t}^p, e_{f,t+3}^p) &= \sigma_{\bar{e}^p}^2 + \sigma_{\bar{e}^p, \bar{q}^p} + \sigma_{\bar{e}^p, \bar{n}^p} + \frac{(\alpha_e^p)^3 \sigma_{\epsilon^p, \phi^p}}{1 - \alpha_e^p \alpha_q^p} \\
&+ \left( \frac{r}{1 + r - \alpha_n^p} \right) \frac{(\alpha_n^p)^3 \sigma_{\epsilon^p, \theta^p}}{1 - \alpha_e^p \alpha_n^p} + \left( \frac{r}{1 + r - \alpha_e^p} \right) \frac{(\alpha_e^p)^3 \sigma_{\epsilon^p}^2}{1 - (\alpha_e^p)^2} \quad (E.72)
\end{aligned}$$

$$\begin{aligned}
Cov(c_{f,t}^p, n_{f,t+3}^p) &= \sigma_{\bar{n}^p}^2 + \sigma_{\bar{q}^p, \bar{n}^p} + \sigma_{\bar{e}^p, \bar{n}^p} + \frac{(\alpha_n^p)^3 \sigma_{\theta^p, \phi^p}}{1 - \alpha_n^p \alpha_q^p} \\
&+ \left( \frac{r}{1 + r - \alpha_e^p} \right) \frac{(\alpha_e^p)^3 \sigma_{\epsilon^p, \theta^p}}{1 - \alpha_e^p \alpha_n^p} + \left( \frac{r}{1 + r - \alpha_e^p} \right) \frac{(\alpha_n^p)^3 \sigma_{\theta^p}^2}{1 - (\alpha_n^p)^2} \quad (E.73)
\end{aligned}$$

### Non-contemporaneous Covariances (lag 3) for Child

$$\begin{aligned}
Cov(e_{f,t}^k, e_{f,t+3}^k) &= (\gamma + \lambda_e)^2 \sigma_{\bar{e}^p}^2 + (\rho_e + \lambda_e)^2 \sigma_{\bar{n}^p}^2 + \lambda_e^2 \sigma_{\bar{q}^p}^2 + \sigma_{\bar{e}^k}^2 + \frac{(\alpha_e^k)^3 \sigma_{\epsilon^k}^2}{1 - (\alpha_e^k)^2} \\
&+ 2[(\gamma + \lambda_e)(\rho_e + \lambda_e) \sigma_{\bar{e}^p, \bar{n}^p} + \lambda_e(\gamma + \lambda_e) \sigma_{\bar{e}^p, \bar{q}^p} + \lambda_e(\rho_e + \lambda_e) \sigma_{\bar{n}^p, \bar{q}^p}] \quad (E.74)
\end{aligned}$$

$$\begin{aligned}
Cov(n_{f,t}^k, n_{f,t+3}^k) &= (\gamma_n + \lambda_n)^2 \sigma_{\bar{e}^p}^2 + (\rho + \lambda_n)^2 \sigma_{\bar{n}^p}^2 + \lambda_n^2 \sigma_{\bar{q}^p}^2 + \sigma_{\bar{n}^k}^2 + \frac{(\alpha_n^k)^3 \sigma_{\theta^k}^2}{1 - (\alpha_n^k)^2} \\
&+ 2[(\gamma_n + \lambda_n)(\rho + \lambda_n) \sigma_{\bar{e}^p, \bar{n}^p} + \lambda_n(\gamma_n + \lambda_n) \sigma_{\bar{e}^p, \bar{q}^p} + \lambda_n(\rho + \lambda_n) \sigma_{\bar{n}^p, \bar{q}^p}] \quad (E.75)
\end{aligned}$$

$$\begin{aligned}
Cov(e_{f,t}^k, n_{f,t+3}^k) &= (\gamma + \lambda_e)(\gamma_n + \lambda_n) \sigma_{\bar{e}^p}^2 + (\rho + \lambda_n)(\rho_e + \lambda_e) \sigma_{\bar{n}^p}^2 + \lambda_e \lambda_n \sigma_{\bar{q}^p}^2 + \sigma_{\bar{e}^k, \bar{n}^k} + \frac{(\alpha_n^k)^3 \sigma_{\epsilon^k, \theta^k}}{1 - \alpha_e^k \alpha_n^k} \\
&+ [(\rho + \lambda_n)(\gamma + \lambda_e) + (\rho_e + \lambda_e)(\gamma_n + \lambda_n)] \sigma_{\bar{e}^p, \bar{n}^p} \\
&+ [\lambda_n(\gamma + \lambda_e) + \lambda_e(\gamma_n + \lambda_n)] \sigma_{\bar{e}^p, \bar{q}^p} + [\lambda_n(\rho_e + \lambda_e) + \lambda_e(\rho + \lambda_n)] \sigma_{\bar{n}^p, \bar{q}^p} \quad (E.76)
\end{aligned}$$

$$\begin{aligned}
Cov(n_{f,t}^k, e_{f,t+3}^k) &= (\gamma + \lambda_e)(\gamma_n + \lambda_n) \sigma_{\bar{e}^p}^2 + (\rho + \lambda_n)(\rho_e + \lambda_e) \sigma_{\bar{n}^p}^2 + \lambda_e \lambda_n \sigma_{\bar{q}^p}^2 + \sigma_{\bar{e}^k, \bar{n}^k} + \frac{(\alpha_e^k)^3 \sigma_{\epsilon^k, \theta^k}}{1 - \alpha_e^k \alpha_n^k} \\
&+ [(\rho + \lambda_n)(\gamma + \lambda_e) + (\rho_e + \lambda_e)(\gamma_n + \lambda_n)] \sigma_{\bar{e}^p, \bar{n}^p} \\
&+ [\lambda_n(\gamma + \lambda_e) + \lambda_e(\gamma_n + \lambda_n)] \sigma_{\bar{e}^p, \bar{q}^p} + [\lambda_n(\rho_e + \lambda_e) + \lambda_e(\rho + \lambda_n)] \sigma_{\bar{n}^p, \bar{q}^p} \quad (E.77)
\end{aligned}$$

$$\begin{aligned}
Cov(c_{f,t}^k, c_{f,t+3}^k) &= (\lambda + \lambda_e + \lambda_n)^2 \sigma_{\bar{q}^p}^2 + (\gamma + \gamma_n + \lambda_e + \lambda_n)^2 \sigma_{\bar{e}^p}^2 + (\rho + \rho_e + \lambda_e + \lambda_n)^2 \sigma_{\bar{n}^p}^2 \\
&+ 2(\gamma + \gamma_n + \lambda_e + \lambda_n)(\lambda + \lambda_e + \lambda_n) \sigma_{\bar{q}^p, \bar{e}^p} \\
&+ 2(\rho + \rho_e + \lambda_e + \lambda_n)(\lambda + \lambda_e + \lambda_n) \sigma_{\bar{q}^p, \bar{n}^p} \\
&+ 2(\rho + \rho_e + \lambda_e + \lambda_n)(\gamma + \gamma_n + \lambda_e + \lambda_n) \sigma_{\bar{e}^p, \bar{n}^p} \\
&+ \sigma_{\bar{q}^k}^2 + \sigma_{\bar{e}^k}^2 + \sigma_{\bar{n}^k}^2 + 2[\sigma_{\bar{e}^k, \bar{n}^k} + \sigma_{\bar{e}^k, \bar{q}^k} + \sigma_{\bar{n}^k, \bar{q}^k}] \\
&+ \left(\frac{r}{1+r-\alpha_e^k}\right) \frac{((\alpha_e^k)^3 + (\alpha_q^k)^3) \sigma_{\xi^k, \omega^k}}{1 - \alpha_e^k \alpha_q^k} + \left(\frac{r}{1+r-\alpha_n^k}\right) \frac{((\alpha_n^k)^3 + (\alpha_q^k)^3) \sigma_{\theta^k, \phi^k}}{1 - \alpha_n^k \alpha_q^k} \\
&+ \left(\frac{r}{1+r-\alpha_e^k}\right)^2 \frac{(\alpha_e^k)^3 \sigma_{\epsilon^k}^2}{1 - (\alpha_e^k)^2} + \left(\frac{r}{1+r-\alpha_n^k}\right)^2 \frac{(\alpha_n^k)^3 \sigma_{\theta^k}^2}{1 - (\alpha_n^k)^2} + \frac{(\alpha_q^k)^3 \sigma_{\phi^k}^2}{1 - (\alpha_q^k)^2} \\
&+ \left(\frac{r}{1+r-\alpha_e^k}\right) \left(\frac{r}{1+r-\alpha_n^k}\right) \frac{((\alpha_e^k)^3 + (\alpha_n^k)^3) \sigma_{\epsilon^k, \theta^k}}{1 - \alpha_e^k \alpha_n^k} \tag{E.78}
\end{aligned}$$

$$\begin{aligned}
Cov(e_{f,t}^k, c_{f,t+3}^k) &= (\gamma + \lambda_e)(\gamma + \gamma_n + \lambda_e + \lambda_n) \sigma_{\bar{e}^p}^2 + (\rho_e + \lambda_e)(\rho + \rho_e + \lambda_e + \lambda_n) \sigma_{\bar{n}^p}^2 + \frac{(\alpha_q^k)^3 \sigma_{\epsilon^k, \phi^k}}{1 - \alpha_e^k \alpha_q^k} \\
&+ \lambda_e(\lambda + \lambda_e + \lambda_n) \sigma_{\bar{q}^p}^2 + \sigma_{\bar{\delta}^k}^2 + \sigma_{\bar{e}^k, \bar{n}^k} + \sigma_{\bar{e}^k, \bar{q}^k} + \left(\frac{r}{1+r-\alpha_n^k}\right) \frac{(\alpha_n^k)^3 \sigma_{\epsilon^k, \theta^k}}{1 - \alpha_e^k \alpha_n^k} \\
&+ [(\gamma + \lambda_e)(\lambda + \lambda_e + \lambda_n) + \lambda_e(\gamma + \gamma_n + \lambda_e + \lambda_n)] \sigma_{\bar{e}^p, \bar{q}^p} + \left(\frac{r}{1+r-\alpha_e^k}\right) \frac{(\alpha_e^k)^3 \sigma_{\epsilon^k}^2}{1 - (\alpha_e^k)^2} \\
&+ [(\theta + \chi)(\phi + \chi + \kappa) + \chi(\rho + \rho_e + \lambda_e + \lambda_n)] \sigma_{\bar{n}^p, \bar{q}^p} \\
&+ [(\gamma + \lambda_e)(\rho + \rho_e + \lambda_e + \lambda_n) + (\rho_e + \lambda_e)(\gamma + \gamma_n + \lambda_e + \lambda_n)] \sigma_{\bar{e}^p, \bar{n}^p} \tag{E.79}
\end{aligned}$$

$$\begin{aligned}
Cov(n_{f,t}^k, c_{f,t+3}^k) &= (\gamma_n + \lambda_n)(\gamma + \gamma_n + \lambda_e + \lambda_n) \sigma_{\bar{e}^p}^2 + (\rho + \lambda_n)(\rho + \rho_e + \lambda_e + \lambda_n) \sigma_{\bar{n}^p}^2 + \frac{(\alpha_q^k)^3 \sigma_{\theta^k, \phi^k}}{1 - \alpha_n^k \alpha_q^k} \\
&+ \lambda_n(\lambda + \lambda_e + \lambda_n) \sigma_{\bar{q}^p}^2 + \sigma_{\bar{n}^k}^2 + \sigma_{\bar{e}^k, \bar{n}^k} + \sigma_{\bar{n}^k, \bar{q}^k} + \left(\frac{r}{1+r-\alpha_e^k}\right) \frac{(\alpha_e^k)^3 \sigma_{\epsilon^k, \theta^k}}{1 - \alpha_e^k \alpha_n^k} \\
&+ [(\gamma_n + \lambda_n)(\lambda + \lambda_e + \lambda_n) + \lambda_n(\gamma + \gamma_n + \lambda_e + \lambda_n)] \sigma_{\bar{e}^p, \bar{q}^p} + \left(\frac{r}{1+r-\alpha_n^k}\right) \frac{(\alpha_n^k)^3 \sigma_{\theta^k}^2}{1 - (\alpha_n^k)^2} \\
&+ [(\rho + \lambda_n)(\lambda + \lambda_e + \lambda_n) + \lambda_n(\rho + \rho_e + \lambda_e + \lambda_n)] \sigma_{\bar{n}^p, \bar{q}^p} \\
&+ [(\gamma_n + \lambda_n)(\rho + \rho_e + \lambda_e + \lambda_n) + (\rho + \lambda_n)(\gamma + \gamma_n + \lambda_e + \lambda_n)] \sigma_{\bar{e}^p, \bar{n}^p} \tag{E.80}
\end{aligned}$$

$$\begin{aligned}
Cov(c_{f,t}^k, e_{f,t+3}^k) &= (\gamma + \lambda_e)(\gamma + \gamma_n + \lambda_e + \lambda_n) \sigma_{\bar{e}^p}^2 + (\rho_e + \lambda_e)(\rho + \rho_e + \lambda_e + \lambda_n) \sigma_{\bar{n}^p}^2 + \frac{(\alpha_e^k)^3 \sigma_{\epsilon^k, \phi^k}}{1 - \alpha_e^k \alpha_q^k} \\
&+ \lambda_e(\lambda + \lambda_e + \lambda_n) \sigma_{\bar{q}^p}^2 + \sigma_{\bar{\epsilon}^k}^2 + \sigma_{\bar{\epsilon}^k, \bar{n}^k} + \sigma_{\bar{\epsilon}^k, \bar{q}^k} + \left( \frac{r}{1 + r - \alpha_n^k} \right) \frac{(\alpha_e^k)^3 \sigma_{\epsilon^k, \theta^k}}{1 - \alpha_e^k \alpha_n^k} \\
&+ [(\gamma + \lambda_e)(\lambda + \lambda_e + \lambda_n) + \lambda_e(\gamma + \gamma_n + \lambda_e + \lambda_n)] \sigma_{\bar{e}^p, \bar{q}^p} + \left( \frac{r}{1 + r - \alpha_e^k} \right) \frac{(\alpha_e^k)^3 \sigma_{\epsilon^k}^2}{1 - (\alpha_e^k)^2} \\
&+ [(\rho_e + \lambda_e)(\lambda + \lambda_e + \lambda_n) + \lambda_e(\rho + \rho_e + \lambda_e + \lambda_n)] \sigma_{\bar{n}^p, \bar{q}^p} \\
&+ [(\gamma + \lambda_e)(\rho + \rho_e + \lambda_e + \lambda_n) + (\rho_e + \lambda_e)(\gamma + \gamma_n + \lambda_e + \lambda_n)] \sigma_{\bar{e}^p, \bar{n}^p} \quad (E.81)
\end{aligned}$$

$$\begin{aligned}
Cov(c_{f,t}^k, n_{f,t+3}^k) &= (\gamma_n + \lambda_n)(\gamma + \gamma_n + \lambda_e + \lambda_n) \sigma_{\bar{e}^p}^2 + (\rho + \lambda_n)(\rho + \rho_e + \lambda_e + \lambda_n) \sigma_{\bar{n}^p}^2 + \frac{(\alpha_n^k)^3 \sigma_{\theta^k, \phi^k}}{1 - \alpha_n^k \alpha_q^k} \\
&+ \lambda_n(\lambda + \lambda_e + \lambda_n) \sigma_{\bar{q}^p}^2 + \sigma_{\bar{n}^k}^2 + \sigma_{\bar{\epsilon}^k, \bar{n}^k} + \sigma_{\bar{n}^k, \bar{q}^k} + \left( \frac{r}{1 + r - \alpha_e^k} \right) \frac{(\alpha_n^k)^3 \sigma_{\epsilon^k, \theta^k}}{1 - \alpha_e^k \alpha_n^k} \\
&+ [(\gamma_n + \lambda_n)(\lambda + \lambda_e + \lambda_n) + \lambda_n(\gamma + \gamma_n + \lambda_e + \lambda_n)] \sigma_{\bar{e}^p, \bar{q}^p} + \left( \frac{r}{1 + r - \alpha_n^k} \right) \frac{(\alpha_n^k)^3 \sigma_{\theta^k}^2}{1 - (\alpha_n^k)^2} \\
&+ [(\rho + \lambda_n)(\lambda + \lambda_e + \lambda_n) + \lambda_n(\rho + \rho_e + \lambda_e + \lambda_n)] \sigma_{\bar{n}^p, \bar{q}^p} \\
&+ [(\gamma_n + \lambda_n)(\rho + \rho_e + \lambda_e + \lambda_n) + (\rho + \lambda_n)(\gamma + \gamma_n + \lambda_e + \lambda_n)] \sigma_{\bar{e}^p, \bar{n}^p} \quad (E.82)
\end{aligned}$$

There are 43 parameters to be identified from 75 equations - (E.8) through (E.82). We will proceed with the identification argument in the following nine groups of parameters:

(i)  $[\alpha_e^p, \alpha_n^p, \sigma_{\epsilon^p}^2, \sigma_{\theta^p}^2, \sigma_{\epsilon^p}^2, \sigma_{\theta^p}^2]$ : Consider the following four equations: (E.8), (E.29), (E.47) and (E.65). We can take the following three differences of those four moment conditions:

$$Var(e_{f,t}^p) - Cov(e_{f,t}^p, e_{f,t+2}^p) = \sigma_{\epsilon^p}^2 + \sigma_{\epsilon^p}^2 \quad (E.83)$$

$$Cov(e_{f,t}^p, e_{f,t+1}^p) - Cov(e_{f,t}^p, e_{f,t+2}^p) = \frac{\alpha_e^p \sigma_{\epsilon^p}^2}{1 + \alpha_e^p} \quad (E.84)$$

$$Cov(e_{f,t}^p, e_{f,t+1}^p) - Cov(e_{f,t}^p, e_{f,t+3}^p) = \alpha_e^p \sigma_{\epsilon^p}^2 \quad (E.85)$$

Combining (E.84) and (E.85), we identify  $\alpha_e^p$  as  $\left[ \frac{Cov(e_{f,t}^p, e_{f,t+1}^p) - Cov(e_{f,t}^p, e_{f,t+3}^p)}{Cov(e_{f,t}^p, e_{f,t+1}^p) - Cov(e_{f,t}^p, e_{f,t+2}^p)} - 1 \right]$ . Once  $\alpha_e^p$  is identified, equation (E.85) can be used to identify  $\sigma_{\epsilon^p}^2$ , and consequently  $\sigma_{\epsilon^p}^2$  is identified from equation (E.83). This exact sequence of arguments to identify the three parameters related to parental earnings process —  $\alpha_e^p$ ,  $\sigma_{\epsilon^p}^2$  and  $\sigma_{\epsilon^p}^2$ , can be repeated for identifying the three parameters pertaining to parental other income process —  $\alpha_n^p$ ,  $\sigma_{\theta^p}^2$  and  $\sigma_{\theta^p}^2$  using the following four moment conditions: (E.9), (E.30), (E.48) and (E.66).

(ii)  $[\alpha_e^k, \alpha_n^k, \sigma_{\epsilon^k}^2, \sigma_{\theta^k}^2, \sigma_{\epsilon^k}^2, \sigma_{\theta^k}^2]$ : Proceeding just like in point (i) above, one can identify the set of parameters,  $\{\alpha_e^k, \sigma_{\epsilon^k}^2, \sigma_{\epsilon^k}^2\}$  using the following four moment conditions: (E.11), (E.38), (E.56)

and (E.74), and the set of parameters,  $\{\alpha_n^k, \sigma_{\theta^k}^2, \sigma_{\vartheta^k}^2\}$  using the following four moment conditions: (E.12), (E.39), (E.57) and (E.75).

(iii)  $[\sigma_{\bar{e}^p}^2, \sigma_{\bar{n}^p}^2, \sigma_{\bar{e}^p, \bar{n}^p}, \sigma_{\epsilon^p, \theta^p}, \sigma_{\epsilon^k, \theta^k}]$ : One can identify  $\sigma_{\bar{e}^p}^2$  and  $\sigma_{\bar{n}^p}^2$  from equations (E.8) and (E.9) respectively. Next, considering the equations (E.32) and (E.33) simultaneously, one can identify the two parameters  $\sigma_{\bar{e}^p, \bar{n}^p}$  and  $\sigma_{\epsilon^p, \theta^p}$ . Finally, subtracting equation (E.40) from equation (E.41), we notice that the difference is a function of only one so-far unidentified parameter,  $\sigma_{\epsilon^k, \theta^k}$ .

(iv)  $[\alpha_q^p, \sigma_{\epsilon^p, \phi^p}, \sigma_{\bar{e}^p, \bar{q}^p}]$ : Consider equation (E.34). Collect all the so-far identified parameters and the empirical moment to one side of the equation and define it as  $A$ . Then  $A = z + \frac{x \cdot y}{1 - ax}$ , where  $a \equiv \alpha_e^p$ ,  $x \equiv \alpha_q^p$ ,  $y \equiv \sigma_{\epsilon^p, \phi^p}$  and  $z \equiv \sigma_{\bar{e}^p, \bar{q}^p}$ . Similarly, equation (E.36) can be re-arranged as  $B = z + \frac{ay}{1 - ax}$ , equation (E.52) can be re-arranged as  $C = z + \frac{x^2 y}{1 - ax}$  and equation (E.54) can be re-arranged as  $D = z + \frac{a^2 y}{1 - ax}$ . Note that  $\{x, y, z\}$  needs to be identified while  $\{a, A, B, C, D\}$  is already identified. Then,  $\frac{C-D}{A-B} - a = \frac{\frac{x^2 y - a^2 y}{1 - ax}}{\frac{xy - ay}{1 - ax}} - a = \frac{x^2 - a^2}{x - a} - a = (x + a) - a = x$ , implying  $\alpha_q^p$  is now identified. Consequently,  $y = \frac{(A-B)(1-ax)}{x-a}$ , implying  $\sigma_{\epsilon^p, \phi^p}$  is also identified. Finally,  $z = A - \frac{xy}{1-ax}$ , implying the identification of  $\sigma_{\bar{e}^p, \bar{q}^p}$ .

(v)  $[\sigma_{\theta^p, \phi^p}, \sigma_{\bar{n}^p, \bar{q}^p}, \sigma_{\bar{q}^p}^2, \sigma_{\phi^p}^2]$ : The two equations (E.35) and (E.37) can be simultaneously used to identify the parameters  $\sigma_{\bar{n}^p, \bar{q}^p}$  and  $\sigma_{\theta^p, \phi^p}$ . This leaves  $\sigma_{\bar{q}^p}^2$  and  $\sigma_{\phi^p}^2$  to be identified from equations (E.31) and (E.49).

(vi)  $[\gamma, \rho, \gamma_n, \rho_e, \lambda, \lambda_e, \lambda_n]$ : Considering equations (E.22), (E.24) and (E.27) together, we notice that these are 3 equations in 3 unknown parameter combinations —  $(\gamma + \lambda_e)$ ,  $(\rho_e + \lambda_e)$  and  $\lambda_e$ , because the rest of the parameters in these equations have already been identified above. Therefore, these equations can be used to simultaneously identify  $\gamma$ ,  $\rho_e$  and  $\lambda_e$ . Similarly, equations (E.23), (E.25) and (E.26) can be used to identify  $\rho$ ,  $\gamma_n$  and  $\lambda_n$  simultaneously. The remaining inter-generational persistence parameter,  $\lambda$  is then identified from equation (E.20).

(vii)  $[\alpha_q^k, \sigma_{\epsilon^k, \phi^k}]$ : Consider equation (E.43). Collect all the so-far identified parameters and the empirical moment to one side of the equation and define it as  $A'$ . Then,  $A' = z' + \frac{x' y'}{1 - a' x'}$ , where  $a' \equiv \alpha_e^k$ ,  $x' \equiv \alpha_q^k$ ,  $y' \equiv \sigma_{\epsilon^k, \phi^k}$  and  $z' \equiv (\sigma_{\bar{e}^k}^2 + \sigma_{\bar{e}^k, \bar{n}^k} + \sigma_{\bar{e}^k, \bar{q}^k})$ . Similarly, equation (E.45) can be re-arranged as  $B' = z' + \frac{a' y'}{1 - a' x'}$ , equation (E.61) can be re-arranged as  $C' = z' + \frac{x'^2 y'}{1 - a' x'}$  and equation (E.63) can be re-arranged as  $D' = z' + \frac{a'^2 y'}{1 - a' x'}$ . Note that  $\{x', y', z'\}$  needs to be identified while  $\{a', A', B', C', D'\}$  is already identified. However, we do not intend to identify  $z'$  as it is a function of multiple parameters of our model. Then,  $\frac{C'-D'}{A'-B'} - a' = \frac{\frac{x'^2 y' - a'^2 y'}{1 - a' x'}}{\frac{x' y' - a' y'}{1 - a' x'}} - a' = \frac{x'^2 - a'^2}{x' - a'} - a' = (x' + a') - a' = x'$ , implying  $\alpha_q^k$  is now identified. Consequently,  $y' = \frac{(A'-B')(1-a'x')}{x'-a'}$ , implying  $\sigma_{\epsilon^k, \phi^k}$  is also identified.

(viii)  $[\sigma_{\bar{e}^k, \bar{n}^k}, \sigma_{\theta^k, \phi^k}, \sigma_{\phi^k}^2]$ :  $\sigma_{\bar{e}^k, \bar{n}^k}$  can be directly identified from equation (E.41). Subtracting equation (E.44) from equation (E.46), we notice that the difference is a function of only one so-far unidentified parameter,  $\sigma_{\theta^k, \phi^k}$ , ensuring its identification. Subtracting equation (E.60) from equation (E.42), we notice that the difference is a function of only one so-far unidentified parameter,  $\sigma_{\phi^k}^2$ , ensuring its identification.

(ix)  $[\sigma_{\bar{e}^k}^2, \sigma_{\bar{n}^k}^2, \sigma_{\bar{e}^k, \bar{q}^k}, \sigma_{\bar{n}^k, \bar{q}^k}, \sigma_{\bar{q}^k}^2, \sigma_{\varphi^p}^2, \sigma_{\varphi^k}^2]$ : Equations (E.38) and (E.39) directly identify  $\sigma_{\bar{e}^k}^2$  and

$\sigma_{\tilde{n}^k}^2$  respectively. This leaves  $\sigma_{\tilde{e}^k, \tilde{q}^k}$  and  $\sigma_{\tilde{n}^k, \tilde{q}^k}$  to be identified from equations (E.43) and (E.44) respectively. Finally,  $\sigma_{\tilde{q}^k}^2$  is identified from equation (E.42), and equations (E.10) and (E.13) can be used to directly identify  $\sigma_{\varphi^p}^2$  and  $\sigma_{\varphi^k}^2$  respectively.

**Estimation.** The above model has 43 parameters to be identified and estimated from 75 moment conditions calculated on 761 parent-child pairs. Although we have shown the theoretical identification of the parameters above, we are concerned that there is not enough empirical variation in our relatively small sample to pin down all the parameters precisely. Hence, we calibrate all the shock parameters and hold them fixed while performing the GMM estimation of the remaining parameters in Tables 31 and 33. Moreover, we assume the innovations to the AR(1) persistent shocks to be uncorrelated with each other, that is, assume  $\sigma_{\epsilon^g, \theta^g}, \sigma_{\epsilon^g, \phi^g}, \sigma_{\theta^g, \phi^g} = 0$  for each generation  $g \in \{p, k\}$ . Below we detail the steps involved in calibrating the shock parameters.

**Step 1:** We purge the variables off individual fixed effects. The residuals are the sums of the persistent and transitory shocks to the corresponding variables and are denoted as follows:

- (i)  $S_{f,t}^{e,g} = \mathcal{E}_{f,t}^g + \varepsilon_{f,t}^g$  for earnings,
- (ii)  $S_{f,t}^{n,g} = \Theta_{f,t}^g + \vartheta_{f,t}^g$  for other income, and
- (iii)  $S_{f,t}^{c,g} = \Phi_{f,t}^g + \varphi_{f,t}^g + \frac{r\mathcal{E}_{f,t}^g}{1+r-\alpha_e^g} + \frac{r\Theta_{f,t}^g}{1+r-\alpha_n^g} + \frac{r}{1+r} (\varepsilon_{f,t}^g + \vartheta_{f,t}^g)$  for consumption.

Since we have assumed that the AR(1) shocks are uncorrelated with the transitory shocks and with each other, we have, for each generation  $g \in \{p, k\}$ ,

- (a)  $Var(S_{f,t}^{e,g}) = \sigma_{\mathcal{E}^g}^2 + \sigma_{\varepsilon^g}^2$ ,
- (b)  $Var(S_{f,t}^{n,g}) = \sigma_{\Theta^g}^2 + \sigma_{\vartheta^g}^2$ , and
- (c)  $Var(S_{f,t}^{c,g}) = \sigma_{\Phi^g}^2 + \sigma_{\varphi^g}^2 + \left(\frac{r}{1+r-\alpha_e^g}\right)^2 \sigma_{\mathcal{E}^g}^2 + \left(\frac{r}{1+r-\alpha_n^g}\right)^2 \sigma_{\Theta^g}^2 + \left(\frac{r}{1+r}\right)^2 (\sigma_{\varepsilon^g}^2 + \sigma_{\vartheta^g}^2)$ .

Note that we can calculate the variances of the total shocks,  $Var(S^{x,g})$  for each  $x \in \{e, n, c\}$  and each generation  $g \in \{p, k\}$  by simply noting the variance of the residuals from the individual fixed effects regressions.

**Step 2:** Bound et al. (1994) estimate the variance of measurement error in earnings in the nationally representative PSID sample to be between 3.4% and 3.9% of the cross-sectional variance of earnings, based on a measurement error variance of about 20% of the cross-sectional variance in their verification sample from a particular firm. We interpret the transitory shocks in our framework as classical measurement error, and assume that the variance of the transitory shocks in earnings, other income and consumption have the same size relative to the cross-sectional variance of the corresponding variables. Of course, there can be transitory shocks beyond simple measurement error. As a starting point, we present results for the transitory shock variance to be 5% of the cross-sectional variance, that is,  $\sigma_{\varepsilon^g}^2 = 0.05 * Var(\bar{e}_f^g)$ ,  $\sigma_{\vartheta^g}^2 = 0.05 * Var(\bar{n}_f^g)$  and  $\sigma_{\varphi^g}^2 + \left(\frac{r}{1+r}\right)^2 (\sigma_{\varepsilon^g}^2 + \sigma_{\vartheta^g}^2) = 0.05 * Var(\bar{c}_f^g)$ , and then show robustness for transitory shock variance to be 10% and 20% of cross-sectional variance. From Table 1, we know the values of  $Var(\bar{x}_f^g)$  for each  $x \in \{e, n, c\}$ , implying we can get estimates of  $\sigma_{\varepsilon^g}^2$ ,  $\sigma_{\vartheta^g}^2$  and  $\sigma_{\varphi^g}^2$ . Subtracting the estimates of  $\sigma_{\varepsilon^g}^2$  and  $\sigma_{\vartheta^g}^2$  from the estimates of  $Var(S_{f,t}^{e,g})$  and  $Var(S_{f,t}^{n,g})$  respectively in Step 1, we can get values for  $\sigma_{\mathcal{E}^g}^2$  and  $\sigma_{\Theta^g}^2$ .

**Step 3:** We run OLS regressions of the form  $S_{f,t}^{x,g} = \alpha_x^{S,g} S_{f,t-1}^{x,g} + \Upsilon_{f,t}^{x,g}$ , for each  $x \in \{e, n, c\}$  and each  $g \in \{p, k\}$  to get estimates for the persistence parameters,  $\alpha_x^{S,g}$ . We note that for earnings  $Cov(S_{f,t}^{e,g}, S_{f,t-1}^{e,g}) = \alpha_e^{S,g} Var(S_{f,t}^{e,g})$  and  $Cov(\mathcal{E}_{f,t}^g, \mathcal{E}_{f,t-1}^g) = \alpha_e^g \sigma_{\mathcal{E}^g}^2$ . However, since the transitory shock,  $\varepsilon_{f,t}^g$  does not have any autocorrelation by definition,  $Cov(S_{f,t}^{e,g}, S_{f,t-1}^{e,g}) = Cov(\mathcal{E}_{f,t}^g, \mathcal{E}_{f,t-1}^g)$ , implying  $\alpha_e^g = \frac{\alpha_e^{S,g} Var(S_{f,t}^{e,g})}{\sigma_{\mathcal{E}^g}^2}$ . Similarly, for other income,  $\alpha_n^g = \frac{\alpha_n^{S,g} Var(S_{f,t}^{n,g})}{\sigma_{\Theta^g}^2}$ . Therefore, we now have estimates of the original AR(1) persistence parameters in our model,  $\alpha_e^g$  and  $\alpha_n^g$ .

**Step 4:** From Step 1, we note that  $\sigma_{\Phi^g}^2 = Var(S_{f,t}^{c,g}) - \sigma_{\varphi^g}^2 - \left(\frac{r}{1+r-\alpha_e^g}\right)^2 \sigma_{\mathcal{E}^g}^2 - \left(\frac{r}{1+r-\alpha_n^g}\right)^2 \sigma_{\Theta^g}^2 - \left(\frac{r}{1+r}\right)^2 (\sigma_{\varepsilon^g}^2 + \sigma_{\vartheta^g}^2)$ , where all terms on the right hand side have already been identified in the previous steps. Hence,  $\sigma_{\Phi^g}^2$  is now estimated.

**Step 5:** The derivation for  $\alpha_q^g$  follows the same principle as in Step 3:

$$\begin{aligned} \alpha_c^{S,g} Var(S_{f,t}^{c,g}) &= Cov(\Phi_{f,t}^g, \Phi_{f,t-1}^g) + \left(\frac{r}{1+r-\alpha_e^g}\right)^2 Cov(\mathcal{E}_{f,t}^g, \mathcal{E}_{f,t-1}^g) + \left(\frac{r}{1+r-\alpha_n^g}\right)^2 Cov(\Theta_{f,t}^g, \Theta_{f,t-1}^g) \\ \implies \alpha_q^g &= \frac{1}{\sigma_{\Phi^g}^2} \left[ \alpha_c^{S,g} Var(S_{f,t}^{c,g}) - \left(\frac{r}{1+r-\alpha_e^g}\right)^2 \alpha_e^g \sigma_{\mathcal{E}^g}^2 - \left(\frac{r}{1+r-\alpha_n^g}\right)^2 \alpha_n^g \sigma_{\Theta^g}^2 \right]. \end{aligned}$$

Note that all terms on the right hand side is pre-determined and thus  $\alpha_q^g$  is now estimated. Note that the OLS regressions in Step 3 do not account for the possibility that the innovations to these AR(1) processes can be correlated contemporaneously within a generation. Therefore, these estimates of the  $\alpha$ 's should be interpreted as estimates for the case when  $\sigma_{\varepsilon^g, \theta^g}, \sigma_{\varepsilon^g, \phi^g}, \sigma_{\theta^g, \phi^g} = 0$  for  $g \in \{p, k\}$ . However, it would be straightforward to run the OLS regressions as a system of simultaneous regressions with potentially correlated error terms, which can allow for non-zero covariances among  $\varepsilon$ ,  $\theta$  and  $\phi$  within each generation.

**Step 6:** To get the variances of the innovations to the AR(1) persistent shocks, we note that  $\sigma_{\varepsilon^g}^2 = \sigma_{\mathcal{E}^g}^2 (1 - (\alpha_e^g)^2)$ ,  $\sigma_{\theta^g}^2 = \sigma_{\Theta^g}^2 (1 - (\alpha_n^g)^2)$  and  $\sigma_{\phi^g}^2 = \sigma_{\Phi^g}^2 (1 - (\alpha_q^g)^2)$ ,  $\forall g \in \{p, k\}$ .

The above 6 steps of calibrating the shock parameters yields the following values when the variances of the transitory shocks are assumed to be 5% of the cross-sectional variances of the corresponding outcome variables.

**(a) Variances of Transitory Shocks** —  $\sigma_{\varepsilon^p}^2 = 0.015$ ,  $\sigma_{\vartheta^p}^2 = 0.040$  and  $\sigma_{\varphi^p}^2 = 0.005$  are the variances of the transitory shocks to earnings, other income and consumption-shifters respectively for the parents' generations, while those for the children's generation are  $\sigma_{\varepsilon^k}^2 = 0.012$ ,  $\sigma_{\vartheta^k}^2 = 0.027$  and  $\sigma_{\varphi^k}^2 = 0.006$  respectively.

**(b) Variances of Innovations to AR(1) Shocks** —  $\sigma_{\varepsilon^p}^2 = 0.108$ ,  $\sigma_{\theta^p}^2 = 0.324$  and  $\sigma_{\phi^p}^2 = 0.075$  are the variances of the innovations to the AR(1) persistent shocks to earnings, other income and consumption-shifters respectively for the parents' generations, while those for the children's generation are  $\sigma_{\varepsilon^k}^2 = 0.097$ ,  $\sigma_{\theta^k}^2 = 0.322$  and  $\sigma_{\phi^k}^2 = 0.093$  respectively.

**(c) Persistence of AR(1) Shocks** —  $\alpha_e^p = 0.386$ ,  $\alpha_n^p = 0.318$  and  $\alpha_q^p = 0.095$  are the persistence of the AR(1) shocks to earnings, other income and consumption-shifters respectively for the parents' generations, while those for the children's generation are  $\alpha_e^k = 0.327$ ,  $\alpha_n^k = 0.322$  and  $\alpha_q^k = 0.109$  respectively.

Table 31: Estimates: Intergenerational Elasticities (75 Moments)

Variables	Parameters	Full Model (1)	$\lambda_e, \lambda_n = 0$ (2)	No Persistent Shock (3)	No Persistent Shock; $\lambda_e, \lambda_n = 0$ (4)
Head Earnings	$\gamma$	0.423 (0.082)	0.403 (0.059)	0.384 (0.073)	0.378 (0.045)
Other Income	$\rho$	0.106 (0.068)	0.116 (0.064)	0.102 (0.056)	0.112 (0.066)
$\bar{e}_f^p$ on $\bar{n}_f^k$	$\gamma_n$	0.130 (0.137)	0.172 (0.074)	0.123 (0.097)	0.163 (0.077)
$\bar{n}_f^p$ on $\bar{e}_f^k$	$\rho_e$	0.076 (0.055)	0.072 (0.057)	0.075 (0.046)	0.074 (0.049)
Consumption Shifters	$\lambda$	0.203 (0.080)	0.204 (0.084)	0.197 (0.071)	0.199 (0.081)
Parental Transfers ( $\bar{e}_f^p$ ) on $\bar{e}_f^k$	$\lambda_e$	-0.049 (0.151)	0	-0.019 (0.141)	0
Parental Transfers ( $\bar{e}_f^p$ ) on $\bar{n}_f^k$	$\lambda_n$	0.102 (0.187)	0	0.104 (0.146)	0
No. of Parent-Child Pairs	$N$	761	761	761	761

**Note:** Bootstrap standard errors (25 repetitions) in parentheses. All columns use data that is purged of year and birth-cohort effects. The other income measure is a sum of wife earnings and total transfer income of the head and his wife. The consumption measure is only food expenditure. Columns (1) and (2) use the values for the shock parameters derived above, while columns (3) and (4) allow joint estimation of the transitory shock variances (not reported) along with the other parameters in the GMM.

Table 32: Parental Importance for Child Inequality (75 Moments)

Variables	Full Model (1)	$\lambda_e, \lambda_n = 0$ (2)	No Persistent Shock (3)	No Persistent Shock; $\lambda_e, \lambda_n = 0$ (4)
Head Earnings	20.2 (12.4)	20.0 (12.2)	17.9 (11.7)	17.9 (11.7)
Other Income	4.0 (1.7)	4.1 (1.7)	3.6 (1.6)	3.6 (1.7)
Consumption	47.0 (22.3)	46.5 (22.0)	43.3 (20.9)	42.1 (20.4)

**Note:** All numbers are percentages and based on parameter estimates in Tables 31 and 33 with 761 parent-child pairs using 75 moment restrictions. The numbers outside the parentheses are the importance of parents in permanent heterogeneity in children's generation, while those in parentheses are importance of parents in total observed child heterogeneity.

Table 33: Estimates: Idiosyncratic Fixed Effects (75 Moments)

Variables	Parameters	Full Model (1)	$\lambda_e, \lambda_n = 0$ (2)	No Persistent Shock (3)	No Persistent Shock; $\lambda_e, \lambda_n = 0$ (4)
<b><u>Parental Variances</u></b>					
Permanent Head Earnings	$\sigma_{\bar{e}p}^2$	0.223 (0.018)	0.223 (0.025)	0.241 (0.024)	0.241 (0.021)
Permanent Other Income	$\sigma_{\bar{n}p}^2$	0.362 (0.037)	0.362 (0.041)	0.380 (0.031)	0.380 (0.025)
Permanent Consumption Shifters	$\sigma_{\bar{q}p}^2$	0.508 (0.040)	0.507 (0.051)	0.536 (0.039)	0.535 (0.031)
<b><u>Child Idiosyncratic Variances</u></b>					
Permanent Head Earnings	$\sigma_{\bar{e}k}^2$	0.164 (0.017)	0.165 (0.016)	0.180 (0.015)	0.180 (0.016)
Permanent Other Income	$\sigma_{\bar{n}k}^2$	0.318 (0.024)	0.318 (0.033)	0.348 (0.025)	0.348 (0.020)
Permanent Consumption Shifters	$\sigma_{\bar{q}k}^2$	0.476 (0.041)	0.476 (0.044)	0.513 (0.033)	0.512 (0.029)
<b><u>Parental Covariances</u></b>					
Consumption Shifters & Head Earnings	$\sigma_{\bar{e}p, \bar{q}p}$	-0.194 (0.021)	-0.194 (0.023)	-0.210 (0.025)	-0.210 (0.019)
Consumption Shifters & Other Income	$\sigma_{\bar{n}p, \bar{q}p}$	-0.365 (0.038)	-0.365 (0.043)	-0.380 (0.032)	-0.380 (0.024)
Head Earnings and Other Income	$\sigma_{\bar{e}p, \bar{n}p}$	0.052 (0.014)	0.052 (0.011)	0.052 (0.011)	0.052 (0.010)
<b><u>Child Idiosyncratic Covariances</u></b>					
Consumption Shifters & Head Earnings	$\sigma_{\bar{e}k, \bar{q}k}$	-0.187 (0.022)	-0.187 (0.023)	-0.200 (0.019)	-0.199 (0.017)
Consumption Shifters & Other Income	$\sigma_{\bar{n}k, \bar{q}k}$	-0.319 (0.029)	-0.318 (0.043)	-0.346 (0.023)	-0.344 (0.020)
Head Earnings & Other Income	$\sigma_{\bar{e}k, \bar{n}k}$	0.052 (0.016)	0.051 (0.011)	0.053 (0.012)	0.052 (0.012)
No. of Parent-Child Pairs	$N$	761	761	761	761

**Note:** See notes to Table 31.

The numbers for parental importance for explaining heterogeneity in the child outcomes in Table 32 reveals two observations - first, shutting off the direct channel of parental consumption on child income processes matter very little, and second, ignoring persistent shocks in the model underestimates the parental importance slightly.

Tables 31 through 33 use 75 moments to estimate the parameters. However, once all the shock parameters are calibrated externally, or even when persistent shocks are not taken into account, the GMM does not require the long run auto-covariances as moments to identify the remaining parameters. To see the impact of restricting the set of auto-covariances to only a lead of 2 years,

we present in Table 34 the parental importance numbers corresponding to parameter estimates obtained by using only 39 moments, from (E.8) through (E.46). Restricting the use of long-lead auto-covariances implies a slight decrease in the parental importance for explaining heterogeneity in child outcomes.

Table 34: Parental Importance for Child Inequality (39 Moments)

Variables	Full Model (1)	$\lambda_e, \lambda_n = 0$ (2)	No Persistent Shock (3)	No Persistent Shock; $\lambda_e, \lambda_n = 0$ (4)
Head Earnings	18.6 (11.7)	18.3 (11.5)	14.6 (10.5)	14.7 (10.6)
Other Income	3.6 (1.6)	3.6 (1.6)	3.0 (1.5)	3.0 (1.5)
Consumption	43.0 (21.7)	42.5 (21.4)	34.3 (19.1)	32.9 (18.3)

**Note:** All numbers are percentages corresponding to 761 parent-child pairs using 39 moment restrictions. The *Other Income* variable is measured as the sum of wife earnings and total transfer income of the household head and his wife. The numbers outside the parentheses are the importance of parents in permanent heterogeneity in children’s generation, while those in parentheses are importance of parents in total observed child heterogeneity.

**Robustness to Calibration of Shock Parameters.** So far, we have used 5% of the cross-sectional variance in the time-average of each outcome variable as the variance of the corresponding transitory shocks. As discussed above, this choice was motivated by the finding in Bound et al. (1994) about the size of the variance of classical measurement error in PSID earnings data. However, there is reason to believe that our transitory shocks not only captures classical measurement error but also other i.i.d. disturbance terms that cannot be separately identified. Therefore, in Table 35, we show the robustness of our main finding, namely, the importance of parental income and consumption for the heterogeneity in the child generation, to different calibrations of the transitory shock variances.

In Table 36, we show the robustness of our parental importance estimates for heterogeneity in child generation for different choices of the persistence parameters in the AR(1) shock processes. Instead of estimating the AR(1) persistences from a lagged dependent variable regression like discussed above in Step 3, we simply check how would the parental importance change for different counterfactual values of the persistence of the AR(1) shocks. Note that such calibrations do not change the variance of the transitory shocks but changes the variances of the innovations to the AR(1) shocks so as to match the total variance of shocks estimated in Step 1 above. We see that lower persistence of the AR(1) shocks translates to a monotonically lower role of parents in child heterogeneity but the decrease in the parental importance is much more pronounced for heterogeneity in child fixed effects, while that for total observed child heterogeneity is negligible.

Table 35: Parental Importance for Child Inequality: Robustness to Transitory Shock Variance

Variable	Transitory Shock Variance as Share of Cross-Sectional Variance (CSV)		
	5% of CSV	10% of CSV	20% of CSV
	(1)	(2)	(3)
Head Earnings	20.2 (12.4)	20.4 (12.5)	21.0 (12.6)
Other Income	4.0 (1.7)	4.0 (1.7)	4.1 (1.7)
Consumption	47.0 (22.3)	47.1 (22.4)	48.0 (22.7)

**Note:** All numbers are percentages corresponding to 761 parent-child pairs. The numbers outside the parentheses are the importance of parents in permanent heterogeneity in children's generation, while those in parentheses are importance of parents in total observed child heterogeneity. Column (1) is the same as column (1) in Table 32. Column (2) uses parameter estimates from a GMM that uses the following externally calibrated values of the shock parameters: the persistence of the AR(1) shocks —  $\alpha_e^p = 0.436$ ,  $\alpha_n^p = 0.358$ ,  $\alpha_q^p = 0.100$ ,  $\alpha_e^k = 0.369$ ,  $\alpha_n^k = 0.347$ ,  $\alpha_q^k = 0.116$ ; the variances of the innovations to the AR(1) shocks —  $\sigma_{\epsilon^p}^2 = 0.091$ ,  $\sigma_{\theta^p}^2 = 0.279$ ,  $\sigma_{\phi^p}^2 = 0.070$ ,  $\sigma_{\epsilon^k}^2 = 0.083$ ,  $\sigma_{\theta^k}^2 = 0.293$ ,  $\sigma_{\phi^k}^2 = 0.087$ ; and the variances of the transitory shocks —  $\sigma_{\epsilon^p}^2 = 0.029$ ,  $\sigma_{\theta^p}^2 = 0.081$ ,  $\sigma_{\phi^p}^2 = 0.009$ ,  $\sigma_{\epsilon^k}^2 = 0.025$ ,  $\sigma_{\theta^k}^2 = 0.053$ ,  $\sigma_{\phi^k}^2 = 0.011$ . Column (3) uses the following calibrated values of the shock parameters: the persistence of the AR(1) shocks —  $\alpha_e^p = 0.589$ ,  $\alpha_n^p = 0.478$ ,  $\alpha_q^p = 0.111$ ,  $\alpha_e^k = 0.497$ ,  $\alpha_n^k = 0.414$ ,  $\alpha_q^k = 0.131$ ; the variances of the innovations to the AR(1) shocks —  $\sigma_{\epsilon^p}^2 = 0.054$ ,  $\sigma_{\theta^p}^2 = 0.185$ ,  $\sigma_{\phi^p}^2 = 0.060$ ,  $\sigma_{\epsilon^k}^2 = 0.054$ ,  $\sigma_{\theta^k}^2 = 0.231$ ,  $\sigma_{\phi^k}^2 = 0.076$ ; and the variances of the transitory shocks —  $\sigma_{\epsilon^p}^2 = 0.058$ ,  $\sigma_{\theta^p}^2 = 0.161$ ,  $\sigma_{\phi^p}^2 = 0.019$ ,  $\sigma_{\epsilon^k}^2 = 0.050$ ,  $\sigma_{\theta^k}^2 = 0.107$ ,  $\sigma_{\phi^k}^2 = 0.023$ . All columns assume  $\sigma_{\epsilon^g, \theta^g}, \sigma_{\epsilon^g, \phi^g}, \sigma_{\theta^g, \phi^g} = 0$  for  $g \in \{p, k\}$ .

Table 36: Parental Importance for Child Inequality: Robustness to Persistence of Shocks

Variables	Estimated $\alpha$ 's	$\alpha's = 0.75$	$\alpha's = 0.50$	$\alpha's = 0.25$	$\alpha's = 0.10$
	(1)	(2)	(3)	(4)	(5)
Head Earnings	20.2 (12.4)	30.6 (15.5)	22.8 (13.2)	19.3 (12.0)	18.1 (11.6)
Other Income	4.0 (1.7)	9.1 (2.5)	5.1 (1.9)	3.9 (1.7)	3.5 (1.6)
Consumption	47.0 (22.3)	91.3 (26.2)	59.2 (22.9)	48.2 (21.8)	45.0 (21.4)

**Note:** All numbers are percentages corresponding to 761 parent-child pairs. The *Other Income* variable is measured as sum of household head's wife earnings and total transfer income. The numbers outside the parentheses are the importance of parents in permanent heterogeneity in children's generation, while those in parentheses are importance of parents in total observed child heterogeneity. Each column uses a different set of calibrated values for the persistent shock parameters. The transitory shock parameters are held constant at the values used in column (1).

## E.2 Model with Permanent Income as Random Walk

In this appendix, we consider the identification and estimation of the parameters of the model presented in Section 6.2 of the paper. Identification of intergenerational persistence in permanent life-cycle shocks involves calculating the growth rates of the outcome variables, which precludes identification of the persistence in fixed effects, which are differenced out in growth rates.

### E.2.1 Moment Conditions

#### Parent Variance

$$Var(\Delta e_{f,t}^p) = \sigma_{\epsilon^p}^2 + 2\sigma_{\epsilon^p}^2 \quad (E.86)$$

$$Var(\Delta n_{f,t}^p) = \sigma_{\theta^p}^2 + 2\sigma_{\theta^p}^2 \quad (E.87)$$

$$Var(\Delta c_{f,t}^p) = \omega_{\epsilon^p}^2 \sigma_{\epsilon^p}^2 + \omega_{n^p}^2 \sigma_{\theta^p}^2 + \psi_{\epsilon^p}^2 \sigma_{\epsilon^p}^2 + \psi_{n^p}^2 \sigma_{\theta^p}^2 + \sigma_{\xi^p}^2 \quad (E.88)$$

#### Child Variance

$$Var(\Delta e_{f,t}^k) = \gamma_{\Delta}^2 \sigma_{\epsilon^k}^2 + \sigma_{\epsilon^k}^2 + 2\sigma_{\epsilon^k}^2 \quad (E.89)$$

$$Var(\Delta n_{f,t}^k) = \rho_{\Delta}^2 \sigma_{\theta^k}^2 + \sigma_{\theta^k}^2 + 2\sigma_{\theta^k}^2 \quad (E.90)$$

$$\begin{aligned} Var(\Delta c_{f,t}^k) &= \omega_{\epsilon^k}^2 (\gamma_{\Delta}^2 \sigma_{\epsilon^k}^2 + \sigma_{\epsilon^k}^2) + \psi_{\epsilon^k}^2 \sigma_{\epsilon^k}^2 \\ &\quad + \omega_{n^k}^2 (\rho_{\Delta}^2 \sigma_{\theta^k}^2 + \sigma_{\theta^k}^2) + \psi_{n^k}^2 \sigma_{\theta^k}^2 \\ &\quad + \lambda_{\Delta}^2 \sigma_{\xi^k}^2 + \sigma_{\xi^k}^2 \end{aligned} \quad (E.91)$$

#### Contemporaneous Parent Covariance

$$Cov(\Delta e_{f,t}^p, \Delta c_{f,t}^p) = \omega_{\epsilon^p} \sigma_{\epsilon^p}^2 + \psi_{\epsilon^p} \sigma_{\epsilon^p}^2 \quad (E.92)$$

$$Cov(\Delta n_{f,t}^p, \Delta c_{f,t}^p) = \omega_{n^p} \sigma_{\theta^p}^2 + \psi_{n^p} \sigma_{\theta^p}^2 \quad (E.93)$$

#### Contemporaneous Child Covariance

$$Cov(\Delta e_{f,t}^k, \Delta c_{f,t}^k) = \gamma_{\Delta}^2 \omega_{\epsilon^k} \sigma_{\epsilon^k}^2 + \omega_{\epsilon^k} \sigma_{\epsilon^k}^2 + \psi_{\epsilon^k} \sigma_{\epsilon^k}^2 \quad (E.94)$$

$$Cov(\Delta n_{f,t}^k, \Delta c_{f,t}^k) = \rho_{\Delta}^2 \omega_{n^k} \sigma_{\theta^k}^2 + \omega_{n^k} \sigma_{\theta^k}^2 + \psi_{n^k} \sigma_{\theta^k}^2 \quad (E.95)$$

## Contemporaneous Cross-Generation Covariance

$$Cov(\Delta e_{f,t}^p, \Delta e_{f,t}^k) = \gamma_{\Delta} \sigma_{\epsilon^p}^2 \quad (\text{E.96})$$

$$Cov(\Delta n_{f,t}^p, \Delta n_{f,t}^k) = \rho_{\Delta} \sigma_{\theta^p}^2 \quad (\text{E.97})$$

$$Cov(\Delta c_{f,t}^p, \Delta c_{f,t}^k) = \gamma_{\Delta} \omega_{\epsilon^p} \omega_{\epsilon^k} \sigma_{\epsilon^p}^2 + \rho_{\Delta} \omega_{n^p} \omega_{n^k} \sigma_{\theta^p}^2 + \lambda_{\Delta} \sigma_{\xi^p}^2 \quad (\text{E.98})$$

$$Cov(\Delta e_{f,t}^p, \Delta c_{f,t}^k) = \gamma_{\Delta} \omega_{\epsilon^k} \sigma_{\epsilon^p}^2 \quad (\text{E.99})$$

$$Cov(\Delta n_{f,t}^p, \Delta c_{f,t}^k) = \rho_{\Delta} \omega_{n^k} \sigma_{\theta^p}^2 \quad (\text{E.100})$$

$$Cov(\Delta c_{f,t}^p, \Delta e_{f,t}^k) = \gamma_{\Delta} \omega_{\epsilon^p} \sigma_{\epsilon^p}^2 \quad (\text{E.101})$$

$$Cov(\Delta c_{f,t}^p, \Delta n_{f,t}^k) = \rho_{\Delta} \omega_{n^p} \sigma_{\theta^p}^2 \quad (\text{E.102})$$

## Non-contemporaneous Covariances (lead 1) for Parent

$$Cov(\Delta e_{f,t}^p, \Delta e_{f,t+1}^p) = -\sigma_{\epsilon^p}^2 \quad (\text{E.103})$$

$$Cov(\Delta n_{f,t}^p, \Delta n_{f,t+1}^p) = -\sigma_{\theta^p}^2 \quad (\text{E.104})$$

$$Cov(\Delta c_{f,t}^p, \Delta e_{f,t+1}^p) = -\psi_{\epsilon^p} \sigma_{\epsilon^p}^2 \quad (\text{E.105})$$

$$Cov(\Delta c_{f,t}^p, \Delta n_{f,t+1}^p) = -\psi_{n^p} \sigma_{\theta^p}^2 \quad (\text{E.106})$$

## Non-contemporaneous Covariances (lead 1) for Child

$$Cov(\Delta e_{f,t}^k, \Delta e_{f,t+1}^k) = -\sigma_{\epsilon^k}^2 \quad (\text{E.107})$$

$$Cov(\Delta n_{f,t}^k, \Delta n_{f,t+1}^k) = -\sigma_{\theta^k}^2 \quad (\text{E.108})$$

$$Cov(\Delta c_{f,t}^k, \Delta e_{f,t+1}^k) = -\psi_{\epsilon^k} \sigma_{\epsilon^k}^2 \quad (\text{E.109})$$

$$Cov(\Delta c_{f,t}^k, \Delta n_{f,t+1}^k) = -\psi_{n^k} \sigma_{\theta^k}^2 \quad (\text{E.110})$$

### E.2.2 Identification

There are 21 parameters to be identified from 25 moment conditions. It is straightforward to see the identification of  $\sigma_{\epsilon^p}^2$ ,  $\sigma_{\theta^p}^2$ ,  $\psi_{\epsilon^p}$ ,  $\psi_{n^p}$ ,  $\sigma_{\epsilon^k}^2$ ,  $\sigma_{\theta^k}^2$ ,  $\psi_{\epsilon^k}$  and  $\psi_{n^k}$  from equations (E.103) through (E.110). Subsequently,  $\sigma_{\epsilon^p}^2$  and  $\sigma_{\theta^p}^2$  can be identified from equations (E.86) and (E.87). This allows identification of  $\gamma_{\Delta}$  and  $\rho_{\Delta}$  from equations (E.96) and (E.97); and consequently  $\omega_{\epsilon^k}$ ,  $\omega_{n^k}$ ,  $\omega_{\epsilon^p}$  and  $\omega_{n^p}$  from equations (E.99) through (E.102) respectively. Now, equations (E.88), (E.89) and (E.90) can identify  $\sigma_{\xi^p}^2$ ,  $\sigma_{\epsilon^k}^2$  and  $\sigma_{\theta^k}^2$  respectively. Finally,  $\lambda_{\Delta}$  is identified from equation (E.98), which leaves  $\sigma_{\xi^k}^2$  to be identified from (E.91).

### E.2.3 Results and Empirical Moments

The PSID becomes biennial from 1998 onwards. To maintain parity throughout our sample period, we use two calendar year differences to measure the time-differences denoted by  $\Delta$  in the data, and take a lead of two calendar years for measuring a lead of  $t + 1$  for any variable. In what follows, we present two sets of estimates — the first set is based on imputed expenditure data; the second set is obtained using only directly observed food expenditures as a measure of consumption.

Table 37: Intergenerational Growth Elasticities

	Parameters	Imputed (1)	Food (2)
Earnings Growth	$\gamma_{\Delta}$	0.242 (0.160)	0.257 (0.173)
Other Income Growth	$\rho_{\Delta}$	0.097 (0.071)	0.099 (0.078)
Consumption Growth Shifter	$\lambda_{\Delta}$	0.007 (0.048)	0.043 (0.072)
<i>No. of Parent-Child Pairs</i>	$N$	761	761

**Note:** Bootstrap standard errors (100 repetitions) in parentheses. Data is purged of year and cohort effects.

Table 37 shows that contemporaneous permanent innovations to earnings and other income and transitory shock to consumption growth display no statistically significant persistence across generations. Of course, differencing consumption data can exacerbate measurement error and reduce significance, but we find no evidence of intergenerational linkages in the accrual rate of permanent innovations. This stands in stark contrast to the significant linkages that we estimate for the permanent components of income and consumption and indicates that the baseline model provides a better empirical representation of the cross-generational relationship present in parent-child data.

Estimates of the intragenerational insurance parameters, and of the variances of both permanent and transitory life-cycle heterogeneity, are shown in Tables 38 and 39. Blundell, Pistaferri and Preston (2008) point out that “...using food would provide an estimate of insurance that is ...higher than with imputed consumption data” and “...may give misleading evidence on the size and the stability of the insurance parameters.” Not surprisingly, therefore, Table 38 shows that we estimate higher value of consumption insurance when using food expenditures rather than imputed consumption data.

Table 38: Partial Insurance Parameters

	Parameters	Imputed (1)	Food (2)
<b><u>Parents</u></b>			
Permanent Earnings	$\omega_e^p$	0.229 (0.040)	0.108 (0.077)
Permanent Other Income	$\omega_n^p$	0.068 (0.013)	0.030 (0.027)
Transitory Earnings	$\psi_e^p$	0.150 (0.041)	0.058 (0.076)
Transitory Other Income	$\psi_n^p$	0.035 (0.040)	-0.044 (0.051)
<b><u>Children</u></b>			
Permanent Earnings	$\omega_e^k$	0.232 (0.054)	0.029 (0.175)
Permanent Other Income	$\omega_n^k$	0.150 (0.030)	0.088 (0.031)
Transitory Earnings	$\psi_e^k$	0.203 (0.039)	0.028 (0.073)
Transitory Other Income	$\psi_n^k$	0.037 (0.023)	-0.029 (0.043)
<i>No. of Parent-Child Pairs</i>	<i>N</i>	761	761

**Note:** See note to 37.

Table 39: Variances of Shocks

	Parameters	Imputed (1)	Food (2)
<b><u>Parental Shocks</u></b>			
Transitory Earnings	$\sigma_{\varepsilon^p}^2$	0.048 (0.005)	0.048 (0.005)
Transitory Other Income	$\sigma_{\vartheta^p}^2$	0.068 (0.015)	0.068 (0.015)
Permanent Earnings	$\sigma_{\varepsilon^p}^2$	0.066 (0.007)	0.066 (0.007)
Permanent Other Income	$\sigma_{\theta^p}^2$	0.218 (0.025)	0.217 (0.029)
Consumption Growth	$\sigma_{\xi^p}^2$	0.036 (0.002)	0.141 (0.009)
<b><u>Child Shocks</u></b>			
Transitory Earnings	$\sigma_{\varepsilon^k}^2$	0.048 (0.005)	0.049 (0.006)
Transitory Other Income	$\sigma_{\vartheta^k}^2$	0.111 (0.029)	0.112 (0.032)
Idiosyncratic Permanent Earnings	$\sigma_{\varepsilon^k}^2$	0.049 (0.008)	0.047 (0.012)
Idiosyncratic Permanent Other Income	$\sigma_{\theta^k}^2$	0.161 (0.027)	0.161 (0.028)
Idiosyncratic Consumption Growth	$\sigma_{\xi^k}^2$	0.033 (0.002)	0.176 (0.012)
<i>No. of Parent-Child Pairs</i>	<i>N</i>	761	761

**Note:** See note to Table 37.

Table 40: Empirical Moments

Moments	Imputed (1)	Food (2)
$Var(\Delta e_{f,t}^p)$	0.161 (0.009)	0.161 (0.007)
$Var(\Delta n_{f,t}^p)$	0.351 (0.036)	0.351 (0.036)
$Var(\Delta c_{f,t}^p)$	0.041 (0.002)	0.142 (0.007)
$Var(\Delta e_{f,t}^k)$	0.148 (0.01)	0.148 (0.009)
$Var(\Delta n_{f,t}^k)$	0.366 (0.033)	0.366 (0.034)
$Var(\Delta c_{f,t}^k)$	0.042 (0.001)	0.177 (0.011)
$Cov(\Delta e_{f,t}^p \Delta e_{f,t}^k)$	0.017 (0.011)	0.017 (0.012)
$Cov(\Delta n_{f,t}^p \Delta n_{f,t}^k)$	0.020 (0.014)	0.020 (0.013)
$Cov(\Delta c_{f,t}^p \Delta c_{f,t}^k)$	0.001 (0.002)	0.007 (0.008)
$Cov(\Delta e_{f,t}^p \Delta e_{f,t+1}^p)$	-0.048 (0.005)	-0.048 (0.004)
$Cov(\Delta n_{f,t}^p \Delta n_{f,t+1}^p)$	-0.068 (0.015)	-0.068 (0.016)
$Cov(\Delta e_{f,t}^k \Delta e_{f,t+1}^k)$	-0.049 (0.005)	-0.049 (0.006)
$Cov(\Delta n_{f,t}^k \Delta n_{f,t+1}^k)$	-0.087 (0.013)	-0.087 (0.013)
$Cov(\Delta e_{f,t}^p \Delta c_{f,t}^p)$	0.023 (0.002)	0.011 (0.003)
$Cov(\Delta e_{f,t+1}^p \Delta c_{f,t}^p)$	-0.006 (0.002)	-0.002 (0.004)
$Cov(\Delta n_{f,t}^p \Delta c_{f,t}^p)$	0.017 (0.003)	0.004 (0.003)
$Cov(\Delta n_{f,t+1}^p \Delta c_{f,t}^p)$	-0.002 (0.002)	0.003 (0.005)
$Cov(\Delta e_{f,t}^k \Delta c_{f,t}^k)$	0.023 (0.002)	0.004 (0.003)
$Cov(\Delta e_{f,t+1}^k \Delta c_{f,t}^k)$	-0.008 (0.002)	0.000 (0.003)
$Cov(\Delta n_{f,t}^k \Delta c_{f,t}^k)$	0.028 (0.003)	0.010 (0.004)
$Cov(\Delta n_{f,t+1}^k \Delta c_{f,t}^k)$	-0.004 (0.002)	0.003 (0.005)
$Cov(\Delta e_{f,t}^p \Delta c_{f,t}^k)$	-0.001 (0.004)	-0.003 (0.009)
$Cov(\Delta n_{f,t}^p \Delta c_{f,t}^k)$	0.005 (0.003)	0.006 (0.006)
$Cov(\Delta c_{f,t}^p \Delta e_{f,t}^k)$	0.001 (0.003)	-0.003 (0.006)
$Cov(\Delta c_{f,t}^p \Delta n_{f,t}^k)$	-0.003 (0.008)	-0.002 (0.011)

**Note:** These empirical moments are used to generate the parameter estimates in Tables 37, 38 and 39 through GMM. Bootstrap standard errors are reported in parentheses.  $\Delta$  refers to change over 2 calendar years and  $t+1$  implies 2-calendar-year lead.

### E.3 Estimates by Child Birth-Cohort

In this Appendix subsection we present further results of our baseline specification with the sample being split by child birth cohorts. In Section 6.3 of the main paper, we had split our baseline sample of 761 parent-child pairs into two 15-year-long sub-cohorts. However, in each of those sub-cohorts, the average age of the parents and their adult children were very different. This might introduce life-cycle bias in our estimates, and make the inter-cohort comparison difficult. To address the issue of observing parents and kids at different stages of their life-cycle, in this Appendix we restrict the age of both parents and children to be between 30 and 40 years. This reduces our sample size from 761 to 337 unique parent-child pairs. To maintain a somewhat balanced sample size for the two sub-cohorts, we re-define the sub-cohorts as 1960s and 1970s born children.

Table 41: Intergenerational Elasticity by Child Cohort (Age: 30-40)

	Parameters	1960s & 1970s Cohorts (1)	1960s Cohort (2)	1970s Cohort (3)
Head Earnings	$\gamma$	0.212 (0.056)	0.252 (0.071)	0.197 (0.096)
Other Income	$\rho$	0.042 (0.047)	-0.006 (0.057)	0.100 (0.090)
$\bar{e}_f^p$ on $\bar{n}_f^k$	$\gamma_n$	0.212 (0.073)	0.201 (0.113)	0.236 (0.129)
$\bar{n}_f^p$ on $\bar{e}_f^k$	$\rho_e$	0.040 (0.027)	0.009 (0.044)	0.079 (0.042)
Consumption Shifters	$\lambda$	0.076 (0.070)	-0.029 (0.088)	0.201 (0.119)
<i>No. of Parent-Child Pairs</i>	<i>N</i>	337	166	171

**Note:** Bootstrap standard errors (100 repetitions) in parentheses. Food expenditure is used as the measure of consumption. All columns use cross-sectional data, net of cohort and year effects. Age range for both children and parents is restricted to be between 30 and 40 years. Average parental ages are 36 and 35 years, and average ages of the children are 34 and 35 years for the 1960s and 1970s child cohorts respectively.

Table 42: Variance-Covariance of Idiosyncratic Components by Child Cohort (Age: 30-40)

	Parameters	1960s & 1970s Cohorts	1960s Cohort	1970s Cohort
		(1)	(2)	(3)
<b><u>Parental Variances</u></b>				
Permanent Head Earnings	$\sigma_{\bar{e}^p}^2$	0.200 (0.018)	0.172 (0.018)	0.225 (0.030)
Permanent Other Income	$\sigma_{\bar{n}^p}^2$	0.844 (0.112)	0.946 (0.163)	0.749 (0.129)
Permanent Consumption Shifters	$\sigma_{\bar{q}^p}^2$	0.909 (0.114)	0.978 (0.150)	0.835 (0.162)
<b><u>Child Idiosyncratic Variances</u></b>				
Permanent Head Earnings	$\sigma_{\bar{e}^k}^2$	0.240 (0.018)	0.232 (0.028)	0.244 (0.029)
Permanent Other Income	$\sigma_{\bar{n}^k}^2$	0.659 (0.070)	0.561 (0.092)	0.749 (0.108)
Permanent Consumption Shifters	$\sigma_{\bar{q}^k}^2$	0.875 (0.086)	0.817 (0.115)	0.911 (0.129)
<b><u>Parental Covariances</u></b>				
Consumption Shifters & Head Earnings	$\sigma_{\bar{e}^p, \bar{q}^p}$	-0.126 (0.033)	-0.060 (0.039)	-0.186 (0.058)
Consumption Shifters & Other Income	$\sigma_{\bar{n}^p, \bar{q}^p}$	-0.796 (0.111)	-0.887 (0.155)	-0.707 (0.136)
Head Earnings and Other Income	$\sigma_{\bar{e}^p, \bar{n}^p}$	-0.007 (0.023)	-0.045 (0.032)	0.028 (0.045)
<b><u>Child Idiosyncratic Covariances</u></b>				
Consumption Shifters & Head Earnings	$\sigma_{\bar{e}^k, \bar{q}^k}$	-0.233 (0.025)	-0.269 (0.039)	-0.189 (0.037)
Consumption Shifters & Other Income	$\sigma_{\bar{n}^k, \bar{q}^k}$	-0.657 (0.077)	-0.584 (0.103)	-0.720 (0.116)
Head Earnings & Other Income	$\sigma_{\bar{e}^k, \bar{n}^k}$	0.048 (0.024)	0.078 (0.028)	0.014 (0.037)
<i>No. of Parent-Child Pairs</i>	<i>N</i>	337	166	171

**Note:** See notes to Table 41 for details.

## E.4 No Income Cross-Effects, Random Match, Imputed Consumption & No Marital Status Restriction

Table 43: Robustness: Variance-Covariance of Idiosyncratic Components

Parameters	Baseline (1)	$\gamma_n = \rho_e = 0$ (2)	Random Match (3)	Imputed Consumption (4)	All Marital Status (5)
<b><u>Parental Outcomes: Variances</u></b>					
Permanent Head Earnings: $\sigma_{\bar{e}^p}^2$	0.296 (0.020)	0.290 (0.021)	0.291 (0.022)	0.292 (0.021)	0.298 (0.014)
Permanent Other Income: $\sigma_{\bar{n}^p}^2$	0.805 (0.058)	0.805 (0.063)	0.808 (0.071)	0.805 (0.069)	0.775 (0.048)
Permanent Consumption Shifters: $\sigma_{\bar{q}^p}^2$	1.027 (0.064)	1.049 (0.073)	1.032 (0.073)	0.859 (0.067)	1.014 (0.055)
<b><u>Child Idiosyncratic Heterogeneity: Variances</u></b>					
Permanent Head Earnings: $\sigma_{\bar{e}^k}^2$	0.229 (0.014)	0.215 (0.013)	0.247 (0.015)	0.226 (0.012)	0.273 (0.015)
Permanent Other Income: $\sigma_{\bar{n}^k}^2$	0.511 (0.041)	0.523 (0.043)	0.533 (0.048)	0.508 (0.040)	1.120 (0.073)
Permanent Consumption Shifters: $\sigma_{\bar{q}^k}^2$	0.733 (0.058)	0.745 (0.059)	0.752 (0.069)	0.576 (0.044)	1.779 (0.102)
<b><u>Parental Outcomes: Covariances</u></b>					
Consumption Shifters & Head Earnings: $\sigma_{\bar{e}^p, \bar{q}^p}$	-0.270 (0.026)	-0.278 (0.026)	-0.263 (0.028)	-0.222 (0.023)	-0.285 (0.019)
Consumption Shifters & Other Income: $\sigma_{\bar{n}^p, \bar{q}^p}$	-0.816 (0.060)	-0.831 (0.065)	-0.821 (0.069)	-0.767 (0.068)	-0.791 (0.050)
Head Earnings and Other Income: $\sigma_{\bar{e}^p, \bar{n}^p}$	0.069 (0.017)	0.084 (0.018)	0.067 (0.017)	0.067 (0.017)	0.082 (0.013)
<b><u>Child Idiosyncratic Heterogeneity: Covariances</u></b>					
Consumption Shifters & Head Earnings: $\sigma_{\bar{e}^k, \bar{q}^k}$	-0.250 (0.024)	-0.256 (0.024)	-0.263 (0.025)	-0.216 (0.018)	-0.422 (0.031)
Consumption Shifters & Other Income: $\sigma_{\bar{n}^k, \bar{q}^k}$	-0.523 (0.046)	-0.533 (0.047)	-0.542 (0.055)	-0.481 (0.042)	-1.307 (0.082)
Head Earnings & Other Income: $\sigma_{\bar{e}^k, \bar{n}^k}$	0.076 (0.017)	0.093 (0.017)	0.095 (0.019)	0.073 (0.015)	0.194 (0.021)
<i>No. of Parent-Child Pairs</i>	761	761	761	761	1038

**Note:** See notes to Tables 12 and 13.

## E.5 Effect of Income Tax

To study the effect of income taxes on our baseline results, we subtract the value of Federal income tax from our income variables. However, since we consider two separate sources of income for a family, and income taxes are filed jointly in the U.S. for married couples, we consider the following

three scenarios for tax incidence:

**Case A:** The entire burden of Federal income tax is incident on head earnings.

**Case B:** The burden of the Federal income tax is split between head earnings and other income based on the proportion of head and wife earnings respectively. This is the ‘post-tax’ case reported in the main body of the paper.

**Case C:** The entire tax burden is incident on other income.

Below we present estimates for the above three cases along with the pre-tax case for comparison.

Table 44: Effect of Federal Income Tax: Intergenerational Elasticities

Variables	Parameters	Pre-tax (1)	Case A (2)	Case B (3)	Case C (4)
Head Earnings	$\gamma$	0.229 (0.026)	0.167 (0.029)	0.225 (0.026)	0.268 (0.032)
Other Income	$\rho$	0.097 (0.027)	0.115 (0.033)	0.091 (0.028)	0.098 (0.038)
$\bar{e}_f^p$ on $\bar{n}_f^k$	$\gamma_n$	0.203 (0.034)	0.223 (0.034)	0.199 (0.039)	0.097 (0.041)
$\bar{n}_f^p$ on $\bar{e}_f^k$	$\rho_e$	0.052 (0.017)	0.048 (0.016)	0.044 (0.014)	0.019 (0.022)
Consumption Shifters	$\lambda$	0.150 (0.035)	0.127 (0.039)	0.119 (0.033)	0.122 (0.037)
<i>No. of Parent-Child Pairs</i>	$N$	755	755	755	700

**Note:** Bootstrap standard errors (100 repetitions) in parentheses. All columns use data that is purged of year and birth cohort effects only. *Case C* leads to negative other income for some families, and they are dropped from the analysis since logarithm of negative values are not defined. This leads to the loss of 55 parent-child pairs.

Table 45: Effect of Federal Income Tax: Estimates of Variances and Covariances of Fixed Effects

	Parameters	Pre-tax (1)	Case A (2)	Case B (3)	Case C (4)
<b><u>Parental Variances</u></b>					
Permanent Head Earnings	$\sigma_{\bar{e}^p}^2$	0.294 (0.021)	0.251 (0.017)	0.231 (0.017)	0.250 (0.015)
Permanent Other Income	$\sigma_{\bar{n}^p}^2$	0.806 (0.063)	0.800 (0.072)	0.734 (0.061)	0.861 (0.097)
Permanent Consumption Shifters	$\sigma_{\bar{q}^p}^2$	1.031 (0.071)	0.871 (0.069)	0.862 (0.065)	0.996 (0.088)
<b><u>Child Idiosyncratic Variances</u></b>					
Permanent Head Earnings	$\sigma_{\bar{e}^k}^2$	0.222 (0.010)	0.198 (0.013)	0.179 (0.010)	0.190 (0.011)
Permanent Other Income	$\sigma_{\bar{n}^k}^2$	0.505 (0.040)	0.500 (0.046)	0.458 (0.037)	0.547 (0.042)
Permanent Consumption Shifters	$\sigma_{\bar{q}^k}^2$	0.712 (0.053)	0.573 (0.046)	0.571 (0.042)	0.693 (0.050)
<b><u>Parental Covariances</u></b>					
Consumption Shifters & Head Earnings	$\sigma_{\bar{e}^p, \bar{q}^p}$	-0.271 (0.024)	-0.171 (0.022)	-0.177 (0.020)	-0.213 (0.024)
Consumption Shifters & Other Income	$\sigma_{\bar{n}^p, \bar{q}^p}$	-0.819 (0.066)	-0.734 (0.069)	-0.714 (0.062)	-0.823 (0.089)
Head Earnings and Other Income	$\sigma_{\bar{e}^p, \bar{n}^p}$	0.071 (0.015)	-0.008 (0.014)	0.024 (0.014)	0.030 (0.018)
<b><u>Child Idiosyncratic Covariances</u></b>					
Consumption Shifters & Head Earnings	$\sigma_{\bar{e}^k, \bar{q}^k}$	-0.239 (0.018)	-0.156 (0.014)	-0.161 (0.014)	-0.169 (0.019)
Consumption Shifters & Other Income	$\sigma_{\bar{n}^k, \bar{q}^k}$	-0.511 (0.043)	-0.435 (0.044)	-0.429 (0.039)	-0.529 (0.043)
Head Earnings & Other Income	$\sigma_{\bar{e}^k, \bar{n}^k}$	0.071 (0.012)	-0.001 (0.011)	0.028 (0.012)	0.030 (0.013)
<i>No. of Parent-Child Pairs</i>	<i>N</i>	755	755	755	700

**Note:** See note to Table 44.

Table 46: Effect of Income Tax: Parental Importance for Child Inequality

Variables	Pre-tax	Case A	Case B	Case C
	(1)	(2)	(3)	(4)
Earnings	8.0%	4.2%	7.0%	8.9%
	[4.4%, 11.6%]	[1.5%, 6.9%]	[4.0%, 10.1%]	[4.7%, 13.1%]
Other Income	4.2%	4.3%	3.4%	2.0%
	[1.4%, 7.1%]	[1.3%, 7.4%]	[0.7%, 6.1%]	[-0.7%, 4.7%]
Consumption	29.4%	22.3%	25.6%	17.4%
	[20.3%, 38.4%]	[14.6%, 29.9%]	[17.4%, 33.8%]	[8.9%, 25.8%]
<i>No. of Parent-Child Pairs</i>	755	755	755	700

**Note:** Results are based on parameter estimates in Tables 44 and 45 of Appendix E.5. The sample size in columns (1) through (3) is smaller by 6 parent-child pairs from our baseline sample because of non-availability of tax data for those households. Case C leads to negative other income for some families, and they are dropped from the analysis since logarithm of negative values are not defined. This leads to the loss of 55 parent-child pairs in column (4). Numbers in parentheses are 95% confidence intervals, calculated using bootstrap standard errors with 100 repetitions.