Consumption and Income Inequality across Generations*

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Abstract

This paper characterizes the joint evolution of cross-sectional inequality in income and consumption across generations. We estimate a model of intergenerational persistence and separately identify influences of parental heterogeneity and idiosyncratic factors. We find evidence of family persistence in earnings and consumption, and of marital sorting. Idiosyncratic heterogeneity, however, accounts for most of cross-sectional inequality. Within-family insurance represents a modest part of overall consumption insurance and is largest for the richest quartile. Insurance among the poorest comes from outside the family. Our findings suggest intergenerational persistence would have to be much higher to induce, by itself, substantial increases in inequality.

Keywords: income, consumption, intergenerational persistence, inequality
JEL codes: D15, D64, E21

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1 Introduction

Parents influence their children's life-cycle outcomes in many ways: through choices about education, through transmission of ability and preferences, as well as through inter-vivos and bequest transfers affecting wealth and consumption.[1] These different channels of family influence are interrelated and mechanisms may be substitutes: investing in a child's education to increase their earnings potential may imply less transfers of wealth. Typically, studies have looked at either income or consumption in isolation and focused on the estimation of intergenerational persistence parameters. In this paper, we pursue a different approach and develop a parsimonious model of the ***joint*** evolution of expenditures, earnings and other income across generations. Rather than focusing on persistence alone, our focus is on understanding the importance of different aspects of family heterogeneity for cross-sectional inequality in income and consumption. Our work has three 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; third, to examine the role of families in consumption insurance.

To assess the importance of parental heterogeneity, we model intergenerationally linked households that choose optimal consumption given their income processes. We consider three channels of parental influence: through earned income of the male household head, through other income including earnings of the spouse as well as public and private transfers, and through consumption. Parental impacts on child inequality depend on the magnitude of (i) the intergenerational elasticity parameters, (ii) the heterogeneity in the parents' generation, and (iii) family-independent idiosyncratic variation in the children's generation. A decomposition of inequality into parental and idiosyncratic factors requires estimates of all three channels. We use theoretical restrictions on the variances of income and consumption of parents and adult children, and on the covariances both within and between generations. These moments identify jointly the parameters dictating intergenerational linkages and idiosyncratic components of income and consumption. We use a generalized method of moments (GMM) approach to estimate the model.

In our framework, the processes for earnings, other income and consumption are each the sum of individual fixed effects and transitory and persistent idiosyncratic shocks. We allow for parent to child persistence across generations and estimate model parameters under three different specifications: (i) using time-averaged data; (ii) using full panel variation under the assumption

[1]Research on family outcomes across generations focuses on income and earnings persistence (for a survey, see Aaronson 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, 2022). Boar (2021) documents parental precautionary motives geared to insure children. Abbott et al. (2019) study family transfers in an equilibrium setting. 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.

of stationary shocks; and (iii) assuming that the persistent shocks follow a random walk. For estimation we employ data from the Panel Study of Income Dynamics (PSID) on household income, expenditures and other family characteristics. We link families across generations covering birth-cohorts of children born between the early 1950s and the early 1980s. 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 as well as a separate process in an extension of the baseline model. The availability of expenditure data varies across survey waves.[2] Our baseline estimation uses food consumption going back to the late 1960s but we also replicate the analysis for sample periods that have detailed expenditure records for most categories and 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. The intra-family elasticity for other income is only 0.10 and mostly reflects similarities in spousal earnings across generations. This emphasizes a trait of family influences whereby men tend to marry women who have similar economic outcomes as their mothers (Fernandez, Fogli and Olivetti, 2004). In addition, there is a cross-elasticity with higher father earnings associated with higher spousal earnings for their sons. Ignoring this leads to biased estimates of parental influences. We estimate a significant pass-through in consumption expenditures from parent to child, which is shaped both by persistence in earnings and other income and by direct consumption persistence within the family. An important part of persistence is due to observable characteristics, with educational attainment playing a crucial role.[3]

The central question that we address in the debate on the role of family background is whether cross-sectional inequality in the children generation would be very different if parental heterogeneity had no impact. Various specifications and sample selection criteria consistently indicate that idiosyncratic variation, independent of family, accounts for most of the cross-sectional dispersion in income and expenditures. The largest impact of parental factors is on consumption inequality, with baseline estimates attributing about a third of it to family background. By comparison, the size of parental influence on head earnings inequality is about 8% in the baseline specification, while it is 4% for other sources of income. These findings are consistent with the well-established result that permanent heterogeneity is the main contributor to life-cycle inequality (see Keane and Wolpin, 1997; Huggett, Ventura and Yaron, 2011). For example, our estimate that parental heterogeneity accounts for 8% of earnings inequality is in line with Daruich and Kozlowski (2020). Using a heterogeneous-agents model they find that, while over 50% of the total life-cycle variance

[2] The PSID initially recorded only housing and food-related expenditures. After 1997 more consumption categories were added. Since 2005 the PSID covers all the categories in the Consumption Expenditure Survey (CEX), which has detailed data on multiple consumption categories since the 1980s. However, the CEX follows individuals for a maximum of four quarters only, making it unsuitable for intergenerational consumption analysis.

[3] See Abbott and Gallipoli (2016), Landersø and Heckman (2017) and Gayle, Golan and Soytas (2018) for evidence on the importance of education and human capital for intergenerational persistence.

in earnings can be accounted through differences in fixed effects, removing the correlation between parental and child outcomes would lower earnings inequality by roughly 7%.

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). In related work on the relationship between inequality and mobility, Becker et al. (2018) have shown that increases in inequality may or may not go hand in hand with lower mobility.[4] Dynastic models often struggle to generate enough intergenerational persistence (see discussion in Cordoba, Liu and Ripoll, 2016). Our estimates complement this literature by showing that intergenerational persistence would need to be much higher to induce, by itself, considerable increases in inequality for subsequent generations.

An implication of our findings is that insurance motives within the family may add to cross-sectional inequality if richer parents are better able to insure their children (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. By contrast, intra-generational insurance (e.g., through government taxes and transfers) generally reduces inequality. We report estimates of both types of insurance. We find some evidence of within-family consumption insurance against idiosyncratic shocks in the younger generation; however, overall consumption insurance in the cross-section of children is much larger (see also Attanasio, Meghir and Mommaerts, 2018). The importance of channels of insurance vary with parental income: family insurance is considerable for the richest quartile but insurance among the poorest comes largely from outside the family.

The rest of the paper is organized as follows. In Section 2 we introduce the general framework featuring intergenerational linkages between income sources and consumption. Section 3 discusses parameter identification and estimation with results in Section 4. In Section 5 we discuss the interpretation and implications of our estimates for the evolution of cross-sectional inequality and consumption insurance across generations. We delve deeper into the underlying mechanisms in Section 6, and document robustness in Section 7. Section 8 provides a brief summary and 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 processes for earnings and other income of

[4]Mechanically, a negative association between inequality and mobility can arise in the presence of strong intergenerational pass-through, which induce dispersion in the children's generation. Such an association would be consistent with the 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).

parents and children, along with a mechanism mapping them into distributions of family outcomes through multiple parent-child linkages.

To provide context, and further motivate the baseline model, in Appendix A.1 we report reduced-form estimates of the intergenerational pass-through of head earnings, family income and consumption over several decades. We find little evidence of changes in the intergenerational elasticities over time. 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 expenditure, 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:

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

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; β 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 in a separate household. Due to the lack of consistent records of transfers made to offspring over the life-cycle 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 further below, unobserved transfers made to the offspring are subsumed in components of the consumption process that vary across families.

In addition, we study a specification 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 enjoy a warm-glow from making transfers to their offspring. We derive an empirical counterpart for this specification in Section 6.3 and show that inference about intergenerational linkages and inequality, relative to the baseline model, is unaffected.

Earnings and Other Income. We assume the following processes for household income. In year t the parent in family f has pre-tax log head earnings $e^p_{f,t}$ consisting of an individual fixed effect $\bar{e}^p_f$, a persistent AR(1) shock, $\mathcal{E}^p_{f,t} = \alpha^p_e \mathcal{E}^p_{f,t-1} + \epsilon^p_{f,t}$, and a transitory shock, $\varepsilon^p_{f,t}$. Similarly, the process for the log of other income, $n^p_{f,t}$ comprises a fixed effect $\bar{n}^p_f$, an AR(1) shock $\Theta^p_{f,t} = \alpha^p_n \Theta^p_{f,t-1} + \theta^p_{f,t}$, and a transitory innovation, $\vartheta^p_{f,t}$:

$$\begin{aligned} e^p_{f,t} &= \bar{e}^p_f + \mathcal{E}^p_{f,t} + \varepsilon^p_{f,t} \quad (2)\\ n^p_{f,t} &= \bar{n}^p_f + \Theta^p_{f,t} + \vartheta^p_{f,t} \quad (3) \end{aligned}$$

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

The income processes for adult children of family f have a similar structure, but the child fixed effects, $\bar{e}^k_f$ and $\bar{n}^k_f$, depend on parental fixed effects, $\bar{e}^p_f$ and $\bar{n}^p_f$, as well as on idiosyncratic components independent of parents, $\breve{e}^k_f$ and $\breve{n}^k_f$. Thus, for the children of family f this structure results in the following income components:

$$\begin{aligned} e^k_{f,t} &= \underbrace{\gamma \bar{e}^p_f + \rho_e \bar{n}^p_f}_{\text{Parental Channel}} + \underbrace{\breve{e}^k_f + \mathcal{E}^k_{f,t} + \varepsilon^k_{f,t}}_{\text{Child Idiosyncratic Channel}} \quad (4)\\ n^k_{f,t} &= \underbrace{\rho \bar{n}^p_f + \gamma_n \bar{e}^p_f}_{\text{Parental Channel}} + \underbrace{\breve{n}^k_f + \Theta^k_{f,t} + \vartheta^k_{f,t}}_{\text{Child Idiosyncratic Channel}} \quad (5) \end{aligned}$$

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 γ) and a direct channel from other income of parents to other income of children (through ρ), the specification features cross-effects so that parental earnings can influence other income of children (through γ_n), and other income of parents can affect earnings of children (through ρ_e).[5] The per-period perturbations to the child's income processes are governed by a different set of parameters: α^k_e and α^k_n denote the persistence of the child AR(1) components, $\sigma^2_{\epsilon^k}$ and $\sigma^2_{\theta^k}$ are the variances of the innovations to the AR(1) processes, and $\sigma^2_{\varepsilon^k}$ and $\sigma^2_{\vartheta^k}$ are the variances of the transitory shocks to child earnings and other income, respectively.

[5]Direct elasticity parameters have no subscript, e.g., γ is the direct link from parental earnings to child earnings, ρ is the direct link of other income. Cross-elasticities, linking different variables, have a subscript for the child variable impacted, e.g., γ_n is the pass-through from head earnings to child other income n.

In the baseline framework, intergenerational income linkages operate through individual fixed effects. In Section 7.2 we consider a different form of family persistence where per-period permanent shocks are correlated across generations. That specification, derived within a model where income processes follow random walks, generalizes Blundell, Pistaferri and Preston (2008) to an intergenerational setting.

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.2 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 $q^g_{f,t}$ consists of a consumption fixed effect $\bar{q}^g_f$, a persistent AR(1) shock, $\Phi^g_{f,t} = \alpha^g_q \Phi^g_{f,t-1} + \phi^g_{f,t}$ and a transitory shock $\varphi^g_{f,t}$, for each generation $g \in \{p,k\}$. The innovation to the AR(1) shock $\phi^g_{f,t}$ and the transitory shock $\varphi^g_{f,t}$ are mean zero white noise processes with variances $\sigma^2_{\phi^g}$ and $\sigma^2_{\varphi^g}$ respectively.

From Income to Consumption. The variable $q_{f,t}$ subsumes the annuitized value of unobserved resources and potential higher-order preference terms due to precautionary motives. In addition, the $q_{f,t}$ component accounts for 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 the estimation, we acknowledge this co-movement both within and between generations by allowing the consumption fixed effect $\bar{q}_f$ to be correlated with the fixed effects in both earnings ($\bar{e}_f$) and other income ($\bar{n}_f$).

In this framework, and consistent with the permanent income hypothesis, there is a unitary direct pass-through from permanent income to consumption. In addition, the marginal propensity to consume (MPC) features an indirect component operating through the covariation between consumption and income fixed effects. The MPC out of permanent income ($\bar{y} = \bar{e} + \bar{n}$) is equal to $\left(1 + \frac{d\bar{q}}{d\bar{y}}\right)$, which is less than one as long as $d\bar{q}/d\bar{y}$ is negative. In other words, by explicitly allowing for covariation between these fixed effects, the MPC can depend non-linearly on income levels and be heterogeneous across households.

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

$$c^p_{f,t} = \bar{q}^p_f + \bar{e}^p_f + \bar{n}^p_f + \Phi^p_{f,t} + \left[\frac{r}{1+r-\alpha^p_e}\right]\mathcal{E}^p_{f,t} + \left[\frac{r}{1+r-\alpha^p_n}\right]\Theta^p_{f,t} + \varphi^p_{f,t} + \frac{r}{1+r}\left(\varepsilon^p_{f,t} + \vartheta^p_{f,t}\right) \quad (6)$$

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 fixed effect. The individual fixed effect in the child generation comprises an inherited component and a child-specific component, $\bar{q}^k_f = \lambda\bar{q}^p_f + \breve{q}^k_f$. 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) the inherited consumption channel. Substituting these intra-family transmission mechanisms into the consumption process for children, we obtain:

$$c^k_{f,t} = \underbrace{\lambda\bar{q}^p_f + (\gamma+\gamma_n)\,\bar{e}^p_f + (\rho+\rho_e)\,\bar{n}^p_f}_{\text{Parental Channel}} + \underbrace{\breve{q}^k_f + \breve{e}^k_f + \breve{n}^k_f}_{\text{Child Idiosyncratic Permanent Components}} + \underbrace{\Phi^k_{f,t} + \left[\frac{r}{1+r-\alpha^k_e}\right]\mathcal{E}^k_{f,t} + \left[\frac{r}{1+r-\alpha^k_n}\right]\Theta^k_{f,t}}_{\text{Child Idiosyncratic Persistent Shocks}} + \underbrace{\varphi^k_{f,t} + \frac{r}{1+r}\left(\varepsilon^k_{f,t} + \vartheta^k_{f,t}\right)}_{\text{Child Idiosyncratic Transitory Shocks}} \quad (7)$$

A set of six equations, (2) through (7), describing the earnings, other income and consumption processes for the parent and child generations, summarizes our 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.

3 Identification and Estimation

To mitigate concerns about measurement error and attenuation biases, in the baseline implementation we define the unit of observation as the time-average of each outcome variable at the household level. In what follows we overview identification and estimation procedures for this specification. In Section 7.1 we present estimates for an unrestricted specification featuring panel variation with transitory and persistent shocks to each process. Identification and estimation of that full model are discussed in Appendix F.1.

3.1 Identification

Identification proceeds in three steps. First, we use cross-sectional moments for parents to identify variances and covariances among 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 in Appendix B.1.

(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:

$$\text{Var}\left(\bar{e}_f^p\right) = \sigma^2_{\bar{e}^p} \tag{8}$$
$$\text{Var}\left(\bar{n}_f^p\right) = \sigma^2_{\bar{n}^p} \tag{9}$$
$$\text{Var}\left(\bar{c}_f^p\right) = \sigma^2_{\bar{q}^p} + \sigma^2_{\bar{e}^p} + \sigma^2_{\bar{n}^p} + 2\left(\sigma_{\bar{e}^p,\bar{q}^p} + \sigma_{\bar{n}^p,\bar{q}^p} + \sigma_{\bar{e}^p,\bar{n}^p}\right) \tag{10}$$

Equation (10) highlights how parental consumption inequality depends not only on the dispersion of fixed effects, but also on their covariances. Accounting for the co-dependence between consumption propensities and income turns out to be quantitatively important (see also 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 in the parents' generation, we consider the following relationships:

$$\text{Cov}\left(\bar{e}_f^p, \bar{n}_f^p\right) = \sigma_{\bar{e}^p,\bar{n}^p} \tag{11}$$
$$\text{Cov}\left(\bar{e}_f^p, \bar{c}_f^p\right) = \sigma^2_{\bar{e}^p} + \sigma_{\bar{e}^p,\bar{q}^p} + \sigma_{\bar{e}^p,\bar{n}^p} \tag{12}$$
$$\text{Cov}\left(\bar{n}_f^p, \bar{c}_f^p\right) = \sigma^2_{\bar{n}^p} + \sigma_{\bar{n}^p,\bar{q}^p} + \sigma_{\bar{e}^p,\bar{n}^p} \tag{13}$$

Equations (8), (9) and (11) deliver $\sigma^2_{\bar{e}^p}$, $\sigma^2_{\bar{n}^p}$ 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 fixed effects, $\sigma^2_{\bar{q}^p}$ 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 $\sigma^2_{\bar{e}^p}$, $\sigma^2_{\bar{n}^p}$ 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 γ and ρ_e.

$$\text{Cov}\left(\bar{e}_f^p, \bar{e}_f^k\right) = \gamma\sigma^2_{\bar{e}^p} + \rho_e\sigma_{\bar{e}^p,\bar{n}^p} \tag{14}$$
$$\text{Cov}\left(\bar{n}_f^p, \bar{e}_f^k\right) = \gamma\sigma_{\bar{e}^p,\bar{n}^p} + \rho_e\sigma^2_{\bar{n}^p} \tag{15}$$

Similarly, the pass-through parameters ρ and γ_n are identified from equations (16) and (17) below.

$$\begin{aligned} \operatorname{Cov}\left(\bar{n}_f^p, \bar{n}_f^k\right) &= \rho\sigma_{\bar{n}^p}^2 + \gamma_n \sigma_{\bar{e}^p,\bar{n}^p} && (16) \\ \operatorname{Cov}\left(\bar{e}_f^p, \bar{n}_f^k\right) &= \rho\sigma_{\bar{e}^p,\bar{n}^p} + \gamma_n \sigma_{\bar{e}^p}^2. && (17) \end{aligned}$$

Finally, the intra-family persistence of consumption fixed effects, λ, is identified from equation (18).

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

Additional cross-generational moments can be used as over-identifying restrictions in the estimation exercise. We present these moments in Appendix B.1.

(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 their time-averages can be mapped into the following cross-sectional variances:

$$\begin{aligned} \operatorname{Var}\left(\bar{e}_f^k\right) &= \gamma^2\sigma_{\bar{e}^p}^2 + \rho_e^2\sigma_{\bar{n}^p}^2 + 2\gamma\rho_e\sigma_{\bar{e}^p,\bar{n}^p} + \sigma_{\breve{e}^k}^2 && (19) \\ \operatorname{Var}\left(\bar{n}_f^k\right) &= \rho^2\sigma_{\bar{n}^p}^2 + \gamma_n^2\sigma_{\bar{e}^p}^2 + 2\rho\gamma_n\sigma_{\bar{e}^p,\bar{n}^p} + \sigma_{\breve{n}^k}^2 && (20) \\ \operatorname{Var}\left(\bar{c}_f^k\right) &= \lambda^2\sigma_{\bar{q}^p}^2 + \left(\gamma + \gamma_n\right)^2\sigma_{\bar{e}^p}^2 + \left(\rho + \rho_e\right)^2\sigma_{\bar{n}^p}^2 \\ &\quad + 2\left[\left(\gamma + \gamma_n\right)\lambda\sigma_{\bar{e}^p,\bar{q}^p} + \left(\rho + \rho_e\right)\lambda\sigma_{\bar{n}^p,\bar{q}^p} + \left(\rho + \rho_e\right)\left(\gamma + \gamma_n\right)\sigma_{\bar{e}^p,\bar{n}^p}\right] \\ &\quad + \sigma_{\breve{e}^k}^2 + \sigma_{\breve{n}^k}^2 + \sigma_{\breve{q}^k}^2 + 2\left[\sigma_{\breve{e}^k,\breve{n}^k} + \sigma_{\breve{e}^k,\breve{q}^k} + \sigma_{\breve{n}^k,\breve{q}^k}\right] && (21) \end{aligned}$$

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

$$\begin{aligned} \operatorname{Cov}\left(\bar{e}_f^k, \bar{n}_f^k\right) &= \left(\rho\gamma + \rho_e\gamma_n\right)\sigma_{\bar{e}^p,\bar{n}^p} + \gamma\gamma_n\sigma_{\bar{e}^p}^2 + \rho\rho_e\sigma_{\bar{n}^p}^2 + \sigma_{\breve{e}^k,\breve{n}^k} && (22) \\ \operatorname{Cov}\left(\bar{e}_f^k, \bar{c}_f^k\right) &= \gamma\left(\gamma + \gamma_n\right)\sigma_{\bar{e}^p}^2 + \rho_e\left(\rho_e + \rho\right)\sigma_{\bar{n}^p}^2 + \lambda\gamma\sigma_{\bar{e}^p,\bar{q}^p} + \lambda\rho_e\sigma_{\bar{n}^p,\bar{q}^p} \\ &\quad + \left[\gamma\left(\rho + \rho_e\right) + \rho_e\left(\gamma + \gamma_n\right)\right]\sigma_{\bar{e}^p,\bar{n}^p} + \sigma_{\breve{e}^k}^2 + \sigma_{\breve{e}^k,\breve{q}^k} + \sigma_{\breve{e}^k,\breve{n}^k} && (23) \\ \operatorname{Cov}\left(\bar{n}_f^k, \bar{c}_f^k\right) &= \gamma_n\left(\gamma + \gamma_n\right)\sigma_{\bar{e}^p}^2 + \rho\left(\rho_e + \rho\right)\sigma_{\bar{n}^p}^2 + \lambda\gamma_n\sigma_{\bar{e}^p,\bar{q}^p} + \lambda\rho\sigma_{\bar{n}^p,\bar{q}^p} \\ &\quad + \left[\gamma_n\left(\rho + \rho_e\right) + \rho\left(\gamma + \gamma_n\right)\right]\sigma_{\bar{e}^p,\bar{n}^p} + \sigma_{\breve{n}^k}^2 + \sigma_{\breve{e}^k,\breve{n}^k} + \sigma_{\breve{n}^k,\breve{q}^k} && (24) \end{aligned}$$

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

3.2 Decomposition of Inequality in the Younger Generation

Earnings inequality among children given by Equation (19) depends on four factors: (i) the dispersion of earnings ($\sigma^2_{\bar{e}^p}$) and other income ($\sigma^2_{\bar{n}^p}$) among parents, (ii) the covariance between the two parental income channels, $\sigma_{\bar{e}^p,\bar{n}^p}$, (iii) the magnitude of intergenerational pass-through parameters, γ and ρ_e, and (iv) the variance of the family-independent component in earnings fixed effect, $\sigma^2_{\breve{e}^k}$. The first three factors account for the parental impacts on earnings heterogeneity among children; that is, $\text{Var}\left[\bar{e}^k\left(p\right)\right] = \gamma^2\sigma^2_{\bar{e}^p} + \rho_e^2\sigma^2_{\bar{n}^p} + 2\gamma\rho_e\sigma_{\bar{e}^p,\bar{n}^p}$. This illustrates that pass-through parameters, which are often the 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 variables is $\text{Var}\left[\bar{n}^k\left(p\right)\right] = \rho^2\sigma^2_{\bar{n}^p} + \gamma_n^2\sigma^2_{\bar{e}^p} + 2\rho\gamma_n\sigma_{\bar{e}^p,\bar{n}^p}$. For expenditures, the first two rows of equation (21) describe how family heterogeneity affects dispersion in the offspring generation, $\text{Var}\left[\bar{c}^k\left(p\right)\right]$, while the third row captures factors that are independent of parental variables.

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 (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 $\hat{x}^{(1)}_{f,t}$, are our baseline outcome measures. Next, we regress the baseline outcomes $\hat{x}^{(1)}_{f,t}$ on a set of observables: dummies for family size, number of children, state of residence, employment status, race and education. We denote the fitted values from this step as $\hat{x}^{(2)}_{f,t}$. With these in hand, we employ the GMM estimator to recover parameter estimates using either baseline variation, $\hat{x}^{(1)}_{f,t}$ or fitted variation through observables alone, $\hat{x}^{(2)}_{f,t}$. Comparing these two sets of estimates for the structural parameters is informative about 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 in the U.S. because the offspring of sample members become part of the survey sample when they establish their 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. For each generation, we only consider income and expenditures between ages 25 and 65 years, to avoid confounding effects related to retirement and unstable employment. We also restrict the sample to families with positive head labour earnings and total family income. We select out households whose heads work more than 5,840 hours in a year, earn wages less than half of the federal minimum wage, or experience annual earnings growth above 400% or below -200%. To reduce noise due to weak labour market attachment and variation in marital status, we sample households that are observed over five years or longer. The baseline sample also requires that heads be married for at least five observations, although not necessarily observed continuously.[6] Our focus on father-son pairs avoids sample issues associated with the structure of the PSID (see Hryshko and Manovskii, 2019). These restrictions deliver 761 unique pairs for our baseline analysis, and we examine robustness of estimates using a variety of alternative sampling restrictions. Details about data and sampling are in Appendix B.2.

Labour earnings for head and spouse are readily available for all survey waves. Data on transfers from public and private sources are also available for most years since 1969. In contrast, expenditure measures are not consistently available through a single set of variables in the PSID. Expenditure on food is the only category observed almost continuously since 1967 and we use food outlays as the baseline consumption measure. In Section 7.5 we examine robustness to alternative consumption measures. The first approach, suggested by Attanasio and Pistaferri (2014), uses imputed measures. This relies on 11 major categories of consumption outlays that are reported since 1998. We estimate a demand system on post-1998 food and non-food expenditures, and their relative prices, along with household-level demographic and socioeconomic variables; by inverting the demand system, one can recover the non-food outlays for the years before 1998. Details about the variables, their availability in the survey and the demand system are in Appendix B.3. In a second sensitivity exercise we restrict the sample to the post-1999 period when imputation of non-food consumption is not necessary. Household expenditures are adjusted using the OECD adult equivalence scale.

4 Baseline Results

We begin by presenting the cross-sectional variances that capture the raw inequality of income and consumption outcomes. We then report estimates of pass-through parameters and of the variances and covariances of the underlying components of the income and consumption processes.

[6] The restriction is not inconsequential, as intergenerational insurance may come into play at the time of relationship breakdown (Fisher and Low, 2015). In Section 7 we relax the marital status restrictions.

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 lifetime income variables are more dispersed than expenditures in both generations, suggesting the presence of cross-sectional consumption smoothing. This smoothing may occur through taxes and transfers by the government as well as through family insurance and heterogeneous saving behaviours across households, as we discuss further in Section 5.2. The relative magnitudes of earnings and consumption dispersion in Table 1 are consistent with findings in Krueger and Perri (2006) and Attanasio and Pistaferri (2014). Figure 3 in Appendix C.1 shows the evolution of cross-sectional earnings and consumption inequality over the four decades of our sample. Other income, comprising of spousal earnings and transfer income of the couple, is much more dispersed than head earnings. The variances in Table 1, as well as the covariances amongst outcome variables, are used to estimate model parameters. Figure 4 in Appendix C.2 summarizes the within-sample fit for each target moment and shows that the GMM estimator can accurately match empirical second moments.

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
Parent-Child Pairs	761	761

Since we do not observe the later part of the offspring work lives, our estimates reflect how parental heterogeneity impacts dispersion among children in the earlier decades of adulthood.[7] Differences in the variances in Table 1 do not imply a decline in income inequality across generations. Rather, they reflect the accrual of income at different stages of the life-cycle. In Section 5.3 we report variances measured from a smaller sample where we restrict both parent and child ages between 30 and 40. These measures show an increase in dispersion among children, consistent with the well-established observation of growing inequality over the sample period (Heathcote, Perri and Violante, 2010).

Intergenerational Elasticities. Table 2 reports estimates of intergenerational pass-through parameters. Among baseline estimates, in column (1), the elasticity is highest for head earnings, with the pass-through γ estimated at 0.23. The elasticity for other income ρ is 0.10 and that

[7] The incremental accrual of life-cycle shocks in later phases of adult life would imply even stronger idiosyncratic dispersion among children (Grawe, 2006; Gouskova, Chiteji and Stafford, 2010; Halvorsen, Ozkan and Salgado, 2022).

for consumption fixed effects λ is 0.15. The significant pass-through of consumption fixed effects, above and beyond income channels, is evidence of direct persistence in saving and consumption propensities across generations.

Table 2: Estimates of Intergenerational Elasticity

Variables	**Parameters**	**Baseline** (1)	**Observable** (2)
Head Earnings	γ	0.229	0.338
		(0.028)	(0.025)
Other Income	ρ	0.099	0.248
		(0.027)	(0.042)
$\bar{e}_f^p$ on $\bar{n}_f^k$	γ_n	0.208	0.258
		(0.035)	(0.026)
$\bar{n}_f^p$ on $\bar{e}_f^k$	ρ_e	0.055	0.112
		(0.019)	(0.028)
Consumption	λ	0.153	0.452
		(0.037)	(0.045)
Parent-Child Pairs	*N*	761	761

Note: Bootstrap standard errors (100 repetitions) in parentheses. *Baseline* refers to data that is purged of year and birth cohort effects, $\hat{x}_{f,t}^{(1)}$. *Observable* refers to the fitted values $\hat{x}_{f,t}^{(2)}$ from a regression of $\hat{x}_{f,t}^{(1)}$ on a set of observable characteristics: dummies for family size, state of residence, number of children, employment status, race and education. 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 for offspring, with the cross-elasticity γ_n equal to 0.21. Other household income has a smaller effect on children earnings, with the elasticity ρ_e estimated to be about a quarter of γ_n. We show in Section 7.4 that ignoring these cross-effects may lead to inaccurate inference about family influences on cross-sectional inequality in the younger generation.

Column (2) in Table 2 reports estimates of pass-through parameters based on the predicted components of the outcome variables; that is, we measure the parent-child persistence in fitted values based on observable characteristics. The predicted components of earnings, other income and consumption exhibit higher persistence relative to baseline measures. Among observable characteristics, education plays an important role in the pass-through of predicted earnings (see Appendix

C.3). This observation corroborates evidence from previous studies (among others, Eshaghnia et al., 2021; Abbott et al., 2019; Landersø and Heckman, 2017; Lefgren, Sims and Lindquist, 2012).

Table 3: Estimates of Variances and Covariances of Fixed Effects

	Parameters	Baseline (1)	Observable (2)
Variances of Parental Fixed Effects			
Head Earnings	$\sigma^2_{\bar{e}^p}$	0.296	0.095
		(0.020)	(0.005)
Other Income	$\sigma^2_{\bar{n}^p}$	0.805	0.084
		(0.058)	(0.009)
Consumption	$\sigma^2_{\bar{q}^p}$	1.027	0.196
		(0.064)	(0.018)
Variances of Child Idiosyncratic Components			
Head Earnings	$\sigma^2_{\breve{e}^k}$	0.229	0.041
		(0.014)	(0.002)
Other Income	$\sigma^2_{\breve{n}^k}$	0.511	0.062
		(0.041)	(0.004)
Consumption	$\sigma^2_{\breve{q}^k}$	0.733	0.105
		(0.058)	(0.007)
Covariances among Parental Fixed Effects			
Consumption & Head Earnings	$\sigma_{\bar{e}^p,\bar{q}^p}$	-0.270	-0.120
		(0.026)	(0.009)
Consumption & Other Income	$\sigma_{\bar{n}^p,\bar{q}^p}$	-0.816	-0.115
		(0.060)	(0.013)
Head Earnings and Other Income	$\sigma_{\bar{e}^p,\bar{n}^p}$	0.069	0.059
		(0.017)	(0.006)
Covariances among Child Idiosyncratic Components			
Consumption & Head Earnings	$\sigma_{\breve{e}^k,\breve{q}^k}$	-0.250	-0.058
		(0.024)	(0.003)
Consumption & Other Income	$\sigma_{\breve{n}^k,\breve{q}^k}$	-0.523	-0.069
		(0.046)	(0.005)
Head Earnings & Other Income	$\sigma_{\breve{e}^k,\breve{n}^k}$	0.076	0.031
		(0.017)	(0.003)
Parent-Child Pairs	*N*	761	761

Note: See note to Table 2.

Variances and Covariances of the Underlying Processes. Table 3 reports estimates of the variances and covariances of the individual fixed effects in earnings, other income and consumption. We document large negative covariation between the consumption fixed effect and the two sources of income, which reflects the lower propensity to consume of high income families. This reconciles the model with the cross-sectional observation that consumption is less dispersed than income (Attanasio and Pistaferri, 2016; Straub, 2018; Abbott and Gallipoli, 2022).

5 Implications and Interpretation

We address three questions using these estimates. First, how much of the inequality in the younger generation is explained by heterogeneity among parents. Second, how much consumption insurance is there against idiosyncratic income shocks and how does it relate to within-family insurance. Third, what do our estimates imply for long run inequality.

5.1 Parental Heterogeneity and Inequality

The impact 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 how much of the variance of earnings, other income and consumption can be accounted through parental heterogeneity; second, we show how the cross-sectional distributions of these outcomes would change if differences in parental characteristics were removed.

Variance Decomposition. Table 4 summarizes the impacts of parental heterogeneity on the variances of children outcomes. Column (1) shows again the raw cross-sectional variance in each of the children's outcome variables from Table 1. In column (2) we report the share of the raw variance that can be accounted for by parental variables. Finally, column (3) shows the share of the raw variances explained by predicted components of parental variables through observable characteristics.

Specifically, for each outcome $x \in \{e, n, c\}$, we denote as $\text{Var}\left[\bar{x}^k(p)\right]$ the variance in the children's generation that is explained by parental variables while $\text{Var}\left(\bar{x}^k\right)$ is the cross-sectional variance in the children's generation. The explained component $\text{Var}\left[\bar{x}^k(p)\right]$ can be computed for either our baseline measures of children outcomes or for their fitted values based on observables. We refer to each of these measures as, respectively, $\text{Var}\left[\bar{x}^k(p)\right]_{base}$ and $\text{Var}\left[\bar{x}^k(p)\right]_{obs}$. Then, column (2) of Table 4 shows the ratio $\frac{\text{Var}\left[\bar{x}^k(p)\right]_{base}}{\text{Var}\left(\bar{x}^k\right)}$, while column (3) reports $\frac{\text{Var}\left[\bar{x}^k(p)\right]_{obs}}{\text{Var}\left(\bar{x}^k\right)}$.

Family factors account for a small fraction of income variation: 8% and 4% for head earnings and other income respectively. Parental heterogeneity has its largest influence on consumption dispersion, explaining up to 30% of inequality in the children generation. The consumption variance is itself considerably smaller than the variance of income sources, reflecting different channels of insurance. In Section 5.2, we discuss consumption insurance both within and outside the family.

Table 4: Parental Impact on Variance of Child Outcomes

Variables	**Child Variance**	**Parental Contribution**	
		Overall	**Observables**
	(1)	(2)	(3)
Head Earnings	0.249	7.9%	6.6%
		[3.5%, 12.4%]	[4.7%, 8.5%]
Other Income	0.535	4.4%	3.6%
		[1.4%, 7.4%]	[2.0%, 5.1%]
Consumption	0.114	30.1%	7.0%
		[19.7%, 40.5%]	[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 parental variables. 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.

The finding that roughly 8% of permanent earnings inequality can be explained through family influences does not imply that permanent heterogeneity among children is less important than other factors for life-cycle outcomes. Rather, our measures quantify the impact of family factors on permanent heterogeneity, which itself accounts for most of income dispersion. Daruich and Kozlowski (2020) show that over 50% of the total life-cycle variance in earnings is explained by differences in permanent heterogeneity (see also Keane and Wolpin, 1997; Huggett, Ventura and Yaron, 2011). Daruich and Kozlowski (2020) show that removing the correlation between parent and child outcomes would lower earnings inequality by about 7%, an estimate close to ours. In addition, our estimates of parental impacts on income inequality are comparable to studies based on alternative approaches. For example, Hufe, Kanbur and Peichl (2021) find that up to 10% of inequality in total disposable income is attributable to parental heterogeneity.

There is a growing recognition that families contribute to children's outcomes through channels that may not be immediately captured by parental earnings, other income or consumption (Caucutt et al., 2021; Seror, 2022). To assess whether this leads to an understatement of parental influences on inequality, we examine the impact of higher parent-child persistence, hypothetically reflecting alternative channels through which families affect permanent income and consumption of their children (Table 17 in Appendix D.3).

Finally, we consider differences in the variation attributed to observed versus unobserved family characteristics. About 80% of the parental contribution to income and earnings heterogeneity of the young occurs through variation in observables; in contrast, heterogeneity through observables accounts for less than a quarter of parental influence on consumption inequality. This suggests that restricting the analysis to observable characteristics may result in a partial account of family persistence across generations.

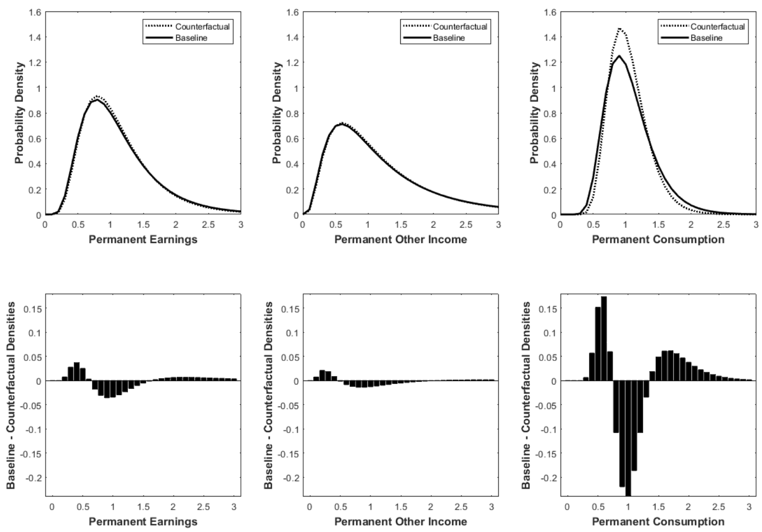

Figure 1: Baseline versus Counterfactual Probability Density Functions

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

Counterfactual Cross-Sectional Distributions. In Figure 1 we plot the observed cross-sectional distribution of each outcome in the children's generation and compare it to a counterfactual distribution obtained in the absence of parental pass-through. The top panels plot the actual and counterfactual distributions, while the bottom panels show the histogram of frequency differences between them.[8] Parental influences increase the spread among families in the tails of all outcome distributions, with the largest impact on consumption.

[8]To simulate distributions, we assume log-normality of the outcome variables and use the parameter estimates in column (1) of Tables 2 and 3. In Appendix D.1 we provide details about the procedure.

5.2 Consumption Insurance within the Family and in the Cross-Section

Parental influences on inequality in the younger generation is partly dictated by the extent of insurance provided within the family and by the wider insurance available to the cross-section of children. Within-family insurance may add to consumption dispersion among the young if richer families are more effective in reducing consumption gaps between parent and child. Such consumption smoothing across two generations of the same family should be distinguished from overall consumption insurance that reduces cross-sectional consumption inequality within a generation through formal and informal transfers. In what follows we present measures of both types of consumption insurance, and report estimates in the aggregate and by parental income quartile.

Insurance in the Younger Generation. We quantify total cross-sectional insurance by measuring the extent to which shocks that impact the young generation's income are passed through to changes in consumption inequality. We define a partial insurance parameter μ such that $\left[\text{Var}\left(\bar{c}^k\right) - \text{Var}\left(\bar{c}^p\right)\right] = \mu^2 \text{Var}\left(\breve{y}^k\right)$, where $\text{Var}\left(\breve{y}^k\right)$ is the variance of innovations to income among children. Since μ is derived from the cross-sectional variances in each generation, its estimate does not depend on information about family linkages. The cross-sectional insurance measure μ generalizes to an intergenerational setting the insurance measure in equation (12) of Blundell, Low and Preston (2013), which in turn builds on Blundell, Pistaferri and Preston (2008). To gain intuition, we notice that μ can be expressed as:

$$\mu = \left[\frac{\text{Var}\left(\bar{c}^k\right) - \text{Var}\left(\bar{c}^p\right)}{\text{Var}\left(\breve{y}^k\right)}\right]^{0.5}$$

In the case of $\mu = 1$, changes in consumption inequality across generations fully track the dispersion of idiosyncratic income shocks in the younger generation, signifying no cross-sectional insurance against such shocks. At the opposite extreme, for $\mu = 0$, changes in consumption inequality do not reflect the dispersion of idiosyncratic income components in the younger generation.

Within-family Insurance. By definition, the parameter μ quantifies partial insurance from both family and formal channels including taxes and government transfers. To separate out the family component, we define a different metric based on within-family consumption deviations. Specifically, we define a measure of within-family insurance, μ_F such that $\text{Var}\left(\bar{c}^k_f - \bar{c}^p_f\right) = \mu_F^2 \text{Var}\left(\breve{y}^k\right)$, which can be written as:

$$\mu_F = \left[\frac{\text{Var}\left(\bar{c}^k_f - \bar{c}^p_f\right)}{\text{Var}\left(\breve{y}^k\right)}\right]^{0.5}$$

By design, μ_F requires information about consumption differences between parent and child within each family f. Since the unit of observation is the parent-child pair, the magnitude of μ_F hinges directly on the covariation between parent and child expenditures. Full consumption smoothing within each family would result in μ_F equal to zero. More generally, μ_F summarizes the extent of within-family consumption deviations due to idiosyncratic income shocks experienced by the young.

Table 5: Measures of Consumption Insurance by Parental Income Quartile

Income Shock	**Measures of Income, y**									
	Head Earnings					**Total Family Income**				
Pass-through	*All*	Q-1	Q-2	Q-3	Q-4	*All*	Q-1	Q-2	Q-3	Q-4
$\mu = \left[\frac{\text{Var}\left(\bar{c}^k_f\right) \quad \text{Var}\left(\bar{c}^p_f\right)}{\text{Var}\left(\breve{y}^k_f\right)}\right]^{0.5}$	*0.29*	0.16	0.58	0.41	0.28	*0.33*	0.21	0.60	0.53	0.39
$\mu_F = \left[\frac{\text{Var}\left(\bar{c}^k_f \quad \bar{c}^p_f\right)}{\text{Var}\left(\breve{y}^k_f\right)}\right]^{0.5}$	*0.82*	0.91	0.84	0.77	0.74	*0.93*	1.01	1.05	0.84	0.82
Parent-Child Pairs	*761*	192	189	190	190	*761*	191	190	190	190

Note: We use pre-tax measures of lifetime income and food consumption after controlling for year and cohort effects. Var $\left(\breve{y}^k_f\right)$ is calculated as the variance of the fitted residuals from an OLS projection of $\bar{y}^k_f$ on $\bar{y}^p_f$. Columns marked as *All* refer to the full sample of parent-child pairs, while columns Q-1 through Q-4 show results by quartile of parental income.

Estimates of μ and μ_F. The analytical relationship between μ and μ_F is described in Appendix D.2. There, we show that $\mu_F \geq \mu$, which means that insurance within the family is never larger than the overall cross-sectional insurance. Table 5 shows estimates of the two insurance metrics μ and μ_F.[9] We report values based on alternative measures of income: head earnings and total family income. Within-family insurance is considerably smaller than overall insurance. While over two-thirds of idiosyncratic shocks to earnings are insured in the cross-section, less than a quarter are insured within the family. When we consider measures based on total family income, both μ and μ_F increase, suggesting less insurance for this broader gauge of income. Estimated magnitudes are in the range of existing estimates of partial insurance against permanent shocks. For example, Blundell, Pistaferri and Preston (2008) find evidence of significant partial insurance in non-durable consumption, with a pass-through from permanent earnings to consumption of 0.22. Blundell, Pistaferri and Preston (2008) also show that the contribution of friends and relatives to total insurance is not large. This is confirmed by Attanasio, Meghir and Mommaerts (2018) who find limited evidence of insurance through the extended family. Like these studies, our estimates

[9] To estimate partial insurance parameters, we must measure the variance of idiosyncratic shocks to income in the children's generation, Var $\left(\breve{y}^k_f\right)$. We use the variance of the fitted residuals from an OLS projection of $\bar{y}^k_f$ on $\bar{y}^p_f$. An alternative is to use the baseline estimates in Table 3. Results are not significantly different.

of μ and μ_F suggest that most consumption insurance is obtained outside the family.

Insurance and Parental Income. Estimates of the average values of μ and μ_F conceal considerable heterogeneity across families. In Table 5, we break down the extent of partial insurance by parental income quartile. Estimates of μ_F monotonically decrease with parental income, consistent with the conjecture that richer parents may provide more insurance to their children. By contrast, when we consider the overall cross-sectional insurance, estimates of μ have an inverse-U relationship with parental income. This indicates that overall insurance is greatest in the bottom and top quartiles, albeit through different channels: family insurance is more prevalent in the richest quartiles whereas insurance among the poorest comes largely from outside the family.

5.3 The Evolution of Inequality across Generations

The PSID covers the working life of children born between the 1950s and the early 1980s. This makes it infeasible to estimate the impact of grandparents on grandchildren, and on generations further apart. Nevertheless, under stationarity of estimated parameters, the model can be used to examine the projected path of inequality starting from current levels.

Table 6: Steady-state Inequality 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. Ages restricted between 30 and 40.

To limit the confounding influence of life-cycle effects, we restrict the baseline sample to parents and children between ages 30 and 40. The cross-sectional variances in the two generations for this sample (see columns (1) and (2) of Table 6) confirm the well-established result of increasing earnings inequality in the U.S. (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. We iterate this VAR system forward until the distribution of outcomes converges to a stationary one. The variances of the resulting long-run distribution are reported in column (3) of Table 6 (details of the simulation are in Appendix D.3).

The steady-state variances are higher than the ones observed in the child generation, although differences are small (columns (2) and (3) in Table 6). The estimated values of the intergenerational pass-through parameters are not large enough to induce significant increases in inequality in the long run. As a result, the influence of family background dissipates over successive generations. This result is a corollary of the finding that inequality among children is primarily driven by their idiosyncratic permanent components. To corroborate the observation that current intergenerational elasticities are not large enough to induce significant increases in inequality, we consider the impact of progressively larger pass-through parameters. Table 17 in Appendix D.3 shows that even with a very large earnings pass-through ($\gamma = 0.5$), parental effects on the variance of earnings would not exceed 15%.

6 Pathways of Intergenerational Influence

To assess the potential relevance of underlying mechanisms for intergenerational linkages, we examine the role of marital sorting, borrowing constraints and a warm-glow motive for parental transfers.

6.1 Spousal Earnings and Family Background

In the baseline analysis, other income is the sum of wife's labour earnings and total transfer income accruing to the couple. To establish the importance of these components, we estimate two versions of the model: (i) using wife earnings alone as the measure of other income (Model B); and (ii) considering three separate income processes for head earnings, wife earnings and transfer income (Model C). The addition of a third income process requires an extension of the baseline model (see identification results for the richer covariance structure in Appendix E.1).

To make comparisons easier, we use a common sample of 459 parent-child pairs for which income and expenditure variables can be consistently defined in each model. Table 7 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 primarily driven by spousal earnings.

When only wife earnings are used to measure other income, we find significant intergenerational pass-through from mothers to sons' wives (see Table 20 in Appendix E.1). This evidence is consistent with findings in Fernandez, Fogli and Olivetti (2004), who document preference formation based on maternal characteristics.[10] The positive elasticity from father earnings to son's spouse

[10]For father-daughter or mother-daughter persistence, see Lee and Solon (2009); Hartley, Lamarche and Ziliak (2022). See Holmlund (2022) for a study of the relationship between marital sorting and intergenerational mobility.

provides additional evidence of marital sorting based on family background. Allowing for three separate income sources lends further support to these findings.

Table 7: Parental Impact on Variance of Child Outcomes: Unpacking *Other Income*

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

Note: Baseline model measures other income as the sum of wife earnings and transfer income. Model B uses wife earnings only, while Model C features three separate income processes for head earnings, wife earnings and transfer income. All models use food expenditure as the measure of consumption and are estimated on time-averaged variables. In the baseline sample we require the sum of wife earnings and transfer income to be positive, which yields 761 parent-child pairs. Restricting both wife earnings and transfer income to be positive, we obtain a sample of 459 pairs. Results in column (1) are computed using parameter estimates in column (1) of Tables 2 and 3; results in columns (2) through (4) are based on parameter estimates from Tables 20 and 21 in Appendix E. Numbers in parentheses are 95% confidence intervals, calculated using bootstrap standard errors with 100 repetitions.

To examine whether sampling restrictions influence these findings, we re-estimate the baseline model using the restricted sample of 459 pairs. Results in columns (1) and (2) of Table 7 are not statistically different from each other. Since most of the sample reduction is due to the presence of zeros in the noisy transfer variable, we also check robustness using an intermediate sample requiring only positive wife earnings. This reduces the sample size by only 11% (from 761 to 674 pairs) and the resulting estimates are not significantly different.

6.2 Liquidity Constraints

There is an ongoing debate about the importance of liquidity constraints for intergenerational persistence. The impact of parental heterogeneity on the dispersion of child outcomes may depend on whether parents are liquidity constrained and on whether they can make optimal investments in their children. A large literature highlights the difficulty in identifying the effect of financial constraints on intergenerational mobility (see Black and Devereux, 2011, for a survey). A recurring concern relates to distinguishing constrained from unconstrained households, especially in the absence of consumption data. While low-income parents experience repeated episodes of financial hardship, other families can also be constrained if their children have high returns to investments. This is likely if financing education for high-return offspring requires a much larger investment (Han and Mulligan, 2001).[11]

To circumvent the limitations of using income measures in isolation, Mulligan (1997) classifies as unconstrained those PSID households that receive substantial bequests and Mazumder (2005) labels households with above-median net worth as unconstrained in SIPP data. Neither study finds significantly larger intergenerational mobility in the unconstrained groups.

An alternative approach is to use data on consumption alongside income. This is useful to establish the prevalence of constraints as it relates directly to the ability to finance expenditures. For example, using a PSID sample of married individuals observed for at least 15 years, Alan, Browning and Ejrnæs (2018) find little evidence of excess sensitivity of consumption to anticipated income changes, a marker of binding liquidity constraints. In what follows, we combine information about income and consumption to construct three alternative definitions of potentially constrained households. We check whether removing these households, in turn, has an effect on estimates. The three definitions result in different households being dropped from the estimation. None of these samples leads to significant differences relative to the baseline results.

Consumption Growth. A credit constraint that binds in period t, but not $t+1$, should be reflected in the consumption growth between the two periods (Crossley and Low, 2014). This insight suggests that constrained households can be recognized from observations where the increase in expenditure is above some threshold. Adopting a conservative 50% consumption growth threshold over two-year intervals, we find that removing potentially constrained observations from the baseline sample does not significantly alter estimates of either persistence or dispersion parameters (Appendix E.2.1).

Measuring the Volatility of Income and Expenditures over the Life Cycle. The availability of panel data on both earnings and expenditures allows one to quantify the sensitivity of consumption relative to income and use it as a measure of potential constraints. We define as

[11] Using measures of skills, income and wealth, Carneiro and Heckman (2003) find that about 8% of youth in the NLSY79 were credit-constrained when accessing higher education. Belley and Lochner (2007) and Abbott et al. (2019) suggest that constraints may be more prevalent in later periods although there is little evidence that they restrict high ability individuals from accessing higher education.

liquidity-constrained those families where the head falls in the top decile according to the ratio of consumption and earnings volatilities over the life-cycle. Dropping these households from the baseline sample and re-estimating the model results in no significant changes (Appendix E.2.2).

Young Families. The presence of credit constraints means that the timing of parental income may matter for the extent of intergenerational persistence (Caucutt and Lochner, 2019; Carneiro et al., 2021; Abbott, 2022). Caucutt and Lochner (2019) stress that noticeable increases in mobility occur only when eliminating credit constraints across the entire life-cycle. To examine the sensitivity of results to the timing of potential constraints, we explore the impact of household resources at different child ages. We do so by taking averages of earnings, other income and consumption of the parents when the child is at different ages. We then estimate intergenerational persistence using these age-specific measures of parental resources. In other words, given the outcomes of the child, we adjust the way we measure parental variables. We find evidence of marginal and insignificant differences of parental impacts across these measures (Appendix E.2.3).

6.3 Parental Motives

The baseline model features intergenerational linkages but does not make parental motives explicit. We extend the framework to distinguish between utility from own consumption and from expenditure on children, assuming additive separability. The household's problem becomes,

$$\begin{aligned} \max_{\{C_{f,s},\mathcal{T}_{f,s}\}_{s=t}^{T}} \quad & \mathsf{E}_t \quad \sum_{j=0}^{T-t} \beta^j \left[\frac{C_{f,t+j}^{1-\sigma}}{1-\sigma} + \mu_1 \cdot \frac{\mathcal{T}_{f,t+j}^{1-\mu_2}}{1-\mu_2} \right] \\ & s.t. \\ A_{f,t+1} \quad = \quad & (1+r)\left(A_{f,t} + E_{f,t} + N_{f,t} - C_{f,t} - \mathcal{T}_{f,t}\right). \end{aligned} \tag{25}$$

The variable $\mathcal{T}_{f,t}$ denotes the parental expenditure on the child at time t. The expenditure can finance investments 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. We also distinguish between expenditures for own consumption and for children in the budget constraint.

Optimality implies that the marginal rate of substitution between own consumption and child expenditures be constant if the relative price is constant (De Nardi, 2004; Becker et al., 2018).[12] This suggests that total parental expenditures, if observed, can serve as a statistic for unobserved parental transfers to the offspring. Therefore, the warm-glow motive points to a direct link between total parental expenditures and observed child outcomes. This additional source of persistence

[12] The intratemporal optimality condition is $\ln C_{f,t} = -\frac{1}{\sigma}\log\mu_1 + \frac{\mu_2}{\sigma}\ln\mathcal{T}_{f,t}$.

implies that the three outcome processes for the offspring can be cast as,

$$\bar{e}^k_f = (\gamma + \lambda_e)\,\bar{e}^p_f + (\rho_e + \lambda_e)\,\bar{n}^p_f + \lambda_e \bar{q}^p_f + \breve{e}^k_f \tag{26}$$

$$\bar{n}^k_f = (\rho + \lambda_n)\,\bar{n}^p_f + (\gamma_n + \lambda_n)\,\bar{e}^p_f + \lambda_n \bar{q}^p_f + \breve{n}^k_f \tag{27}$$

$$\bar{c}^k_f = (\lambda + \lambda_e + \lambda_n)\,\bar{q}^p_f + (\gamma + \gamma_n + \lambda_e + \lambda_n)\,\bar{e}^p_f + (\rho + \rho_e + \lambda_e + \lambda_n)\,\bar{n}^p_f + \breve{e}^k_f + \breve{n}^k_f + \breve{q}^k_f \tag{28}$$

In this framework, parental expenditures can affect directly child earnings and other income through elasticity parameters λ_e and λ_n, respectively. Equations (26), (27) and (28) collapse back to the baseline processes in (4), (5) and (7) if $\lambda_e \simeq \lambda_n = 0$. A full discussion of this extended model and of parameter identification is in Appendix E.3.

Table 8: Parental Impact on Variance of Child Outcomes

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

Note: Results in column (1) are based on parameter estimates in column (1) of Tables 2 and 3. Results in column (2) are based on estimates in column (1) of Tables 28 and 29, Appendix E.3. Numbers in parentheses are 95% confidence intervals, calculated using bootstrap with 100 repetitions.

Estimates of the extended model suggest that neither λ_e nor λ_n are different from zero (Table 28 in Appendix E.3). In columns (1) and (2) of Table 8 we present evidence that accounting for the direct pass-through of parental expenditures into child income does not change estimates of family influence on inequality. The lack of incremental effects through the direct transfer channels indicates that the parsimonious baseline specification is sufficient to characterize intergenerational linkages without imposing a specific behavioral motive. To be clear, these findings do not imply that altruistic or paternalistic motives are absent or inconsequential.[13] Rather, they suggest that, irrespective of motives, parent-child linkages and their impact on inequality are adequately summarized by the pass-through parameters in the baseline model.

[13]See Altonji, Hayashi and Kotlikoff (1997) for a test of altruism in PSID data and Cordoba and Ripoll (2019) for a discussion of altruistic preference structures.

7 Extensions and Robustness

To assess the robustness of our findings we perform several checks. First, we consider more general income specifications. In Section 7.1 we estimate the full model, featuring both persistent and transitory shocks as outlined in Section 2, without time-averaging. In Section 7.2, we consider a special case where persistent income shocks are assumed to have a unit root. This restriction results in an empirical specification linking the growth processes of the outcome variables. In this setting family persistence takes the form of covariation in the shocks to permanent income. In the remainder of the section, we then consider alternative sample, data and model restrictions. In Section 7.3, we construct a sample of randomly matched parent-child pairs to perform a placebo test of family linkages. In Section 7.4, we assess the importance of cross-elasticities between earnings and other income by setting γ_n and ρ_e to zero in the baseline model. In Section 7.5, we employ alternative measures of expenditure. In Section 7.6, we estimate the model on a larger sample including families with less stable marriages. In Section 7.7, we study the effect of income taxation on our estimates of intergenerational persistence and parental influence. Finally, in Section 7.8, we examine potential differences across birth-cohorts of children.

7.1 Panel Variation with Persistent and Transitory Shocks

Due to time-averaging, estimates in our baseline analysis reflect only cross-sectional variation in the outcome variables. Individual fixed effects may partly reflect persistent shocks to income and consumption. To separately account for the variances of confounding components, we estimate a version of the model from Section 2 that takes full advantage of panel variation.

Estimating the variances of both autoregressive and transitory shocks increases the number of parameters from 17 to 43. 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. We establish identification and describe estimation and various sensitivity checks in Appendix F.1.

Table 9 shows that explicitly accounting for per-period shocks to income and consumption does not materially change estimated effects. The only statistically significant difference relative to the time-averaged specification is in parental influence on other income, which becomes indistinguishable from zero in the panel estimation. This is not surprising, given that the attenuation bias from measurement error is stronger when we do not use time averages. As mentioned before, this problem is especially severe in the transfer data used to construct other income.

Table 9: Parental Impact on Variance of Child Outcomes

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 30 and 32, Appendix F.1. Numbers in parentheses are 95% confidence intervals, calculated using panel bootstrap (100 repetitions).

7.2 Permanent Income as a Random Walk

A special case of the persistent and transitory distinction in Section 7.1 is when persistent shocks are permanent and the autoregressive parameters are equal to 1. This corresponds to the framework studied in Blundell, Pistaferri and Preston (2008) extended to account for intergenerational pass-through. In this setting, we explore persistence across generations that occurs through the correlation of innovations between parents and children, rather than transmission through fixed effects as in the baseline model.

The income processes for each generation $g \in \{p, k\}$ are

$$e^g_{f,t} = \bar{e}^g_f + \mathcal{E}^g_{f,t} + \varepsilon^g_{f,t} \quad \text{where} \quad \mathcal{E}^g_{f,t} = \mathcal{E}^g_{f,t-1} + \epsilon^g_{f,t} \tag{29}$$

$$n^g_{f,t} = \bar{n}^g_f + \Theta^g_{f,t} + \vartheta^g_{f,t} \quad \text{where} \quad \Theta^g_{f,t} = \Theta^g_{f,t-1} + \theta^g_{f,t} \tag{30}$$

where the random walk components $\mathcal{E}^g_{f,t}$ and $\Theta^g_{f,t}$ have i.i.d. innovations $\epsilon^p_{f,t}$ and $\theta^p_{f,t}$. The transitory shocks to earnings and other income are also i.i.d. and denoted as $\varepsilon^p_{f,t}$ and $\vartheta^p_{f,t}$.

In this setting, the growth rate of consumption can be expressed as the sum of transitory and permanent innovations to income and of a consumption-specific transitory shock (see Blundell, Pistaferri and Preston, 2008, for a derivation):

$$\Delta c^g_{f,t} = \omega_{e^g} \epsilon^g_{f,t} + \omega_{n^g} \theta^g_{f,t} + \psi_{e^g} \varepsilon^g_{f,t} + \psi_{n^g} \vartheta^g_{f,t} + \xi^g_{f,t} \quad \text{for each } g \in \{p, k\} \tag{31}$$

The equation above has two loading parameters, ω_{e^g} and ω_{n^g}, that can be interpreted as inverse measures of consumption insurance against permanent income shocks. For example, when ω_{e^g}

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 ω_{e^g} close to unity indicates little insurance against innovations to permanent earnings. Similarly, the loading parameters ψ_{e^g} and ψ_{n^g} can be interpreted as inverse measures of insurance against transitory shocks to earnings and other income, respectively. The loading parameters capture the within-generation partial insurance discussed in Blundell, Pistaferri and Preston (2008).

In this non-stationary environment, outcome variables are expressed in first differences and fixed effects cancel out through time-differencing. This means that intergenerational linkages operating through fixed effects are not identified. Instead, we examine potential intergenerational persistence in permanent innovations to income, and the correlation of transitory shocks to consumption changes across generations. These linkages can be expressed as

$$\epsilon^k_{f,t} = \gamma_\Delta \epsilon^p_{f,t} + \breve{\epsilon}^k_{f,t} \tag{32}$$
$$\theta^k_{f,t} = \rho_\Delta \theta^p_{f,t} + \breve{\theta}^k_{f,t} \tag{33}$$
$$\xi^k_{f,t} = \lambda_\Delta \xi^p_{f,t} + \breve{\xi}^k_{f,t}, \tag{34}$$

where the subscript Δ on the pass-through parameters highlights the fact that these parameters operate on the growth rates of outcome variables, rather than through the levels as in the baseline case. Combining equations (29) through (34) yields the following income and consumption growth equations in the two generations:

$$\Delta e^p_{f,t} = \epsilon^p_{f,t} + \Delta\varepsilon^p_{f,t} \tag{35}$$
$$\Delta n^p_{f,t} = \theta^p_{f,t} + \Delta\vartheta^p_{f,t} \tag{36}$$
$$\Delta c^p_{f,t} = \omega_{e^p}\epsilon^p_{f,t} + \omega_{n^p}\theta^p_{f,t} + \psi_{e^p}\varepsilon^p_{f,t} + \psi_{n^p}\vartheta^p_{f,t} + \xi^p_{f,t} \tag{37}$$
$$\Delta e^k_{f,t} = \gamma_\Delta \epsilon^p_{f,t} + \breve{\epsilon}^k_{f,t} + \Delta\varepsilon^k_{f,t} \tag{38}$$
$$\Delta n^k_{f,t} = \rho_\Delta \theta^p_{f,t} + \breve{\theta}^k_{f,t} + \Delta\vartheta^k_{f,t} \tag{39}$$
$$\Delta c^k_{f,t} = \omega_{e^k}\left(\gamma_\Delta \epsilon^p_{f,t} + \breve{\epsilon}^k_{f,t}\right) + \omega_{n^k}\left(\rho_\Delta \theta^p_{f,t} + \breve{\theta}^k_{f,t}\right) + \psi_{e^k}\varepsilon^k_{f,t} + \psi_{n^k}\vartheta^k_{f,t} + \left(\lambda_\Delta \xi^p_{f,t} + \breve{\xi}^k_{f,t}\right) \tag{40}$$

In Appendix F.2 we derive identification results and show parameter estimates for this specification. We find no evidence of intergenerational persistence in permanent innovations to income or in transitory shocks to consumption growth as estimates of pass-through parameters γ_Δ, ρ_Δ and λ_Δ are not statistically different from zero.

7.3 Placebo Test: Random Matching of Parents and Children

Spurious correlations in the data may affect estimates of parent-child pass-through parameters. To account for this, we perform a placebo test using a sample in which parents and children are randomly matched. Estimates based on this sample show no intergenerational pass-through and no role of parental heterogeneity for inequality among the children, as seen in column (2) of Tables 10 and 11.

Table 10: Robustness: Intergenerational Elasticity Estimates

Parameters	**Baseline** (1)	**Random Match** (2)	$\gamma_n = \rho_e = 0$ (3)	**Imputed Consumption** (4)	**All Marital Status** (5)	**Post-tax Income** (6)
Head Earnings: γ	0.229	-0.018	0.340	0.256	0.217	0.225
	(0.028)	(0.028)	(0.027)	(0.024)	(0.029)	(0.026)
Other Income: ρ	0.099	-0.039	0.120	0.096	0.103	0.091
	(0.027)	(0.025)	(0.028)	(0.028)	(0.035)	(0.028)
$\bar{e}_f^p$ on $n_{f,t}^k$: γ_n	0.208	-0.007	0	0.237	0.239	0.199
	(0.035)	(0.035)		(0.031)	(0.039)	(0.039)
$\bar{n}_f^p$ on $e_{f,t}^k$: ρ_e	0.055	-0.015	0	0.052	0.058	0.044
	(0.019)	(0.023)		(0.015)	(0.015)	(0.014)
Consumption: λ	0.153	-0.048	0.108	0.127	0.170	0.119
	(0.037)	(0.034)	(0.029)	(0.033)	(0.042)	(0.033)
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.

7.4 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 that both γ_n and ρ_e be zero. Column (3) in Table 10 reports estimates of pass-through parameters under these restrictions, and column (3) of Table 11 reports the contribution of parental heterogeneity to children inequality. Most of the difference relative to the baseline can be attributed to the restriction that $\gamma_n = 0$, since the magnitude of ρ_e is already close to zero in the baseline model. The point estimate of the earnings elasticity γ increases significantly in the restricted model. This leads to an overstatement of parental impact on earnings inequality. By imposing $\gamma_n = 0$, the estimate of the direct pass-through γ increases to accommodate a stable value of $(\gamma + \gamma_n)$, the total intergenerational pass-through from parental earnings to child outcomes. Restricting the cross-effects between income sources leads to a lower estimate of parental influence on consumption inequality because higher estimates of the direct income elasticities (γ and ρ) are not enough to offset the reduction in the overall pass-through from parental income to child outcomes. Moreover, when only wife earnings are used as a measure of other income, ignoring the income cross-effects has a similar impact (see Table 41 in Appendix F.3). This suggests that ignoring cross-effects introduces a bias in the estimates of persistence parameters and of parental heterogeneity on inequality.

Table 11: Robustness: Parental Impact on Variance of Child Outcomes

Variables	**Baseline**	**Random Match**	$\gamma_n = \rho_e = 0$	**Imputed Consumption**	**All Marital Status**	**Post-tax Income**
	(1)	(2)	(3)	(4)	(5)	(6)
Head Earnings	7.9%	0.1%	13.5%	9.3%	6.4%	7.0%
	[3.5% 12.4%]	[-0.8% 1.0%]	[9.4% 17.6%]	[6.0% 12.6%]	[3.4% 9.4%]	[4.0% 10.1%]
Other Income	4.4%	0.2%	2.2%	5.0%	2.5%	3.4%
	[1.4% 7.4%]	[-0.4% 0.9%]	[0.2% 4.1%]	[2.2% 7.8%]	[0.9% 4.2%]	[0.7% 6.1%]
Consumption	30.1%	0.2%	19.6%	47.6%	26.1%	25.6%
	[19.7% 40.5%]	[-0.9% 1.3%]	[13.5% 25.7%]	[35.4% 59.8%]	[17.2% 35.0%]	[17.4% 33.8%]
Parent-Child Pairs	761	761	761	761	1038	755

Note: Results in columns (1) through (5) are based on parameter estimates in Table 10 and Appendix Table 40, while those in column (6) are based on column (6) of Table 10 and column (3) of Appendix Table 44. Numbers in parentheses are 95% confidence intervals, calculated using bootstrap standard errors with 100 repetitions.

7.5 Alternative Measures of Consumption Expenditure

We use food expenditures as our baseline consumption measure because such records are available for the longest time stretch. We examine the importance of other expenditure categories in two ways: first, using imputed consumption; and second, only using data since 1999.

We impute total consumption using the procedure suggested by Attanasio and Pistaferri (2014); this approach exploits the rich expenditure information available in the PSID since 1999 to approximate household outlays in earlier waves of the survey. We report results for this consumption measure in column (4) of Tables 10 and 11. Estimates based on imputed expenditure suggest a stronger role of parental heterogeneity for consumption dispersion among the young, with roughly half of the total dispersion due to family linkages. This high estimate is arguably an upper bound of the true parental contribution as it partly reflects the latent persistence of family characteristics used to impute total consumption.

When we restrict the sample only to the post-1999 period, there is no need for imputation of non-food consumption. Estimates from this analysis suggest a parental contribution to consumption inequality of roughly 24%, which is comparable to the baseline estimate, although estimates on the restricted sample are more noisy due to smaller sample size (details available on request).

7.6 Relaxing Marital Status Restrictions

The baseline sample is restricted to households with at least 5 (not necessarily continuous) observations for 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 whether sample selection on marital status of household heads has an effect on parameter estimates, we estimate the baseline specification using a sample consisting of all households observed for at least 5 years regardless of their marital status. This increases the number of parent-child pairs from 761 to 1038. Estimates of intergenerational persistence and parental effects on child inequality in this larger sample are reported in column (5) of Tables 10 and 11. These are not statistically or qualitatively different from the baseline. This suggests that marital selection bias in the baseline sample is not quantitatively large. However, the broader sample of all households introduces substantial noise into the measure of other income.

7.7 Income Taxation

To examine the sensitivity of estimates to the use of after-tax income measures, we compute the Federal tax burden of each household using TAXSIM and split it between head earnings and other income in proportion to head and wife earnings.[14] The last columns of Tables 10 and 11 illustrate how the use of after-tax earnings leads to a marginal decrease in estimates of pass-through parameters and of parental influences on inequality. However, none of the reductions are statistically significant.

7.8 Estimates by Child Birth-Cohort

Table 12: Parental Impact on Variance of Child Outcomes by Child Cohort

Variables	**All Cohorts** (1)	**1952-1966 Cohort** (2)	**1967-1981 Cohort** (3)
Head Earnings	7.9%	8.0%	8.3%
	[3.5%, 12.4%]	[3.2%, 12.7%]	[3.0%, 13.6%]
Other Income	4.4%	3.2%	8.3%
	[1.4%, 7.4%]	[0.2%, 6.2%]	[0.5%, 16.1%]
Consumption	30.1%	33.6%	23.9%
	[19.7%, 40.5%]	[21.2%, 46.6%]	[14.6%, 33.2%]
Parent-Child Pairs	761	467	294

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

[14] We consider two alternative splits of the tax burden: one where the entire tax burden is incident on head earnings; another where it is incident only on other income. Results for all three cases are in Appendix F.4.

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 sub-sample. We use one birth-cohort running between 1952 and 1966 and another covering 1967 through 1981. Table 12 shows that parental influences on cross-sectional heterogeneity in the child generation have remained roughly stable across these birth cohorts. In Appendix F.5 we present further results 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.

8 Conclusion

Our analysis provides a novel characterization of how inequality propagates across generations along both the consumption and income dimensions, and estimates the relationship between intergenerational persistence and inequality. We develop a model of intergenerational persistence in earnings, other income and expenditures. We find evidence of significant parental pass-through in the earnings of heads and spouses as well as in consumption. Cross-effects between different income sources and consumption reveal diverse channels of family influence such as marital sorting and heterogeneous propensities to consume. Parental effects contribute to cross-sectional inequality among offspring. However, the largest contribution to both income and consumption inequality comes from idiosyncratic heterogeneity, which diffuses and attenuates the impact of family background. We find that within-family insurance accounts for a modest part of overall consumption insurance, especially for low income households whose insurance comes almost entirely from outside the family. Our estimates imply that intergenerational persistence would have to be much higher to induce, by itself, further substantial increases in inequality over time and across generations. Casting different channels of intergenerational pass-through as endogenous mechanisms that depend on life-cycle choices is a valuable avenue for future work.

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. 2022. "Incomplete markets and parental investments in children." *Review of Economic Dynamics*, 44: 104–124.

Abbott, Brant, and Giovanni Gallipoli. 2016. "Human capital spill-overs and the geography of intergenerational mobility." *Review of Economic Dynamics*, 1–50.

Abbott, Brant, and Giovanni Gallipoli. 2022. "Permanent-Income Inequality." *Quantitative Economics*, 13: 1023–1060.

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, Costas Meghir, and Corina Mommaerts. 2018. "Insurance in extended family networks." *NBER Working Paper Series*, No. 21509.

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 Intergnerational Mobility." *Journal of Political Economy*, 126(S1): S7–S25.

Belley, Philippe, and Lance Lochner. 2007. "The changing role of family income and ability in determining educational achievement." *Journal of Human capital*, 1(1): 37–89.

Bello, Salvatore Lo, and Iacopo Morchio. 2022. "Like Father, Like Son: Occupational Choice, Intergenerational Persistence and Misallocation." *Quantitative Economics*, 13: 629–679.

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, Hamish Low, and Ian Preston. 2013. "Decomposing changes in income risk using consumption data." *Quantitative Economics*, 4(1): 1–37.

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.

Caucutt, Elizabeth, Lance John Lochner, Joseph Mullins, and Youngmin Park. 2021. "Child Skill Production: Accounting for Parental and Market-based Time and Goods Investments." Western University.

Charles, Kerwin Kofi, and Erik Hurst. 2003. "The Correlation of Wealth across Generations." *Journal of Political Economy*, 111(6): 1155–1182.

Charles, Kerwin Kofi, Sheldon Danzinger, Geng Li, and Robert Schoeni. 2014. "The Intergenerational Correlation of Consumption Expnditures." *American Economic Review*, 104(5): 136–140.

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.

Cordoba, Juan Carlos, and Marla Ripoll. 2019. "The Elasticity of Intergenerational Substitution, Parental Altruism, and Fertility Choice." *The Review of Economic Studies*, 86: 1935–1972.

Cordoba, Juan Carlos, Xiying Liu, and Marla Ripoll. 2016. "Fertility, social mobility and long run inequality." *Journal of Monetary Economics*, 77: 103–124.

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. 2004. "Wealth Inequality and Intergenerational Links." *The Review of Economic Studies*, 71(3): 743–768.

Eshaghnia, Sadegh, James J. Heckman, Rasmus Landersø, Rafeh Qureshi, and Victor Ronda. 2021. "The Intergenerational Transmission of Lifetime Wellbeing." *Working Paper*.

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. 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.

Halvorsen, Elin, Serdar Ozkan, and Sergio Salgado. 2022. "Earnings dynamics and its intergenerational transmission: Evidence from Norway." *Quantitative Economics*. forthcoming.

Han, Song, and Casey B. Mulligan. 2001. "Human Capital, Heterogeneity and Estimated Degrees of Intergenerational Mobility." *The Economic Journal*, 111(April): 207–243.

Hartley, Robert Paul, Carlos Lamarche, and James P Ziliak. 2022. "Welfare reform and the intergenerational transmission of dependence." *Journal of Political Economy*, 130(3): 523–565.

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.

Holmlund, Helena. 2022. "How Much Does Marital Sorting Contribute to Intergenerational Socioeconomic Persistence?" *The Journal of Human Resources*, 57(2): 372–399.

Hryshko, Dmytro, and Iourii 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.

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.

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 six appendices, A through F corresponding to Sections 2 through 7 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.[15] 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.[16] 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

[15] 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.

[16] 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.[17]

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.[18] 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 ζ_{fht} as the outcome variable — earnings or consumption, of the child f born in year h observed in year t. We run the regression:

$$\zeta_{fht} = \mu D_t + \beta_t x_{fh} + \gamma a^p_{fh} + \delta a^k_{fht} + \epsilon_{fht} \tag{A.1}$$

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^p_{fh}, 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^k_{fht}. The error term ϵ_{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 β 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^k_{fht} affects the point estimate of β_t in each year but not the time trend.

In Table 13 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

[17] 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.

[18] 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 13: 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 quartile as the parent is high, we say that intergenerational persistence is high for that quartile 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

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

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

Child \ Parent	$Q_{p,1}$	$Q_{p,2}$	$Q_{p,3}$	$Q_{p,4}$
$Q_{k,1}$	**45.98**	27.88	17.29	9.56
$Q_{k,2}$	25.41	**29.64**	27.17	15.93
$Q_{k,3}$	19.75	24.80	**30.44**	23.10
$Q_{k,4}$	8.86	17.69	25.10	**51.41**

Mobility Matrix of Total Consumption

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

Mobility Matrix of Food Consumption

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

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:

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

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:

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

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 $ln\left(C_{f,t}\right)$, $ln\left(A_{f,t}\right)$, $ln\left(E_{f,t}\right)$ and $ln\left(N_{f,t}\right)$ 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,

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

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

The last step follows from the fact that the shocks ε and ϑ 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 Θ are serially correlated to their past period's value through their fractional persistence parameters α_e and α_n respectively.

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

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

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

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

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 $C_{f,t}^{\ \sigma} = \beta(1+r)\,\mathsf{E}_t\left(C_{f,t+1}^{\ \sigma}\right)$, 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 $\mathsf{E}_t\left[\left(\frac{C_{f,t+1}}{C_{f,t}}\right)^{\ \sigma}\right] = 1$. 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 $\mathsf{E}_t\left[h(g_c)\right] = 1$. 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 $\mathsf{E}_t(g_c) = 0$, implying $C_{f,t} = \mathsf{E}_t(C_{f,t+1})$. 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 $C_{f,t} = \mathsf{E}_t(C_{f,t+1})$, we get,

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

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, $\lim_{k\to\infty}\left(\frac{1}{1+r}\right)^k \mathsf{E}_t\left(A_{f,t+k}\right) = 0$.

B Appendix to Section 3

This appendix complements Section 3 in the 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:

$$\begin{aligned}
\text{Cov}\left(\bar{e}_f^p, \bar{c}_f^k\right) &= \left(\gamma+\gamma_n\right)\sigma^2_{\bar{e}^p} + \lambda\sigma_{\bar{e}^p,\bar{q}^p} + \left(\rho+\rho_e\right)\sigma_{\bar{e}^p,\bar{n}^p} && \text{(B.1)}\\
\text{Cov}\left(\bar{n}_f^p, \bar{c}_f^k\right) &= \left(\rho+\rho_e\right)\sigma^2_{\bar{n}^p} + \lambda\sigma_{\bar{n}^p,\bar{q}^p} + \left(\gamma+\gamma_n\right)\sigma_{\bar{e}^p,\bar{n}^p} && \text{(B.2)}\\
\text{Cov}\left(\bar{c}_f^p, \bar{e}_f^k\right) &= \gamma\left(\sigma^2_{\bar{e}^p} + \sigma_{\bar{e}^p,\bar{q}^p} + \sigma_{\bar{e}^p,\bar{n}^p}\right) + \rho_e\left(\sigma^2_{\bar{n}^p} + \sigma_{\bar{n}^p,\bar{q}^p} + \sigma_{\bar{e}^p,\bar{n}^p}\right) && \text{(B.3)}\\
\text{Cov}\left(\bar{c}_f^p, \bar{n}_f^k\right) &= \gamma_n\left(\sigma^2_{\bar{e}^p} + \sigma_{\bar{e}^p,\bar{q}^p} + \sigma_{\bar{e}^p,\bar{n}^p}\right) + \rho\left(\sigma^2_{\bar{n}^p} + \sigma_{\bar{n}^p,\bar{q}^p} + \sigma_{\bar{e}^p,\bar{n}^p}\right) && \text{(B.4)}
\end{aligned}$$

(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, $\sigma^2_{\bar{e}^p}$, and the x-axis represents the intergenerational earnings persistence, γ. To identify this pair of parameters we only use the following three moment conditions:

$$\begin{aligned}
\text{Var}\left(\bar{e}_f^p\right) &= \sigma^2_{\bar{e}^p} && \text{(B.5)}\\
\text{Var}\left(\bar{e}_f^k\right) &= \gamma^2\sigma^2_{\bar{e}^p} + \rho_e^2\sigma^2_{\bar{n}^p} + 2\gamma\rho_e\sigma_{\bar{e}^p,\bar{n}^p} + \sigma^2_{\check{e}^k} && \text{(B.6)}\\
\text{Cov}\left(\bar{e}_f^p, \bar{e}_f^k\right) &= \gamma\sigma^2_{\bar{e}^p} + \rho_e\sigma_{\bar{e}^p,\bar{n}^p} && \text{(B.7)}
\end{aligned}$$

From moment condition (B.5), the variance of parental earnings ($\sigma^2_{\bar{e}^p}$) is uniquely identified by $\text{Var}\left(\bar{e}_f^p\right)$: its value is shown as the horizontal dashed line in Figure 2. The moment condition (B.6) captures the tradeoff between γ and $\sigma^2_{\bar{e}^p}$, holding constant other persistence and variance parameters (i.e., $\rho_e, \sigma^2_{\bar{n}^p}, \sigma_{\bar{e}^p,\bar{n}^p}$ and $\sigma^2_{\check{e}^k}$). 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, γ. However, our model features an additional restriction: the exact location of the pair $(\gamma, \sigma^2_{\bar{e}^p})$ needs to be consistent with the moment condition (B.7), imposing an additional tradeoff between the two parameters (shown by the solid line). That is, $\sigma^2_{\bar{e}^p}$ and γ 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.

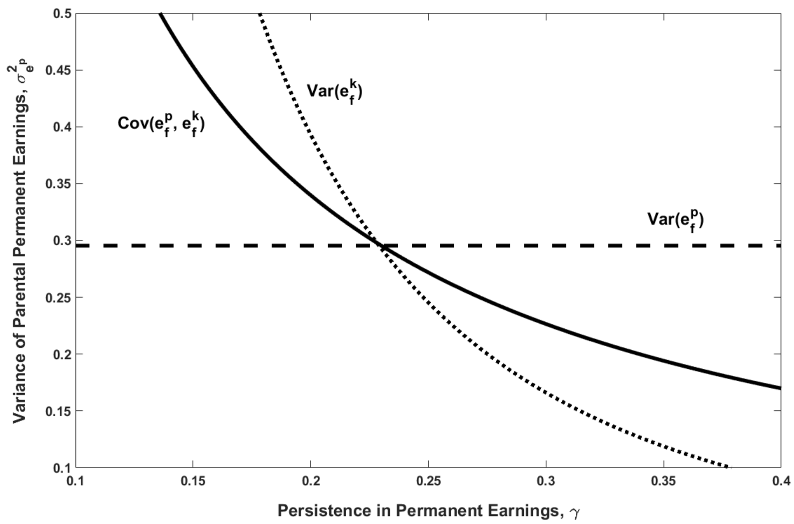

Figure 2: Identification of Persistence and Dispersion Parameters

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 tastes, 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:

$$ln\left(\tilde{C}_{ft}\right) = Z_{ft}^{\prime}\omega + p_t^{\prime}\pi + g(F_{ft};\lambda) + \epsilon_{ft}, \tag{B.8}$$

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, $g(.)$ is a polynomial function, and ϵ_{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. The R^2 of the regression (B.8) is 0.47.

After estimating the logarithm of the net consumption equation by running a pooled OLS regression on equation (B.8), we construct a measure of imputed total consumption as follows

$$\hat{C}_{ft} = F_{ft} + exp\left\{Z_{ft}^{\prime}\hat{\omega} + p_t^{\prime}\hat{\pi} + g\left(F_{ft};\hat{\lambda}\right)\right\}. \tag{B.9}$$

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.

C Appendix to Section 4

This appendix is comprised of the following main sections. Section C.1 presents the evolution of different measures of income and consumption inequality in the U.S. Section C.2 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.3, we show the intergenerational persistence in observable characteristics and the specific role of education in driving the intergenerational linkages in our data.

C.1 Evolution of Income and Consumption Inequality

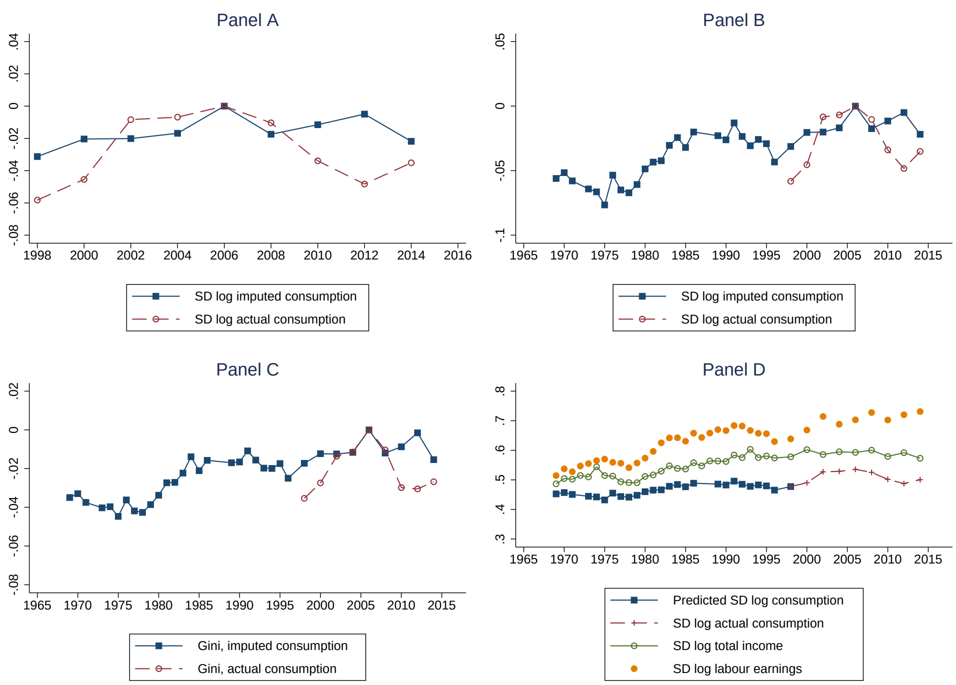

Figure 3: Income and Consumption Inequality in the PSID

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

Figure 3 shows the evolution of inequality in household income and consumption in the U.S. over the past four decades. Panels A through C compare the actual expenditure measure in the PSID with the imputed consumption series in Section B.3, using two alternative measures of inequality: the standard deviations of the log variables and the Gini coefficient. 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. Panel D compares the the standard deviations of actual (pre-1998) and imputed (post-1998) consumption with those of head earnings and total family income. 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.2 Empirical Moments and Baseline Fit

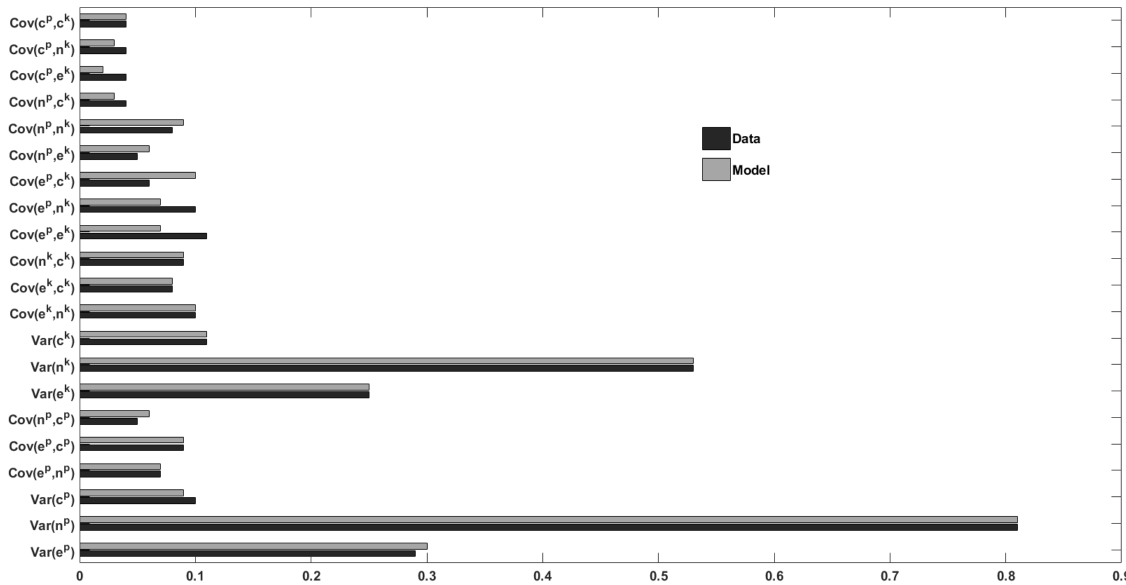

Figure 4: Internal Fit of Baseline Model

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.3 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 14 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 16 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 15.

Table 14: 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 15: Mobility Matrix for Education

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

Table 16: Role of Education among Observables

	Parameters	**All Observables**	**Education Only**	**Observables except Education**
		(2)	(3)	(4)
Head Earnings	γ	0.338	0.255	0.304
		(0.025)	(0.031)	(0.025)
Other Income	ρ	0.248	0.188	0.208
		(0.042)	(0.029)	(0.058)
$\bar{e}_f^p$ on $\bar{n}_f^k$	γ_n	0.258	0.185	0.276
		(0.026)	(0.017)	(0.037)
$\bar{n}_f^p$ on $\bar{e}_f^k$	ρ_e	0.112	0.196	0.055
		(0.028)	(0.044)	(0.027)
Consumption	λ	0.452	0.413	0.358
		(0.045)	(0.029)	(0.076)
Parent-Child Pairs	*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.

D Appendix to Section 5

This appendix is comprised of the following main sections. Section D.1 presents details for computing the counterfactual distribution of outcomes in the children generation when parental influence is eliminated. Section D.2 provides a formal derivation of the relation between the two measures of insurance, μ and μ_F. Section D.3 provides details of the long run evolution of inequality across generations.

D.1 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[19]:

$$\begin{pmatrix} \bar{e}^p_f \\ \bar{n}^p_f \\ \bar{q}^p_f \\ \breve{e}^k_f \\ \breve{n}^k_f \\ \breve{q}^k_f \end{pmatrix} \sim \mathbf{N} \left[\begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma^2_{\bar{e}^p} & \sigma_{\bar{e}^p,\bar{n}^p} & \sigma_{\bar{e}^p,\bar{q}^p} & 0 & 0 & 0 \\ \sigma_{\bar{e}^p,\bar{n}^p} & \sigma^2_{\bar{n}^p} & \sigma_{\bar{n}^p,\bar{q}^p} & 0 & 0 & 0 \\ \sigma_{\bar{e}^p,\bar{q}^p} & \sigma_{\bar{n}^p,\bar{q}^p} & \sigma^2_{\bar{q}^p} & 0 & 0 & 0 \\ 0 & 0 & 0 & \sigma^2_{\breve{e}^k} & \sigma_{\breve{e}^k,\breve{n}^k} & \sigma_{\breve{e}^k,\breve{q}^k} \\ 0 & 0 & 0 & \sigma_{\breve{e}^k,\breve{n}^k} & \sigma^2_{\breve{n}^k} & \sigma_{\breve{n}^k,\breve{q}^k} \\ 0 & 0 & 0 & \sigma_{\breve{e}^k,\breve{q}^k} & \sigma_{\breve{n}^k,\breve{q}^k} & \sigma^2_{\breve{q}^k} \end{pmatrix} \right]$$

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, $\left(\breve{e}^k_f + \breve{n}^k_f + \breve{q}^k_f\right)$, follows a Normal distribution with zero mean and variance equal to $\sigma^2_{\breve{e}^k} + \sigma^2_{\breve{n}^k} + \sigma^2_{\breve{q}^k} + 2\left(\sigma_{\breve{e}^k,\breve{n}^k} + \sigma_{\breve{e}^k,\breve{q}^k} + \sigma_{\breve{n}^k,\breve{q}^k}\right)$. 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.

[19]The mean of the logarithmic variables are zero because we consider de-meaned variables net of year and cohort fixed effects.

D.2 Measuring Intergenerational Consumption Insurance

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

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

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, $\text{Var}\left(\bar{c}_f^k\right) = \text{Var}\left(\bar{c}_f^p\right) = \text{Cov}\left(\bar{c}_f^p, \bar{c}_f^k\right)$, implying, $\mu = \mu_F = 0$, that is, perfect consumption insurance against lifetime average income shocks idiosyncratic to the children's generation.

D.3 Evolution of Inequality across Generations

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

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

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

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

Using parameter estimates, we simulate the VAR forward, iterating until convergence.[20] This delivers simulated data series for $\bar{e}_f^{k_t}$, $\bar{n}_f^{k_t}$, $\bar{q}_f^{k_t}$, $\breve{e}_f^{k_t}$, $\breve{n}_f^{k_t}$ and $\breve{q}_f^{k_t}$. To obtain a series for log consumption, we use the relationship:

$$c_f^{k_t} = \lambda q_f^{k_t \;\; 1} + (\gamma + \gamma_n)\, e_f^{k_t \;\; 1} + (\rho + \rho_e)\, n_f^{k_t \;\; 1} + \breve{e}_f^{k_t} + \breve{n}_f^{k_t} + \breve{q}_f^{k_t},$$

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 6.

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 γ at pre-determined values. By exogenously setting larger or smaller values of γ, we can assess whether, and how much, steady-state inequality might deviate from its initial value. Table 17 shows that for counterfactually high values of γ, 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, γ (column 1) and idiosyncratic heterogeneity, $\sigma^2_{\breve{e}^k}$ (column 2) is evident when explaining the total child variance (column 4).[21]

Despite a falling variance for idiosyncratic innovations, $\sigma^2_{\breve{e}^k}$, steady-state inequality in column 5 increases with the magnitude of γ. 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 $\text{Var}\left(\bar{e}^k\right)$ and $\text{Var}\,(e \;\,)$.[22]

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

[20] 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 45 and 46. The VAR is simulated over 100,000 generations.

[21] When intergenerational persistence γ is set to a higher value, the GMM estimator mechanically delivers a lower variance of idiosyncratic heterogeneity (e.g., for earnings, lower $\sigma^2_{\breve{e}^k}$) since observed cross-sectional inequality among children remains unchanged.

[22] A striking feature of the GMM estimates in Table 17 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 γ is exogenously fixed. To understand this, consider that the moment estimator has to satisfy equation (14), which implies a direct trade-off between γ and $Var(\bar{e}^p)$. Thus, increasing γ tends to decrease $Var(\bar{e}^p)$. On the other hand, whatever the values for γ and $Var(\bar{e}^p)$, the observed value of $Var(\bar{e}^k)$ is always matched exactly by choosing the free parameter $\sigma^2_{\breve{e}^k}$, which does not enter any other moment condition.

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 17, which documents how changes in γ lead to significant variation in the contribution of parental factors to cross-sectional earnings inequality. A larger γ amplifies the contribution of family background: the parental contribution to inequality swings widely, between 1% and 12% (for values of γ between 0.1 and 0.4) even when steady-state earnings dispersion $\widehat{Var}(e\ )$ barely changes.

Table 17: The Importance of Parents: Varying Persistence γ

γ	$\widehat{\sigma^2_{\breve{e}^k}}$	$\widehat{Var}(\bar{e}^p)$	$\widehat{Var}(\bar{e}^k)$	$\widehat{Var}(e\ )$	$\frac{\gamma^2 \widehat{Var}(\bar{e}^p)}{\widehat{Var}(\bar{e}^k)}$
(1)	(2)	(3)	(4)	(5)	(6)
0.10	0.258	0.185	0.260	0.262	0.9%
0.19	**0.253**	**0.183**	**0.260**	**0.265**	**2.7%**
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 γ 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.

It is interesting to contrast the values in column 6 of Table 17 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 D.3 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:

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

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

$$\text{Var}(e_\infty) = \lim_{t \to \infty} \left[\gamma^{2t} \sigma^2_{\bar{e}^p} + \sum_{j=1}^{t} \gamma^{2(t-j)} \sigma^2_{\breve{e}^k} \right] = \frac{\sigma^2_{\breve{e}^k}}{1-\gamma^2} \quad \text{(D.1)}$$

Table 18: Intergenerational Elasticities

	Parameters	**Estimates**
		(1)
Head Earnings	γ	0.280
		(0.041)
Other Income	ρ	0.021
		(0.047)
Consumption	λ	0.006
		(0.051)
Parent-Child Pairs	N	404

Note: Bootstrap standard errors (100 repetitions) in parentheses. Parental and child ages vary between 30 and 40. Parameters γ_n and ρ_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.

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

$$\text{Var}(n\ ) = \frac{\sigma^2_{\breve{n}^k}}{1-\rho^2} \tag{D.2}$$

$$\text{Var}(c\ ) = \frac{\sigma^2_{\breve{q}^k}}{1-\lambda^2} + \frac{\sigma^2_{\breve{e}^k}}{1-\gamma^2} + \frac{\sigma^2_{\breve{n}^k}}{1-\rho^2} + \frac{2\sigma_{\breve{e}^k,\breve{n}^k}}{1-\gamma\rho} + \frac{2\sigma_{\breve{n}^k,\breve{q}^k}}{1-\lambda\rho} + \frac{2\sigma_{\breve{e}^k,\breve{q}^k}}{1-\lambda\gamma}. \tag{D.3}$$

Plugging in estimated values for the parameters in equations (D.1) through (D.3),[23] one can identify the threshold values of the persistence parameters beyond which there will be rising inequality. Using equation (D.1), we identify the threshold value of γ above which the variance of earnings would grow from the value estimated in the parents' generation: this is the value of γ such that $\text{Var}(e\ ) \geq \text{Var}(e^p)$. This threshold value of γ is given by $\gamma^p \equiv \sqrt{1 - \frac{\sigma^2_{\breve{e}^k}}{\text{Var}(e^p)}}$. Any γ larger than γ^p implies growing earnings variance. Based on the parameter estimates in Tables 18 and 19, $\sigma^2_{\breve{e}^k} = 0.246 > \text{Var}\left(e^p\right) = 0.183$, making γ^p an imaginary number. This essentially implies that any non-negative value of γ would result in increasing earnings inequality from the level in the parents' generation. Since our estimate of the current value of γ $(= 0.279)$ 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, $\text{Var}\left(e^{k_1}\right) = 0.261$ is larger than in the parents' one, $\text{Var}\left(e^p\right) = 0.183$.

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

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

This is plotted as the dashed vertical line in Figure 5. Any value of γ to the right of that vertical line implies growing earnings variance. Since our estimate of γ $(= 0.279)$ lies to the right of the new threshold γ^{k_1}, the threshold corresponding to the generation of grandchildren k_2 (denoted by the dotted vertical line in Figure 5) will lie further to the right of γ^{k_1}; one can repeat these calculations over and over again.[24] Eventually, the economy settles down at the stationary distribution of earnings where the threshold is defined as

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

[23] Since we restrict the parameters $\gamma_n = \rho_e = 0$, we need to re-estimate our baseline model with this additional 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 18 and 19.

[24] We find $\gamma^{k_2} = 0.276$, which is larger than γ^{k_1} but still slightly smaller than 0.279.

which is the estimated level of γ.

Table 19: Idiosyncratic Variances & Covariances

	Parameters	**Estimates**
		(1)
Variances of Parental Fixed Effects		.
Head Earnings	$\sigma^2_{\bar{e}^p}$	0.183
		(0.015)
Other Income	$\sigma^2_{\bar{n}^p}$	0.876
		(0.113)
Consumption	$\sigma^2_{\bar{q}^p}$	0.955
		(0.113)
		.
Variances of Child Idiosyncratic Components		.
Head Earnings	$\sigma^2_{\breve{e}^k}$	0.246
		(0.017)
Other Income	$\sigma^2_{\breve{n}^k}$	0.631
		(0.058)
Consumption	$\sigma^2_{\breve{q}^k}$	0.853
		(0.072)
		.
Covariances among Parental Fixed Effects		.
Consumption & Head Earnings	$\sigma_{\bar{e}^p,\bar{q}^p}$	-0.122
		(0.030)
Consumption & 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)
		.
Covariances among Child Idiosyncratic Components		.
Consumption & Head Earnings	$\sigma_{\breve{e}^k,\breve{q}^k}$	-0.248
		(0.025)
Consumption & Other Income	$\sigma_{\breve{n}^k,\breve{q}^k}$	-0.623
		(0.063)
Head Earnings & Other Income	$\sigma_{\breve{e}^k,\breve{n}^k}$	0.057
		(0.023)
Parent-Child Pairs	*N*	404

Note: Bootstrap standard errors (100 repetitions) in parentheses. This table uses the same sample and model specification as Table 18.

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

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

for each generation $g = \{p, k_1, k_2, ...\}$ as a function of γ and λ, holding all other parameters constant. However, there is no combination of γ and λ in the economically meaningful range $[0, 1]$ that satisfies the threshold value equation for 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 Var $\left(c^{k_1}\right) = 0.117 >$ Var $\left(c^p\right) = 0.09$.

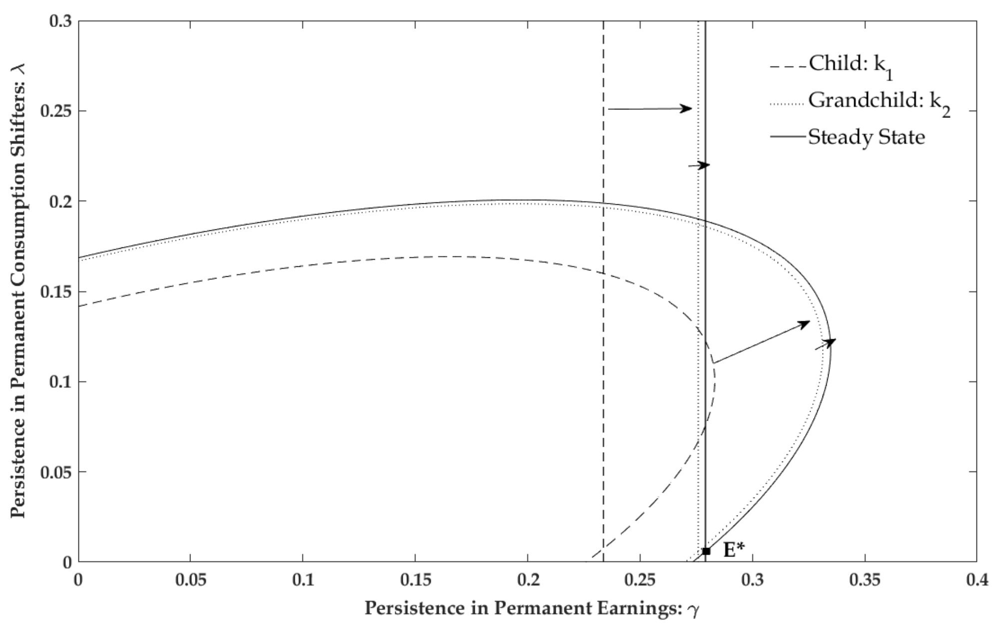

Figure 5: Implication of γ and λ for Long Run Earnings & Consumption Inequality

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 Var$(c^{k_2}) = 0.124 >$ 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 γ and λ in Figure 5.[25]

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 10 and 40 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 γ 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 10 and 40.

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

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

and is shown as the dot-dashed vertical line in Figure 6. Since the estimate of the current value of γ ($= 0.340$) 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 (D.1) again to find the threshold value of γ above which the earnings variance in the child generation should be growing. We find

$$\gamma^{k_1} \equiv \sqrt{1 - \frac{\sigma^2_{\breve{e}k}}{\text{Var}(e^{k1})}} = 0.367,$$

which is less than γ^p. Once again the estimated value of $\gamma = 0.340$ lies to the left of this new threshold γ^{k1}, and so the threshold corresponding to the generation of grandchildren k_2 will lie further to the left of γ^{k_1}, and so on. Eventually, the economy settles down at the stationary distribution of earnings where the threshold is defined as $\gamma \ \equiv \sqrt{1 - \frac{\sigma^2_{\breve{e}k}}{\text{Var}(e\ )}} = 0.340$, which is the estimated level of γ.

We again perform a similar exercise for the consumption variance using equation (D.3). The variance of consumption is a function of three persistence parameters: γ, ρ and λ. We hold ρ

[25] 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 γ and λ. 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 .

constant at its estimated value and study the thresholds of γ and λ that imply increasing or decreasing consumption variance. First we ask what combinations of γ and λ imply that the variance of consumption is increasing across generations. For that we plot the threshold value

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

as a function of γ and λ. 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 γ and λ in Figure 6.

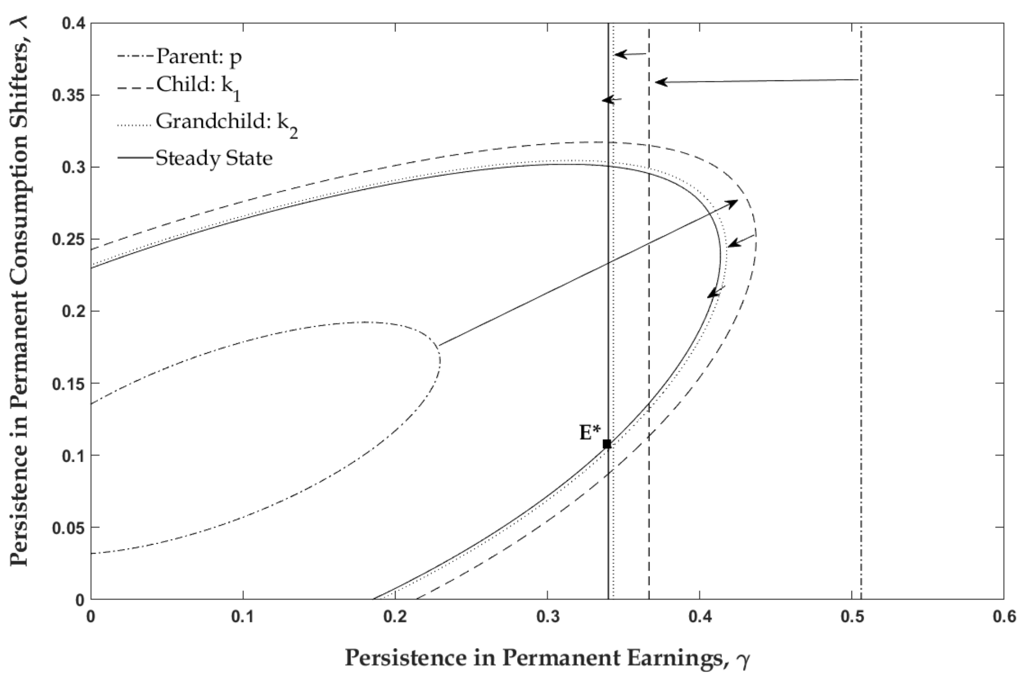

Figure 6: Implication of γ and λ for Long Run Earnings & Consumption Inequality

E Appendix to Section 6

E.1 Role of Marital Selection

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

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:

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

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 - γ, γ_w, γ_π, ρ, ρ_e, ρ_π, ϱ, ϱ_e, ϱ_w, λ, λ_e, λ_w, λ_π; the 4 variances of parental permanent income and consumption - $\sigma^2_{\bar{e}^p}$, $\sigma^2_{\bar{w}^p}$, $\sigma^2_{\bar{\pi}^p}$, $\sigma^2_{\bar{q}^p}$; the 4 variances of child idiosyncratic permanent income and consumption - $\sigma^2_{\breve{e}^k}$, $\sigma^2_{\breve{w}^k}$, $\sigma^2_{\breve{\pi}^k}$, $\sigma^2_{\breve{q}^k}$; the 6 covariances among parental permanent income and consumption components - $\sigma_{\bar{e}^p,\bar{w}^p}$, $\sigma_{\bar{e}^p,\bar{\pi}^p}$, $\sigma_{\bar{e}^p,\bar{q}^p}$, $\sigma_{\bar{w}^p,\bar{\pi}^p}$, $\sigma_{\bar{w}^p,\bar{q}^p}$, $\sigma_{\bar{\pi}^p,\bar{q}^p}$; and the 6 covariances among child idiosyncratic components of income and consumption - $\sigma_{\breve{e}^k,\breve{w}^k}$, $\sigma_{\breve{e}^k,\breve{\pi}^k}$, $\sigma_{\breve{e}^k,\breve{q}^k}$, $\sigma_{\breve{w}^k,\breve{\pi}^k}$, $\sigma_{\breve{w}^k,\breve{q}^k}$, $\sigma_{\breve{\pi}^k,\breve{q}^k}$. Below we present the moment conditions and the identification argument.

Parental Variance

$$Var\left(\bar{e}_f^p\right) = \sigma^2_{\bar{e}^p} \tag{E.1}$$

$$Var\left(\bar{w}_f^p\right) = \sigma^2_{\bar{w}^p} \tag{E.2}$$

$$Var\left(\bar{\pi}_f^p\right) = \sigma^2_{\bar{\pi}^p} \tag{E.3}$$

$$\begin{aligned} Var\left(\bar{c}_f^p\right) &= \sigma^2_{\bar{q}^p} + \sigma^2_{\bar{e}^p} + \sigma^2_{\bar{w}^p} + \sigma^2_{\bar{\pi}^p} \\ &+ 2\left(\sigma_{\bar{e}^p,\bar{w}^p} + \sigma_{\bar{e}^p,\bar{\pi}^p} + \sigma_{\bar{e}^p,\bar{q}^p} + \sigma_{\bar{w}^p,\bar{\pi}^p} + \sigma_{\bar{w}^p,\bar{q}^p} + \sigma_{\bar{\pi}^p,\bar{q}^p}\right) \end{aligned} \tag{E.4}$$

Parental Covariance

$$Cov\left(\bar{e}_f^p, \bar{w}_f^p\right) = \sigma_{\bar{e}^p,\bar{w}^p} \tag{E.5}$$

$$Cov\left(\bar{e}_f^p, \bar{\pi}_f^p\right) = \sigma_{\bar{e}^p,\bar{\pi}^p} \tag{E.6}$$

$$Cov\left(\bar{e}_f^p, \bar{c}_f^p\right) = \sigma^2_{\bar{e}^p} + \sigma_{\bar{e}^p,\bar{w}^p} + \sigma_{\bar{e}^p,\bar{\pi}^p} + \sigma_{\bar{e}^p,\bar{q}^p} \tag{E.7}$$

$$Cov\left(\bar{w}_f^p, \bar{\pi}_f^p\right) = \sigma_{\bar{w}^p,\bar{\pi}^p} \tag{E.8}$$

$$Cov\left(\bar{w}_f^p, \bar{c}_f^p\right) = \sigma^2_{\bar{w}^p} + \sigma_{\bar{e}^p,\bar{w}^p} + \sigma_{\bar{w}^p,\bar{\pi}^p} + \sigma_{\bar{w}^p,\bar{q}^p} \tag{E.9}$$

$$Cov\left(\bar{\pi}_f^p, \bar{c}_f^p\right) = \sigma^2_{\bar{\pi}^p} + \sigma_{\bar{e}^p,\bar{\pi}^p} + \sigma_{\bar{w}^p,\bar{\pi}^p} + \sigma_{\bar{\pi}^p,\bar{q}^p} \tag{E.10}$$

Child Variance

$$\begin{aligned} Var\left(\bar{e}_f^k\right) &= \left(\gamma + \lambda_e\right)^2 \sigma^2_{\bar{e}^p} + \left(\rho_e + \lambda_e\right)^2 \sigma^2_{\bar{w}^p} + \left(\varrho_e + \lambda_e\right)^2 \sigma^2_{\bar{\pi}^p} + \lambda_e^2 \sigma^2_{\bar{q}^p} + \sigma^2_{\breve{e}^k} \\ &+ 2\left(\gamma + \lambda_e\right)\left[\left(\rho_e + \lambda_e\right)\sigma_{\bar{e}^p,\bar{w}^p} + \left(\varrho_e + \lambda_e\right)\sigma_{\bar{e}^p,\bar{\pi}^p} + \lambda_e \sigma_{\bar{e}^p,\bar{q}^p}\right] \\ &+ 2\left(\rho_e + \lambda_e\right)\left[\left(\varrho_e + \lambda_e\right)\sigma_{\bar{w}^p,\bar{\pi}^p} + \lambda_e \sigma_{\bar{w}^p,\bar{q}^p}\right] + 2\lambda_e\left(\varrho_e + \lambda_e\right)\sigma_{\bar{\pi}^p,\bar{q}^p} \end{aligned} \tag{E.11}$$

$$\begin{aligned} Var\left(\bar{w}_f^k\right) &= \left(\gamma_w + \lambda_w\right)^2 \sigma^2_{\bar{e}^p} + \left(\rho + \lambda_w\right)^2 \sigma^2_{\bar{w}^p} + \left(\varrho_w + \lambda_w\right)^2 \sigma^2_{\bar{\pi}^p} + \lambda_w^2 \sigma^2_{\bar{q}^p} + \sigma^2_{\breve{w}^k} \\ &+ 2\left(\gamma_w + \lambda_w\right)\left[\left(\rho + \lambda_w\right)\sigma_{\bar{e}^p,\bar{w}^p} + \left(\varrho_w + \lambda_w\right)\sigma_{\bar{e}^p,\bar{\pi}^p} + \lambda_w \sigma_{\bar{e}^p,\bar{q}^p}\right] \\ &+ 2\left(\rho + \lambda_w\right)\left[\left(\varrho_w + \lambda_w\right)\sigma_{\bar{w}^p,\bar{\pi}^p} + \lambda_w \sigma_{\bar{w}^p,\bar{q}^p}\right] + 2\lambda_w\left(\varrho_w + \lambda_w\right)\sigma_{\bar{\pi}^p,\bar{q}^p} \end{aligned} \tag{E.12}$$

$$\begin{aligned} Var\left(\bar{\pi}_f^p\right) &= \left(\gamma_\pi + \lambda_\pi\right)^2 \sigma^2_{\bar{e}^p} + \left(\rho_\pi + \lambda_\pi\right)^2 \sigma^2_{\bar{w}^p} + \left(\varrho + \lambda_\pi\right)^2 \sigma^2_{\bar{\pi}^p} + \lambda_\pi^2 \sigma^2_{\bar{q}^p} + \sigma^2_{\breve{\pi}^k} \\ &+ 2\left(\gamma_\pi + \lambda_\pi\right)\left[\left(\rho_\pi + \lambda_\pi\right)\sigma_{\bar{e}^p,\bar{w}^p} + \left(\varrho + \lambda_\pi\right)\sigma_{\bar{e}^p,\bar{\pi}^p} + \lambda_\pi \sigma_{\bar{e}^p,\bar{q}^p}\right] \\ &+ 2\left(\rho_\pi + \lambda_\pi\right)\left[\left(\varrho + \lambda_\pi\right)\sigma_{\bar{w}^p,\bar{\pi}^p} + \lambda_\pi \sigma_{\bar{w}^p,\bar{q}^p}\right] + 2\lambda_\pi\left(\varrho + \lambda_\pi\right)\sigma_{\bar{\pi}^p,\bar{q}^p} \end{aligned} \tag{E.13}$$

$$
\begin{aligned}
Var\left(\bar{c}_f^k\right) &= (\lambda+\lambda_e+\lambda_w+\lambda_\pi)^2\sigma^2_{\bar{q}^p}+(\gamma+\lambda_e+\gamma_w+\lambda_w+\gamma_\pi+\lambda_\pi)^2\sigma^2_{\bar{e}^p}+\sigma^2_{\breve{q}^k}+\sigma^2_{\breve{e}^k}+\sigma^2_{\breve{w}^k}+\sigma^2_{\breve{\pi}^k}\\
&+ (\rho_e+\lambda_e+\rho+\lambda_w+\rho_\pi+\lambda_\pi)^2\sigma^2_{\bar{w}^p}+(\varrho_e+\lambda_e+\varrho_w+\lambda_w+\varrho+\lambda_\pi)^2\sigma^2_{\bar{\pi}^p}\\
&+ 2\left[(\gamma+\lambda_e+\gamma_w+\lambda_w+\gamma_\pi+\lambda_\pi)(\rho_e+\lambda_e+\rho+\lambda_w+\rho_\pi+\lambda_\pi)\sigma_{\bar{e}^p,\bar{w}^p}+\sigma_{\breve{e}^k,\breve{w}^k}\right]\\
&+ 2\left[(\gamma+\lambda_e+\gamma_w+\lambda_w+\gamma_\pi+\lambda_\pi)(\varrho_e+\lambda_e+\varrho_w+\lambda_w+\varrho+\lambda_\pi)\sigma_{\bar{e}^p,\bar{\pi}^p}+\sigma_{\breve{e}^k,\breve{\pi}^k}\right]\\
&+ 2\left[(\gamma+\lambda_e+\gamma_w+\lambda_w+\gamma_\pi+\lambda_\pi)(\lambda+\lambda_e+\lambda_w+\lambda_\pi)\sigma_{\bar{e}^p,\bar{q}^p}+\sigma_{\breve{e}^k,\breve{q}^k}\right]\\
&+ 2\left[(\rho_e+\lambda_e+\rho+\lambda_w+\rho_\pi+\lambda_\pi)(\varrho_e+\lambda_e+\varrho_w+\lambda_w+\varrho+\lambda_\pi)\sigma_{\bar{w}^p,\bar{\pi}^p}+\sigma_{\breve{w}^k,\breve{\pi}^k}\right]\\
&+ 2\left[(\rho_e+\lambda_e+\rho+\lambda_w+\rho_\pi+\lambda_\pi)(\lambda+\lambda_e+\lambda_w+\lambda_\pi)\sigma_{\bar{w}^p,\bar{q}^p}+\sigma_{\breve{w}^k,\breve{q}^k}\right]\\
&+ 2\left[(\varrho_e+\lambda_e+\varrho_w+\lambda_w+\varrho+\lambda_\pi)(\lambda+\lambda_e+\lambda_w+\lambda_\pi)\sigma_{\bar{\pi}^p,\bar{q}^p}+\sigma_{\breve{\pi}^k,\breve{q}^k}\right] \qquad \text{(E.14)}
\end{aligned}
$$

Child Covariance

$$
\begin{aligned}
Cov\left(\bar{e}_f^k,\bar{w}_f^k\right) &= (\gamma+\lambda_e)(\gamma_w+\lambda_w)\sigma^2_{\bar{e}^p}+(\rho_e+\lambda_e)(\rho+\lambda_w)\sigma^2_{\bar{w}^p}+(\varrho_e+\lambda_e)(\varrho_w+\lambda_w)\sigma^2_{\bar{\pi}^p}+\lambda_e\lambda_w\sigma^2_{\bar{q}^p}\\
&+ \sigma_{\breve{e}^k,\breve{w}^k}+\left[(\gamma+\lambda_e)(\rho+\lambda_w)+(\rho_e+\lambda_e)(\gamma_w+\lambda_w)\right]\sigma_{\bar{e}^p,\bar{w}^p}\\
&+ \left[(\gamma+\lambda_e)(\varrho_w+\lambda_w)+(\varrho_e+\lambda_e)(\gamma_w+\lambda_w)\right]\sigma_{\bar{e}^p,\bar{\pi}^p}\\
&+ \left[\lambda_w(\gamma+\lambda_e)+\lambda_e(\gamma_w+\lambda_w)\right]\sigma_{\bar{e}^p,\bar{q}^p}\\
&+ \left[(\rho_e+\lambda_e)(\varrho_w+\lambda_w)+(\varrho_e+\lambda_e)(\rho+\lambda_w)\right]\sigma_{\bar{w}^p,\bar{\pi}^p}\\
&+ \left[\lambda_w(\rho_e+\lambda_e)+\lambda_e(\rho+\lambda_w)\right]\sigma_{\bar{w}^p,\bar{q}^p}+\left[\lambda_w(\varrho_e+\lambda_e)+\lambda_e(\varrho_w+\lambda_w)\right]\sigma_{\bar{\pi}^p,\bar{q}^p} \qquad \text{(E.15)}\\
Cov\left(\bar{e}_f^k,\bar{\pi}_f^k\right) &= (\gamma+\lambda_e)(\gamma_\pi+\lambda_\pi)\sigma^2_{\bar{e}^p}+(\rho_e+\lambda_e)(\rho_\pi+\lambda_\pi)\sigma^2_{\bar{w}^p}+(\varrho_e+\lambda_e)(\varrho+\lambda_\pi)\sigma^2_{\bar{\pi}^p}+\lambda_e\lambda_\pi\sigma^2_{\bar{q}^p}\\
&+ \sigma_{\breve{e}^k,\breve{\pi}^k}+\left[(\gamma+\lambda_e)(\rho_\pi+\lambda_\pi)+(\varrho_e+\lambda_e)(\gamma_\pi+\lambda_\pi)\right]\sigma_{\bar{e}^p,\bar{w}^p}\\
&+ \left[(\gamma+\lambda_e)(\varrho+\lambda_\pi)+(\varrho_e+\lambda_e)(\gamma_\pi+\lambda_\pi)\right]\sigma_{\bar{e}^p,\bar{\pi}^p}\\
&+ \left[\lambda_\pi(\gamma+\lambda_e)+\lambda_e(\gamma_\pi+\lambda_\pi)\right]\sigma_{\bar{e}^p,\bar{q}^p}\\
&+ \left[(\rho_e+\lambda_e)(\varrho+\lambda_\pi)+(\varrho_e+\lambda_e)(\rho_\pi+\lambda_\pi)\right]\sigma_{\bar{w}^p,\bar{\pi}^p}\\
&+ \left[\lambda_\pi(\rho_e+\lambda_e)+\lambda_e(\rho_\pi+\lambda_\pi)\right]\sigma_{\bar{w}^p,\bar{q}^p}+\left[\lambda_\pi(\varrho_e+\lambda_e)+\lambda_e(\varrho+\lambda_\pi)\right]\sigma_{\bar{\pi}^p,\bar{q}^p} \qquad \text{(E.16)}\\
Cov\left(\bar{e}_f^k,\bar{c}_f^k\right) &= (\gamma+\lambda_e)(\gamma+\lambda_e+\gamma_w+\lambda_w+\gamma_\pi+\lambda_\pi)\sigma^2_{\bar{e}^p}\\
&+ (\rho_e+\lambda_e)(\rho_e+\lambda_e+\rho+\lambda_w+\rho_\pi+\lambda_\pi)\sigma^2_{\bar{w}^p}\\
&+ (\varrho_e+\lambda_e)(\varrho_e+\lambda_e+\varrho_w+\lambda_w+\varrho+\lambda_\pi)\sigma^2_{\bar{\pi}^p}+\lambda_e(\lambda+\lambda_e+\lambda_w+\lambda_\pi)\sigma^2_{\bar{q}^p}\\
&+ \sigma_{\breve{e}^k,\breve{q}^k}+\sigma_{\breve{e}^k,\breve{w}^k}+\sigma_{\breve{e}^k,\breve{\pi}^k}+\sigma^2_{\breve{e}^k}\\
&+ \left[(\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)\right]\sigma_{\bar{e}^p,\bar{w}^p}\\
&+ \left[(\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)\right]\sigma_{\bar{e}^p,\bar{\pi}^p}\\
&+ \left[(\gamma+\lambda_e)(\lambda+\lambda_e+\lambda_w+\lambda_\pi)+\lambda_e(\gamma+\lambda_e+\gamma_w+\lambda_w+\gamma_\pi+\lambda_\pi)\right]\sigma_{\bar{e}^p,\bar{q}^p}\\
&+ \left[(\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)\right]\sigma_{\bar{w}^p,\bar{\pi}^p}\\
&+ \left[(\rho_e+\lambda_e)(\lambda+\lambda_e+\lambda_w+\lambda_\pi)+\lambda_e(\rho_e+\lambda_e+\rho+\lambda_w+\rho_\pi+\lambda_\pi)\right]\sigma_{\bar{w}^p,\bar{q}^p}\\
&+ \left[(\varrho_e+\lambda_e)(\lambda+\lambda_e+\lambda_w+\lambda_\pi)+\lambda_e(\varrho_e+\lambda_e+\varrho_w+\lambda_w+\varrho+\lambda_\pi)\right]\sigma_{\bar{\pi}^p,\bar{q}^p} \qquad \text{(E.17)}
\end{aligned}
$$

$$
\begin{aligned}
Cov\left(\bar{w}_f^k, \bar{\pi}_f^k\right) &= (\gamma_w + \lambda_w)(\gamma_\pi + \lambda_\pi)\sigma^2_{\bar{e}^p} + (\rho + \gamma_w)(\rho_\pi + \lambda_\pi)\sigma^2_{\bar{w}^p} + (\varrho_w + \lambda_w)(\varrho + \lambda_\pi)\sigma^2_{\bar{\pi}^p} + \lambda_w\lambda_\pi\sigma^2_{\bar{q}^p} \\
&+ \sigma_{\breve{w}^k,\breve{\pi}^k} + \left[(\gamma_w + \lambda_w)(\rho_\pi + \lambda_\pi) + (\rho + \lambda_w)(\gamma_\pi + \lambda_\pi)\right]\sigma_{\bar{e}^p,\bar{w}^p} \\
&+ \left[(\gamma_w + \lambda_w)(\varrho + \lambda_\pi) + (\gamma_\pi + \lambda_\pi)(\varrho_w + \lambda_w)\right]\sigma_{\bar{e}^p,\bar{\pi}^p} \\
&+ \left[\lambda_\pi(\gamma_w + \lambda_w) + \lambda_w(\gamma_\pi + \lambda_\pi)\right]\sigma_{\bar{e}^p,\bar{q}^p} + \left[(\rho + \lambda_w)(\varrho + \lambda_\pi) + (\rho_\pi + \lambda_\pi)(\varrho_w + \lambda_w)\right]\sigma_{\bar{w}^p,\bar{\pi}^p} \\
&+ \left[\lambda_\pi(\rho + \lambda_w) + \lambda_w(\rho_\pi + \lambda_\pi)\right]\sigma_{\bar{w}^p,\bar{q}^p} + \left[\lambda_\pi(\varrho_w + \lambda_w) + \lambda_w(\varrho + \lambda_\pi)\right]\sigma_{\bar{\pi}^p,\bar{q}^p} \qquad \text{(E.18)} \\
Cov\left(\bar{w}_f^k, \bar{c}_f^k\right) &= (\gamma_w + \lambda_w)(\gamma + \lambda_e + \gamma_w + \lambda_w + \gamma_\pi + \lambda_\pi)\sigma^2_{\bar{e}^p} \\
&+ (\rho + \lambda_w)(\rho_e + \lambda_e + \rho + \lambda_w + \rho_\pi + \lambda_\pi)\sigma^2_{\bar{w}^p} \\
&+ (\varrho_w + \lambda_w)(\varrho_e + \lambda_e + \varrho_w + \lambda_w + \varrho + \lambda_\pi)\sigma^2_{\bar{\pi}^p} + \lambda_w(\lambda + \lambda_e + \lambda_w + \lambda_\pi)\sigma^2_{\bar{q}^p} \\
&+ \sigma_{\breve{w}^k,\breve{q}^k} + \sigma_{\breve{e}^k,\breve{w}^k} + \sigma_{\breve{w}^k,\breve{\pi}^k} + \sigma^2_{\breve{w}^k} \\
&+ \left[(\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)\right]\sigma_{\bar{e}^p,\bar{w}^p} \\
&+ \left[(\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)\right]\sigma_{\bar{e}^p,\bar{\pi}^p} \\
&+ \left[(\gamma_w + \lambda_w)(\lambda + \lambda_e + \lambda_w + \lambda_\pi) + \lambda_w(\gamma + \lambda_e + \gamma_w + \lambda_w + \gamma_\pi + \lambda_\pi)\right]\sigma_{\bar{e}^p,\bar{q}^p} \\
&+ \left[(\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)\right]\sigma_{\bar{w}^p,\bar{\pi}^p} \\
&+ \left[(\rho + \lambda_w)(\lambda + \lambda_e + \lambda_w + \lambda_\pi) + \lambda_w(\rho_e + \lambda_e + \rho + \lambda_w + \rho_\pi + \lambda_\pi)\right]\sigma_{\bar{w}^p,\bar{q}^p} \\
&+ \left[(\varrho_w + \lambda_w)(\lambda + \lambda_e + \lambda_w + \lambda_\pi) + \lambda_w(\varrho_e + \lambda_e + \varrho_w + \lambda_w + \varrho + \lambda_\pi)\right]\sigma_{\bar{\pi}^p,\bar{q}^p} \qquad \text{(E.19)} \\
Cov\left(\bar{\pi}_f^k, \bar{c}_f^k\right) &= (\gamma_\pi + \lambda_\pi)(\gamma + \lambda_e + \gamma_w + \lambda_w + \gamma_\pi + \lambda_\pi)\sigma^2_{\bar{e}^p} \\
&+ (\rho_\pi + \lambda_\pi)(\rho_e + \lambda_e + \rho + \lambda_w + \rho_\pi + \lambda_\pi)\sigma^2_{\bar{w}^p} \\
&+ (\varrho + \lambda_\pi)(\varrho_e + \lambda_e + \varrho_w + \lambda_w + \varrho + \lambda_\pi)\sigma^2_{\bar{\pi}^p} + \lambda_\pi(\lambda + \lambda_e + \lambda_w + \lambda_\pi)\sigma^2_{\bar{q}^p} \\
&+ \sigma_{\breve{\pi}^k,\breve{q}^k} + \sigma_{\breve{e}^k,\breve{\pi}^k} + \sigma_{\breve{w}^k,\breve{\pi}^k} + \sigma^2_{\breve{\pi}^k} \\
&+ \left[(\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)\right]\sigma_{\bar{e}^p,\bar{w}^p} \\
&+ \left[(\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)\right]\sigma_{\bar{e}^p,\bar{\pi}^p} \\
&+ \left[(\gamma_\pi + \lambda_\pi)(\lambda + \lambda_e + \lambda_w + \lambda_\pi) + \lambda_\pi(\gamma + \lambda_e + \gamma_w + \lambda_w + \gamma_\pi + \lambda_\pi)\right]\sigma_{\bar{e}^p,\bar{q}^p} \\
&+ \left[(\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)\right]\sigma_{\bar{w}^p,\bar{\pi}^p} \\
&+ \left[(\rho_\pi + \lambda_\pi)(\lambda + \lambda_e + \lambda_w + \lambda_\pi) + \lambda_\pi(\rho_e + \lambda_e + \rho + \lambda_w + \rho_\pi + \lambda_\pi)\right]\sigma_{\bar{w}^p,\bar{q}^p} \\
&+ \left[(\varrho + \lambda_\pi)(\lambda + \lambda_e + \lambda_w + \lambda_\pi) + \lambda_\pi(\varrho_e + \lambda_e + \varrho_w + \lambda_w + \varrho + \lambda_\pi)\right]\sigma_{\bar{\pi}^p,\bar{q}^p} \qquad \text{(E.20)}
\end{aligned}
$$

Cross-Generation Covariance

$$
\begin{aligned}
Cov\left(\bar{e}_f^p, \bar{e}_f^k\right) &= (\gamma + \lambda_e)\sigma^2_{\bar{e}^p} + (\rho_e + \lambda_e)\sigma_{\bar{e}^p,\bar{w}^p} + (\varrho_e + \lambda_e)\sigma_{\bar{e}^p,\bar{\pi}^p} + \lambda_e\sigma_{\bar{e}^p,\bar{q}^p} \qquad \text{(E.21)} \\
Cov\left(\bar{e}_f^p, \bar{w}_f^k\right) &= (\gamma_w + \lambda_w)\sigma^2_{\bar{e}^p} + (\rho + \lambda_w)\sigma_{\bar{e}^p,\bar{w}^p} + (\varrho_w + \lambda_w)\sigma_{\bar{e}^p,\bar{\pi}^p} + \lambda_w\sigma_{\bar{e}^p,\bar{q}^p} \qquad \text{(E.22)} \\
Cov\left(\bar{e}_f^p, \bar{\pi}_f^k\right) &= (\gamma_\pi + \lambda_\pi)\sigma^2_{\bar{e}^p} + (\rho_\pi + \lambda_\pi)\sigma_{\bar{e}^p,\bar{w}^p} + (\varrho + \lambda_\pi)\sigma_{\bar{e}^p,\bar{\pi}^p} + \lambda_\pi\sigma_{\bar{e}^p,\bar{q}^p} \qquad \text{(E.23)} \\
Cov\left(\bar{e}_f^p, \bar{c}_f^k\right) &= (\gamma + \lambda_e + \gamma_w + \lambda_w + \gamma_\pi + \lambda_\pi)\sigma^2_{\bar{e}^p} + (\rho_e + \lambda_e + \rho + \lambda_w + \rho_\pi + \lambda_\pi)\sigma_{\bar{e}^p,\bar{w}^p} \\
&+ (\varrho_e + \lambda_e + \varrho_w + \lambda_w + \varrho + \lambda_\pi)\sigma_{\bar{e}^p,\bar{\pi}^p} + (\lambda + \lambda_e + \lambda_w + \lambda_\pi)\sigma_{\bar{e}^p,\bar{q}^p} \qquad \text{(E.24)}
\end{aligned}
$$

$$
\begin{aligned}
Cov\left(\bar{w}_f^p,\bar{e}_f^k\right) &= \left(\gamma+\lambda_e\right)\sigma_{\bar{e}^p,\bar{w}^p}+\left(\rho_e+\lambda_e\right)\sigma^2_{\bar{w}^p}+\left(\varrho_e+\lambda_e\right)\sigma_{\bar{w}^p,\bar{\pi}^p}+\lambda_e\sigma_{\bar{w}^p,\bar{q}^p} && \text{(E.25)}\\
Cov\left(\bar{w}_f^p,\bar{w}_f^k\right) &= \left(\gamma_w+\lambda_w\right)\sigma_{\bar{e}^p,\bar{w}^p}+\left(\rho+\lambda_w\right)\sigma^2_{\bar{w}^p}+\left(\varrho_w+\lambda_w\right)\sigma_{\bar{w}^p,\bar{\pi}^p}+\lambda_w\sigma_{\bar{w}^p,\bar{q}^p} && \text{(E.26)}\\
Cov\left(\bar{w}_f^p,\bar{\pi}_f^k\right) &= \left(\gamma_\pi+\lambda_\pi\right)\sigma_{\bar{e}^p,\bar{w}^p}+\left(\rho_\pi+\lambda_\pi\right)\sigma^2_{\bar{w}^p}+\left(\varrho+\lambda_\pi\right)\sigma_{\bar{w}^p,\bar{\pi}^p}+\lambda_\pi\sigma_{\bar{w}^p,\bar{q}^p} && \text{(E.27)}\\
Cov\left(\bar{w}_f^p,\bar{c}_f^k\right) &= \left(\gamma+\lambda_e+\gamma_w+\lambda_w+\gamma_\pi+\lambda_\pi\right)\sigma_{\bar{e}^p,\bar{w}^p}+\left(\rho_e+\lambda_e+\rho+\lambda_w+\rho_\pi+\lambda_\pi\right)\sigma^2_{\bar{w}^p}\\
&+ \left(\varrho_e+\lambda_e+\varrho_w+\lambda_w+\varrho+\lambda_\pi\right)\sigma_{\bar{w}^p,\bar{\pi}^p}+\left(\lambda+\lambda_e+\lambda_w+\lambda_\pi\right)\sigma_{\bar{w}^p,\bar{q}^p} && \text{(E.28)}\\
Cov\left(\bar{\pi}_f^p,\bar{e}_f^k\right) &= \left(\gamma+\lambda_e\right)\sigma_{\bar{e}^p,\bar{\pi}^p}+\left(\rho_e+\lambda_e\right)\sigma_{\bar{w}^p,\bar{\pi}^p}+\left(\varrho_e+\lambda_e\right)\sigma^2_{\bar{\pi}^p}+\lambda_e\sigma_{\bar{\pi}^p,\bar{q}^p} && \text{(E.29)}\\
Cov\left(\bar{\pi}_f^p,\bar{w}_f^k\right) &= \left(\gamma_w+\lambda_w\right)\sigma_{\bar{e}^p,\bar{\pi}^p}+\left(\rho+\lambda_w\right)\sigma_{\bar{w}^p,\bar{\pi}^p}+\left(\varrho_w+\lambda_w\right)\sigma^2_{\bar{\pi}^p}+\lambda_w\sigma_{\bar{\pi}^p,\bar{q}^p} && \text{(E.30)}\\
Cov\left(\bar{\pi}_f^p,\bar{\pi}_f^k\right) &= \left(\gamma_\pi+\lambda_\pi\right)\sigma_{\bar{e}^p,\bar{\pi}^p}+\left(\rho_\pi+\lambda_\pi\right)\sigma_{\bar{w}^p,\bar{\pi}^p}+\left(\varrho+\lambda_\pi\right)\sigma^2_{\bar{\pi}^p}+\lambda_\pi\sigma_{\bar{\pi}^p,\bar{q}^p} && \text{(E.31)}\\
Cov\left(\bar{\pi}_f^p,\bar{c}_f^k\right) &= \left(\gamma+\lambda_e+\gamma_w+\lambda_w+\gamma_\pi+\lambda_\pi\right)\sigma_{\bar{e}^p,\bar{\pi}^p}+\left(\rho_e+\lambda_e+\rho+\lambda_w+\rho_\pi+\lambda_\pi\right)\sigma_{\bar{w}^p,\bar{\pi}^p}\\
&+ \left(\varrho_e+\lambda_e+\varrho_w+\lambda_w+\varrho+\lambda_\pi\right)\sigma^2_{\bar{\pi}^p}+\left(\lambda+\lambda_e+\lambda_w+\lambda_\pi\right)\sigma_{\bar{\pi}^p,\bar{q}^p} && \text{(E.32)}\\
Cov\left(\bar{c}_f^p,\bar{e}_f^k\right) &= \left(\gamma+\lambda_e\right)\sigma^2_{\bar{e}^p}+\left(\rho_e+\lambda_e\right)\sigma^2_{\bar{w}^p}+\left(\varrho_e+\lambda_e\right)\sigma^2_{\bar{\pi}^p}+\lambda_e\sigma^2_{\bar{q}^p}\\
&+ \left(\gamma+\rho_e+2\lambda_e\right)\sigma_{\bar{e}^p,\bar{w}^p}+\left(\gamma+\varrho_e+2\lambda_e\right)\sigma_{\bar{e}^p,\bar{\pi}^p}+\left(\gamma+2\lambda_e\right)\sigma_{\bar{e}^p,\bar{q}^p}\\
&+ \left(\rho_e+\varrho_e+2\lambda_e\right)\sigma_{\bar{w}^p,\bar{\pi}^p}+\left(\rho_e+2\lambda_e\right)\sigma_{\bar{w}^p,\bar{q}^p}+\left(\varrho_e+2\lambda_e\right)\sigma_{\bar{\pi}^p,\bar{q}^p} && \text{(E.33)}\\
Cov\left(\bar{c}_f^p,\bar{w}_f^k\right) &= \left(\gamma_w+\lambda_w\right)\sigma^2_{\bar{e}^p}+\left(\rho+\lambda_w\right)\sigma^2_{\bar{w}^p}+\left(\varrho_w+\lambda_w\right)\sigma^2_{\bar{\pi}^p}+\lambda_w\sigma^2_{\bar{q}^p}\\
&+ \left(\gamma_w+\rho+2\lambda_w\right)\sigma_{\bar{e}^p,\bar{w}^p}+\left(\gamma_w+\varrho_w+2\lambda_w\right)\sigma_{\bar{e}^p,\bar{\pi}^p}+\left(\gamma_w+2\lambda_w\right)\sigma_{\bar{e}^p,\bar{q}^p}\\
&+ \left(\rho+\varrho_w+2\lambda_w\right)\sigma_{\bar{w}^p,\bar{\pi}^p}+\left(\rho+2\lambda_w\right)\sigma_{\bar{w}^p,\bar{q}^p}+\left(\varrho_w+2\lambda_w\right)\sigma_{\bar{\pi}^p,\bar{q}^p} && \text{(E.34)}\\
Cov\left(\bar{c}_f^p,\bar{\pi}_f^k\right) &= \left(\gamma_\pi+\lambda_\pi\right)\sigma^2_{\bar{e}^p}+\left(\rho_\pi+\lambda_\pi\right)\sigma^2_{\bar{w}^p}+\left(\varrho+\lambda_\pi\right)\sigma^2_{\bar{\pi}^p}+\lambda_\pi\sigma^2_{\bar{q}^p}\\
&+ \left(\gamma_\pi+\rho_\pi+2\lambda_\pi\right)\sigma_{\bar{e}^p,\bar{w}^p}+\left(\gamma_\pi+\varrho+2\lambda_\pi\right)\sigma_{\bar{e}^p,\bar{\pi}^p}+\left(\gamma_\pi+2\lambda_\pi\right)\sigma_{\bar{e}^p,\bar{q}^p}\\
&+ \left(\rho_\pi+\varrho+2\lambda_\pi\right)\sigma_{\bar{w}^p,\bar{\pi}^p}+\left(\rho_\pi+2\lambda_\pi\right)\sigma_{\bar{w}^p,\bar{q}^p}+\left(\varrho+2\lambda_\pi\right)\sigma_{\bar{\pi}^p,\bar{q}^p} && \text{(E.35)}\\
Cov\left(\bar{c}_f^p,\bar{c}_f^k\right) &= \left(\gamma+\lambda_e+\gamma_w+\lambda_w+\gamma_\pi+\lambda_\pi\right)\sigma^2_{\bar{e}^p}+\left(\rho_e+\lambda_e+\rho+\lambda_w+\rho_\pi+\lambda_\pi\right)\sigma^2_{\bar{w}^p}\\
&+ \left(\varrho_e+\lambda_e+\varrho_w+\lambda_w+\varrho+\lambda_\pi\right)\sigma^2_{\bar{\pi}^p}+\left(\lambda+\lambda_e+\lambda_w+\lambda_\pi\right)\sigma^2_{\bar{q}^p}\\
&+ \left[\gamma+\gamma_w+\gamma_\pi+\rho_e+\rho+\rho_\pi+2\left(\lambda_e+\lambda_w+\lambda_\pi\right)\right]\sigma_{\bar{e}^p,\bar{w}^p}\\
&+ \left[\gamma+\gamma_w+\gamma_\pi+\varrho_e+\varrho_w+\varrho+2\left(\lambda_e+\lambda_w+\lambda_\pi\right)\right]\sigma_{\bar{e}^p,\bar{\pi}^p}\\
&+ \left[\gamma+\gamma_w+\gamma_\pi+\lambda+2\left(\lambda_e+\lambda_w+\lambda_\pi\right)\right]\sigma_{\bar{e}^p,\bar{q}^p}\\
&+ \left[\rho_e+\rho+\rho_\pi+\varrho_e+\varrho_w+\varrho+2\left(\lambda_e+\lambda_w+\lambda_\pi\right)\right]\sigma_{\bar{w}^p,\bar{\pi}^p}\\
&+ \left[\rho_e+\rho+\rho_\pi+\lambda+2\left(\lambda_e+\lambda_w+\lambda_\pi\right)\right]\sigma_{\bar{w}^p,\bar{q}^p}\\
&+ \left[\varrho_e+\varrho_w+\varrho+\lambda+2\left(\lambda_e+\lambda_w+\lambda_\pi\right)\right]\sigma_{\bar{\pi}^p,\bar{q}^p} && \text{(E.36)}
\end{aligned}
$$

There are 36 moment conditions, (E.1) through (E.36), to identify 33 parameters. One can immediately identify the parental parameters, $\sigma^2_{\bar{e}^p}$, $\sigma^2_{\bar{w}^p}$, $\sigma^2_{\bar{\pi}^p}$, $\sigma_{\bar{e}^p,\bar{w}^p}$, $\sigma_{\bar{e}^p,\bar{\pi}^p}$ and $\sigma_{\bar{w}^p,\bar{\pi}^p}$ from the moments (E.1), (E.2), (E.3), (E.5), (E.6) and (E.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 (E.7), (E.9) and (E.10) respectively. This leaves $\sigma^2_{\bar{q}^p}$ to be identified from (E.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 (E.21) through (E.36). First, we notice that (E.21), (E.25), (E.29) and (E.33) are 4 equations in 4 unknows - $(\gamma + \lambda_e)$, $(\rho_e + \lambda_e)$, $(\varrho_e + \lambda_e)$ and λ_e. Thus, these equations can be simulatenously used to identify the parameters γ, ρ_e, ϱ_e and λ_e. A similar argument can be used to identify ρ, γ_w, ϱ_w and λ_w from equations (E.22), (E.26), (E.30) and (E.34) jointly. The parameters ϱ, γ_π, ρ_π and λ_π are also identified by simultaneously considering the 4 equations (E.23), (E.27), (E.31) and (E.35). This leaves λ to be identified from equation (E.24).

Table 20: Intergenerational Elasticities

Variables	**Parameters**	**Model B** (1)	**Model C** (2)
Head Earnings: $\bar{e}^p_f$ on $\bar{e}^k_f$	γ	0.275	0.196
		(0.029)	(0.040)
$\bar{e}^p_f$ on $\bar{w}^k_f$	γ_w	0.232	0.147
		(0.043)	(0.042)
$\bar{e}^p_f$ on $\bar{\pi}^k_f$	γ_π	-	0.065
			(0.077)
Wife Earnings: $\bar{w}^p_f$ on $\bar{w}^k_f$	ρ	0.142	0.035
		(0.040)	(0.044)
$\bar{w}^p_f$ on $\bar{e}^k_f$	ρ_e	0.147	0.051
		(0.032)	(0.038)
$\bar{w}^p_f$ on $\bar{\pi}^k_f$	ρ_π	-	0.035
			(0.071)
Transfer Income: $\bar{\pi}^p_f$ on $\bar{\pi}^k_f$	ϱ	-	0.036
			(0.053)
$\bar{\pi}^p_f$ on $\bar{e}^k_f$	ϱ_e	-	-0.001
			(0.019)
$\bar{\pi}^p_f$ on $\bar{w}^k_f$	ϱ_w	-	0.055
			(0.021)
Consumption: $\bar{q}^p_f$ on $\bar{q}^k_f$	λ	0.374	0.084
		(0.060)	(0.054)
Parent-Child Pairs	*N*	459	459

Note: Bootstrap standard errors (100 repetitions) in parentheses. All columns use data that is purged of year and birth-cohort effects. Baseline II 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, $\sigma^2_{\breve{e}^k}$, $\sigma^2_{\breve{w}^k}$, $\sigma^2_{\breve{\pi}^k}$, $\sigma_{\breve{e}^k,\breve{w}^k}$, $\sigma_{\breve{e}^k,\breve{\pi}^k}$ and $\sigma_{\breve{w}^k,\breve{\pi}^k}$ can be identified from (E.11), (E.12), (E.13), (E.15), (E.16) and (E.18) respectively. This identifies $\sigma_{\breve{e}^k,\breve{q}^k}$, $\sigma_{\breve{w}^k,\breve{q}^k}$, $\sigma_{\breve{\pi}^k,\breve{q}^k}$ and $\sigma^2_{\breve{q}^k}$ from (E.17), (E.19), (E.20) and (E.14) respectively.

Table 21: Variances & Covariances

Variables	Parameters	Model B	Model C
		(1)	(2)
Variances of Parental Fixed Effects			
Head Earnings	$\sigma^2_{\bar{e}^p}$	0.296	0.293
		(0.032)	(0.026)
Wife Earnings	$\sigma^2_{\bar{w}^p}$	0.294	0.301
		(0.022)	(0.019)
Transfer Income	$\sigma^2_{\bar{\pi}^p}$	-	1.300
			(0.136)
Consumption	$\sigma^2_{\bar{q}^p}$	0.501	1.973
		(0.046)	(0.165)
Variances of Child Idiosyncratic Components			
Head Earnings	$\sigma^2_{\breve{e}^k}$	0.197	0.218
		(0.014)	(0.012)
Wife Earnings	$\sigma^2_{\breve{w}^k}$	0.297	0.311
		(0.021)	(0.021)
Transfer Income	$\sigma^2_{\breve{\pi}^k}$	-	1.067
			(0.087)
Consumption	$\sigma^2_{\breve{q}^k}$	0.463	1.828
		(0.029)	(0.124)
Covariances among Parental Fixed Effects			
Head Earnings & Wife Earnings	$\sigma_{\bar{e}^p,\bar{w}^p}$	0.063	0.067
		(0.015)	(0.015)
Head Earnings & Transfer Income	$\sigma_{\bar{e}^p,\bar{\pi}^p}$	-	0.043
			(0.036)
Head Earnings & Consumption	$\sigma_{\bar{e}^p,\bar{q}^p}$	-0.258	-0.298
		(0.030)	(0.049)
Wife Earnings & Transfer Income	$\sigma_{\bar{w}^p,\bar{\pi}^p}$	-	0.066
			(0.033)
Wife Earnings & Consumption	$\sigma_{\bar{w}^p,\bar{q}^p}$	-0.302	-0.389
		(0.031)	(0.046)
Transfer Income & Consumption	$\sigma_{\bar{\pi}^p,\bar{q}^p}$	-	-1.369
			(0.141)
Covariances among Child Idiosyncratic Components			
Head Earnings & Wife Earnings	$\sigma_{\breve{e}^k,\breve{w}^k}$	0.057	0.076
		(0.012)	(0.011)
Head Earnings & Transfer Income	$\sigma_{\breve{e}^k,\breve{\pi}^k}$	-	0.061
			(0.026)
Head Earnings & Consumption	$\sigma_{\breve{e}^k,\breve{q}^k}$	-0.201	-0.304
		(0.016)	(0.033)
Wife Earnings & Transfer Income	$\sigma_{\breve{w}^k,\breve{\pi}^k}$	-	0.098
			(0.030)
Wife Earnings & Consumption	$\sigma_{\breve{w}^k,\breve{q}^k}$	-0.291	-0.423
		(0.021)	(0.035)
Transfer Income & Consumption	$\sigma_{\breve{\pi}^k,\breve{q}^k}$	-	-1.183
			(0.098)
Parent-Child Pairs	*N*	459	459

Note: See Table 20 for details. Parameter estimates for Baseline II model using 459 parent-child pairs are as follows: $\sigma^2_{\bar{e}^p} = 0.296(0.027)$, $\sigma^2_{\bar{n}^p} = 0.457(0.032)$, $\sigma^2_{\bar{q}^p} = 0.646(0.043)$, $\sigma^2_{\breve{e}^k} = 0.207(0.014)$, $\sigma^2_{\breve{n}^k} = 0.442(0.038)$, $\sigma^2_{\breve{q}^k} = 0.594(0.043)$, $\sigma_{\bar{e}^p,\bar{n}^p} = 0.049(0.016)$, $\sigma_{\bar{e}^p,\bar{q}^p} = 0.244(0.026)$, $\sigma_{\bar{n}^p,\bar{q}^p} = 0.455(0.034)$, $\sigma_{\breve{e}^k,\breve{n}^k} = 0.050(0.015)$, $\sigma_{\breve{e}^k,\breve{q}^k} = 0.207(0.020)$, $\sigma_{\breve{n}^k,\breve{q}^k} = 0.423(0.038)$.

E.2 Liquidity Constraints

E.2.1 High Consumption Growth

We classify a household as constrained in year t if its growth rate in food expenditure between years t and $t+2$ is greater than 50% or the growth rate between years $t-2$ and t is less than -25% (i.e., a decrease of more than 50%). This approach (Crossley and Low, 2014) builds on the observation that binding constraints in year t are associated to much lower expenditures than preceding or following unconstrained periods. We estimate our baseline model by excluding such 'constrained' observations in four alternative ways: (i) drop parental observations only for those years in which they are classified as constrained but use the data from the unconstrained years to calculate the time average of the parental variables, (ii) drop all observations for a parent if he is constrained in at least one year in the data, (iii) drop observations for specific years when the households are constrained either in the parent or child generation, and (iv) drop all observations for a parent-child pair if either the parent or the child is constrained at least in one year. Results for these alternative cuts of the data are presented in Tables 22 and 23 below.

Table 22: Estimates of Intergenerational Elasticity

Variables	**Parameters**	**Baseline**	**No Constrained Parent**		**No Constrained Parent or Child**	
			Drop Observations	**Drop Households**	**Drop Observations**	**Drop Households**
		(1)	(2)	(3)	(4)	(5)
Head Earnings	γ	0.229	0.229	0.217	0.224	0.220
		(0.028)	(0.028)	(0.034)	(0.026)	(0.049)
Other Income	ρ	0.099	0.092	0.112	0.092	0.119
		(0.027)	(0.027)	(0.034)	(0.033)	(0.051)
$\bar{e}^p_f$ on $\bar{n}^k_f$	γ_n	0.208	0.207	0.214	0.203	0.262
		(0.035)	(0.035)	(0.047)	(0.031)	(0.069)
$\bar{n}^p_f$ on $\bar{e}^k_f$	ρ_e	0.055	0.059	0.055	0.059	0.080
		(0.019)	(0.019)	(0.024)	(0.017)	(0.034)
Consumption	λ	0.153	0.151	0.158	0.149	0.179
		(0.037)	(0.036)	(0.045)	(0.041)	(0.067)
Parent-Child Pairs	N	761	761	421	761	198

Note: A household in any generation is defined to be constrained for year t if either its consumption increases between years t and $t+2$ by at least 50% or its consumption decreases between years $t-2$ and t by at least 50%. In column (2) we drop parental observations for such constrained years but use data from unconstrained years to calculate the time-average of the variables for that parent. In column (3) we drop all observations for a parent if he is constrained at least once over his entire life cycle in our data. Column (4) is similar to column (2) in that we drop only observations for specific years when the households are constrained but column (4) drops also the constrained years for the children. Column (5) drops a parent-child pair if either the parent or the child is constrained at least once in our data.

Table 23: Parental Impact on Variance of Child Outcomes

Variables	**Baseline**	**No Constrained Parent**		**No Constrained Parent or Child**	
		Drop Observations	**Drop Households**	**Drop Observations**	**Drop Households**
	(1)	(2)	(3)	(4)	(5)
Head Earnings	7.9%	8.2%	8.2%	7.8%	8.0%
Other Income	4.4%	4.2%	5.7%	4.0%	6.2%
Consumption	30.1%	29.9%	32.7%	29.6%	38.9%
Parent-Child Pairs	761	761	421	761	198

Note: Results are based on parameter estimates in Table 22 and variance-covariance estimates not shown here.

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

We drop the top decile of households 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.

Table 24: Estimates of Intergenerational Elasticity

Variables	**Parameters**	**Baseline Sample**	**No Constrained Parent**	**No Constrained Parent or Child**
		(1)	(2)	(3)
Head Earnings	γ	0.229	0.244	0.239
		(0.028)	(0.027)	(0.028)
Other Income	ρ	0.099	0.097	0.087
		(0.027)	(0.029)	(0.033)
$\bar{e}^p_f$ on $\bar{n}^k_f$	γ_n	0.208	0.209	0.193
		(0.035)	(0.037)	(0.037)
$\bar{n}^p_f$ on $\bar{e}^k_f$	ρ_e	0.055	0.072	0.069
		(0.019)	(0.020)	(0.022)
Consumption	λ	0.153	0.190	0.172
		(0.037)	(0.041)	(0.045)
Parent-Child Pairs	*N*	761	648	576

Note: Bootstrap standard errors (100 repetitions) in parentheses. *No Constrained Parent* refers to a sample of parent-child pairs whose parents are in the bottom 90% of their generation in terms of the ratio of variance of food consumption to variance of head earnings over the lifetime. *No Constrained Parent or Child* refers to a sample of parent-child pairs whose households are in the bottom 90% in each generation in terms of the relative consumption volatility.

We show in Tables 24 and 25 that 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. In column (2) we drop the potentially constrained households only from the parental generation while we drop such households from both generations in column (3).

Table 25: Parental Importance for Child Inequality

Variables	Baseline Sample	No Constrained Parent	No Constrained Parent or Child
	(1)	(2)	(3)
Head Earnings	7.9%	9.2%	9.2%
Other Income	4.4%	4.1%	3.8%
Consumption	30.1%	28.7%	29.5%
Parent-Child Pairs	761	648	576

Note: Results are based on parameter estimates from Table 24 and variance-covariance parameter estimates not shown here.

E.2.3 Young Parents

Table 26: Estimates: Intergenerational Elasticities

Parameters	$ParentjAge^k < 35$	$ParentjAge^k < 30$	$ParentjAge^k < 25$	$ParentjAge^k < 20$
	(1)	(2)	(3)	(4)
γ	0.258	0.255	0.229	0.247
	(0.039)	(0.036)	(0.033)	(0.044)
ρ	0.125	0.126	0.118	0.100
	(0.046)	(0.038)	(0.033)	(0.036)
γ_n	0.183	0.190	0.226	0.207
	(0.054)	(0.044)	(0.055)	(0.049)
ρ_e	0.073	0.074	0.070	0.062
	(0.022)	(0.023)	(0.021)	(0.018)
λ	0.203	0.203	0.194	0.174
	(0.055)	(0.044)	(0.042)	(0.044)
λ_e	0.048	0.036	0.079	0.043
	(0.07)	(0.073)	(0.068)	(0.069)
λ_n	0.072	0.068	0.045	0.068
	(0.089)	(0.079)	(0.091)	(0.086)
N	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 (4) 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.

In Table 26, 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 27).

Table 27: Importance of Young Parental Heterogeneity for Child Inequality

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

Note: All numbers are percentages and are based on parameter estimates in Table 26 and the corresponding variance-covariance parameter estimates not shown here.

E.3 Optimal Parental Transfers

The optimization problem of the parent is given by:

$$\begin{aligned} \max_{\{C^p_{f,s},\mathcal{T}_{f,s}\}_{s=t}^{T}} \quad & \mathsf{E}_t \sum_{j=0}^{T-t} \beta^j \left[\frac{\left(C^p_{f,t+j}\right)^{1-\sigma}}{1-\sigma} + \mu_1 . \frac{\mathcal{T}_{f,t+j}^{1-\mu_2}}{1-\mu_2} \right] \\ & s.t. \\ A^p_{f,t+1} \quad = \quad & (1+r)\left(A^p_{f,t} + E^p_{f,t} + N^p_{f,t} - C^p_{f,t} - \mathcal{T}_{f,t}\right), \end{aligned} \tag{E.37}$$

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 $C^p_{f,t}$, one-period ahead resource $A^p_{f,t}$, and child expenditure $\mathcal{T}_{f,t}$ are as follows:

$$\left(C^p_{f,t}\right)^{-\sigma} = \mathsf{L}^p_t (1+r) \tag{E.38}$$

$$\mathsf{L}^p_t = \beta (1+r) \mathsf{E}_t \left(\mathsf{L}^p_{t+1}\right) \tag{E.39}$$

$$\mu_1 . \mathcal{T}_{f,t}^{-\mu_2} = \mathsf{L}^p_t (1+r) \tag{E.40}$$

where L^p_t is the Lagrange multiplier of the parent's period-t budget constraint. Combining equations (E.38) and (E.39) yields the usual consumption Euler equation:

$$\left(C^p_{f,t}\right)^{-\sigma} = \beta (1+r) \mathsf{E}_t \left[\left(C^p_{f,t+1}\right)^{-\sigma}\right] \tag{E.41}$$

Combining the first order conditions (E.38) and (E.40), we get the following intra-temporal optimality condition in logarithms:

$$\begin{aligned} \ln\left(\mathcal{T}_{f,t}\right) \equiv \tau_{f,t} &= \frac{\ln\left(\mu_1\right)}{\mu_2} + \frac{\sigma}{\mu_2}.c^p_{f,t} \\ \implies \bar{\tau}_f &= \frac{\ln\left(\mu_1\right)}{\mu_2} + \frac{\sigma}{\mu_2}.\bar{c}^p_f \end{aligned} \tag{E.42}$$

We assume that the child's human capital, H^k_f is partly determined by the parental expenditure on the child and partly by his own ability to convert that parental expenditure into human capital, Γ^k_f. In particular, we assume a human capital production function: $H^k_f = \Gamma^k_f.\left(\prod_{t=G^p_{25}}^{G^p_{65}} \mathcal{T}_{f,t}\right)^{\frac{\eta_1}{G^p_{65}-G^p_{25}}}$ 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^p_{25} through G^p_{65}). Taking logarithm of the human capital production function, we can express the child's human capital in terms of the average parental log-consumption:

$$\begin{aligned} h^k_f \equiv \ln\left(H^k_f\right) &= \ln\left(\Gamma^k_f\right) + \frac{\eta_1}{G^p_{65} - G^p_{25}}.\sum_{t=G^p_{25}}^{G^p_{65}} \ln\left(\mathcal{T}_{f,t}\right) \\ &= \ln\left(\Gamma^k_f\right) + \frac{\eta_1}{G^p_{65} - G^p_{25}}.\sum_{t=G^p_{25}}^{G^p_{65}} \frac{\ln\left(\mu_1\right) + \sigma.c^p_{f,t}}{\mu_2} \\ &= \ln\left(\Gamma^k_f\right) + \frac{\eta_1 \ln\left(\mu_1\right)}{\mu_2} + \left(\frac{\eta_1\sigma}{\mu_2}\right).\bar{c}^p_f \end{aligned} \tag{E.43}$$

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, $\bar{e}^k_f = \ln(w) + \eta_2.h^k_f$, where w is the labour market return to human capital averaged over the life-cycle of an individual, and the parameter η_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 Γ^k_f to convert parental expenditure on the child $\mathcal{T}_{f,t}$ into human capital H^k_f, the so-called 'smartness' or 'efficiency' of the child, Γ^k_f is partly determined by parental earnings and other income. In particular, we assume, $\ln\left(\Gamma^k_f\right) = \gamma^h \bar{e}^p_f + \rho^h_e \bar{n}^p_f + \breve{h}^k_f$, where $\breve{h}^k_f$ is the idiosyncratic smartness of the child that is not related to family background.

Combining the assumptions above, we get

$$\begin{aligned} \bar{e}^k_f &= \ln(w) + \eta_2 \left[\gamma^h \bar{e}^p_f + \rho^h_e \bar{n}^p_f + \breve{h}^k_f + \frac{\eta_1 \ln(\mu_1)}{\mu_2} + \left(\frac{\eta_1 \sigma}{\mu_2} \right) \bar{c}^p_f \right] \\ \Longrightarrow \bar{e}^k_f &= \left[\ln(w) + \frac{\eta_1 \eta_2 \ln(\mu_1)}{\mu_2} \right] + \gamma \bar{e}^p_f + \rho_e \bar{n}^p_f + \lambda_e \bar{c}^p_f + \breve{e}^k_f \end{aligned} \tag{E.44}$$

where $\gamma = \gamma^h \eta_2$, $\rho_e \equiv \rho^h_e \eta_2$, $\lambda_e \equiv \frac{\eta_1 \eta_2 \sigma}{\mu_2}$, and $\breve{e}^k_f \equiv \breve{h}^k_f \eta_2$. 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 (E.44) to yield equation (E.45):

$$\bar{e}^k_f = \gamma \bar{e}^p_f + \rho_e \bar{n}^p_f + \lambda_e \bar{c}^p_f + \breve{e}^k_f \tag{E.45}$$

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 (E.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 (E.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,

$$\bar{n}^k_f = \rho \bar{n}^p_f + \gamma_n \bar{e}^p_f + \lambda_n \bar{c}^p_f + \breve{n}^k_f \tag{E.46}$$

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 λ_e and λ_n). If either one of λ_e and λ_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

$$\text{Var}\left(\bar{e}_f^p\right) = \sigma_{\bar{e}^p}^2 \tag{E.47}$$

$$\text{Var}\left(\bar{n}_f^p\right) = \sigma_{\bar{n}^p}^2 \tag{E.48}$$

$$\text{Var}\left(\bar{c}_f^p\right) = \sigma_{\bar{q}^p}^2 + \sigma_{\bar{e}^p}^2 + \sigma_{\bar{n}^p}^2 + 2\left(\sigma_{\bar{e}^p,\bar{q}^p} + \sigma_{\bar{n}^p,\bar{q}^p} + \sigma_{\bar{e}^p,\bar{n}^p}\right) \tag{E.49}$$

Parental Covariance

$$\text{Cov}\left(\bar{e}_f^p, \bar{n}_f^p\right) = \sigma_{\bar{e}^p,\bar{n}^p} \tag{E.50}$$

$$\text{Cov}\left(\bar{e}_f^p, \bar{c}_f^p\right) = \sigma_{\bar{e}^p}^2 + \sigma_{\bar{e}^p,\bar{q}^p} + \sigma_{\bar{e}^p,\bar{n}^p} \tag{E.51}$$

$$\text{Cov}\left(\bar{n}_f^p, \bar{c}_f^p\right) = \sigma_{\bar{n}^p}^2 + \sigma_{\bar{n}^p,\bar{q}^p} + \sigma_{\bar{e}^p,\bar{n}^p} \tag{E.52}$$

Child Variance

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

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

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

Child Covariance

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

$$
\begin{aligned}
\mathrm{Cov}\left(\bar{e}_f^k, \bar{c}_f^k\right) &= (\gamma+\lambda_e)(\gamma+\gamma_n+\lambda_e+\lambda_n)\,\sigma^2_{\bar{e}^p} + (\rho_e+\lambda_e)(\rho+\rho_e+\lambda_e+\lambda_n)\,\sigma^2_{\bar{n}^p} \\
&+ \lambda_e(\lambda+\lambda_e+\lambda_n)\,\sigma^2_{\bar{q}^p} + \sigma^2_{\breve{e}^k} + \sigma_{\breve{e}^k,\breve{n}^k} + \sigma_{\breve{e}^k,\breve{q}^k} \\
&+ \left[(\gamma+\lambda_e)(\lambda+\lambda_e+\lambda_n) + \lambda_e(\gamma+\gamma_n+\lambda_e+\lambda_n)\right]\sigma_{\bar{e}^p,\bar{q}^p} \\
&+ \left[(\rho_e+\lambda_e)(\lambda+\lambda_e+\lambda_n) + \lambda_e(\rho+\rho_e+\lambda_e+\lambda_n)\right]\sigma_{\bar{n}^p,\bar{q}^p} \\
&+ \left[(\gamma+\lambda_e)(\rho+\rho_e+\lambda_e+\lambda_n) + (\rho_e+\lambda_n)(\gamma+\gamma_n+\lambda_e+\lambda_n)\right]\sigma_{\bar{e}^p,\bar{n}^p} \qquad \text{(E.57)} \\
\mathrm{Cov}\left(\bar{n}_f^k, \bar{c}_f^k\right) &= (\gamma_n+\lambda_n)(\gamma+\gamma_n+\lambda_e+\lambda_n)\,\sigma^2_{\bar{e}^p} + (\rho+\lambda_n)(\rho+\rho_e+\lambda_e+\lambda_n)\,\sigma^2_{\bar{n}^p} \\
&+ \lambda_n(\lambda+\lambda_e+\lambda_n)\,\sigma^2_{\bar{q}^p} + \sigma^2_{\breve{n}^k} + \sigma_{\breve{e}^k,\breve{n}^k} + \sigma_{\breve{n}^k,\breve{q}^k} \\
&+ \left[(\gamma_n+\lambda_n)(\lambda+\lambda_e+\lambda_n) + \lambda_n(\gamma+\gamma_n+\lambda_e+\lambda_n)\right]\sigma_{\bar{e}^p,\bar{q}^p} \\
&+ \left[(\rho+\lambda_n)(\lambda+\lambda_e+\lambda_n) + \lambda_n(\rho+\rho_e+\lambda_e+\lambda_n)\right]\sigma_{\bar{n}^p,\bar{q}^p} \\
&+ \left[(\gamma_n+\lambda_n)(\rho+\rho_e+\lambda_e+\lambda_n) + (\rho+\lambda_n)(\gamma+\gamma_n+\lambda_e+\lambda_n)\right]\sigma_{\bar{e}^p,\bar{n}^p} \qquad \text{(E.58)}
\end{aligned}
$$

Cross-generation Covariance

$$
\begin{aligned}
\mathrm{Cov}\left(\bar{e}_f^p, \bar{c}_f^k\right) &= (\gamma+\gamma_n+\lambda_e+\lambda_n)\,\sigma^2_{\bar{e}^p} \\
&+ (\lambda+\lambda_e+\lambda_n)\,\sigma_{\bar{e}^p,\bar{q}^p} + (\rho+\rho_e+\lambda_e+\lambda_n)\,\sigma_{\bar{e}^p,\bar{n}^p} \qquad \text{(E.59)} \\
\mathrm{Cov}\left(\bar{n}_f^p, \bar{c}_f^k\right) &= (\rho+\rho_e+\lambda_e+\lambda_n)\,\sigma^2_{\bar{n}^p} \\
&+ (\lambda+\lambda_e+\lambda_n)\,\sigma_{\bar{n}^p,\bar{q}^p} + (\gamma+\gamma_n+\lambda_e+\lambda_n)\,\sigma_{\bar{e}^p,\bar{n}^p} \qquad \text{(E.60)} \\
\mathrm{Cov}\left(\bar{c}_f^p, \bar{e}_f^k\right) &= (\gamma+\lambda_e)\left(\sigma^2_{\bar{e}^p} + \sigma_{\bar{e}^p,\bar{q}^p} + \sigma_{\bar{e}^p,\bar{n}^p}\right) + (\rho_e+\lambda_e)\left(\sigma^2_{\bar{n}^p} + \sigma_{\bar{n}^p,\bar{q}^p} + \sigma_{\bar{e}^p,\bar{n}^p}\right) \\
&+ \lambda_e\left(\sigma^2_{\bar{q}^p} + \sigma_{\bar{e}^p,\bar{q}^p} + \sigma_{\bar{n}^p,\bar{q}^p}\right) \qquad \text{(E.61)} \\
\mathrm{Cov}\left(\bar{c}_f^p, \bar{n}_f^k\right) &= (\gamma_n+\lambda_n)\left(\sigma^2_{\bar{e}^p} + \sigma_{\bar{e}^p,\bar{q}^p} + \sigma_{\bar{e}^p,\bar{n}^p}\right) + (\rho+\lambda_n)\left(\sigma^2_{\bar{n}^p} + \sigma_{\bar{n}^p,\bar{q}^p} + \sigma_{\bar{e}^p,\bar{n}^p}\right) \\
&+ \lambda_n\left(\sigma^2_{\bar{q}^p} + \sigma_{\bar{e}^p,\bar{q}^p} + \sigma_{\bar{n}^p,\bar{q}^p}\right) \qquad \text{(E.62)}
\end{aligned}
$$

$$
\begin{aligned}
\mathrm{Cov}\left(\bar{e}_f^p, \bar{e}_f^k\right) &= (\gamma+\lambda_e)\,\sigma^2_{\bar{e}^p} + (\rho_e+\lambda_e)\,\sigma_{\bar{e}^p,\bar{n}^p} + \lambda_e\sigma_{\bar{e}^p,\bar{q}^p} \qquad \text{(E.63)} \\
\mathrm{Cov}\left(\bar{n}_f^p, \bar{n}_f^k\right) &= (\rho+\lambda_n)\,\sigma^2_{\bar{n}^p} + (\gamma_n+\lambda_n)\,\sigma_{\bar{e}^p,\bar{n}^p} + \lambda_n\sigma_{\bar{n}^p,\bar{q}^p} \qquad \text{(E.64)} \\
\mathrm{Cov}\left(\bar{e}_f^p, \bar{n}_f^k\right) &= (\rho+\lambda_n)\,\sigma_{\bar{e}^p,\bar{n}^p} + (\lambda+\lambda_n)\,\sigma^2_{\bar{e}^p} + \lambda_n\sigma_{\bar{e}^p,\bar{q}^p} \qquad \text{(E.65)} \\
\mathrm{Cov}\left(\bar{n}_f^p, \bar{e}_f^k\right) &= (\gamma+\lambda_e)\,\sigma_{\bar{e}^p,\bar{n}^p} + (\rho_e+\lambda_e)\,\sigma^2_{\bar{n}^p} + \lambda_e\sigma_{\bar{n}^p,\bar{q}^p} \qquad \text{(E.66)} \\
\mathrm{Cov}\left(\bar{c}_f^p, \bar{c}_f^k\right) &= (\lambda+\lambda_e+\lambda_n)\left(\sigma^2_{\bar{q}^p} + \sigma_{\bar{e}^p,\bar{q}^p} + \sigma_{\bar{n}^p,\bar{q}^p}\right) \\
&+ (\gamma+\gamma_n+\lambda_e+\lambda_n)\left(\sigma^2_{\bar{e}^p} + \sigma_{\bar{e}^p,\bar{q}^p} + \sigma_{\bar{e}^p,\bar{n}^p}\right) \\
&+ (\rho+\rho_e+\lambda_e+\lambda_n)\left(\sigma^2_{\bar{n}^p} + \sigma_{\bar{n}^p,\bar{q}^p} + \sigma_{\bar{e}^p,\bar{n}^p}\right) \qquad \text{(E.67)}
\end{aligned}
$$

The parameters $\sigma^2_{\bar{e}^p}$, $\sigma^2_{\bar{n}^p}$ and $\sigma_{\bar{e}^p,\bar{n}^p}$ are directly identified from equations (E.47), (E.48) and (E.50) respectively. Consequently, $\sigma_{\bar{e}^p,\bar{q}^p}$ and $\sigma_{\bar{n}^p,\bar{q}^p}$ are identified from (E.51) and (E.52) respectively, which leaves the last parental variance parameter $\sigma^2_{\bar{q}^p}$ to be identified from (E.49). Considering equations (E.61), (E.63) and (E.66) together, we notice that these are 3 equations in 3 unknown parameter combinations — $(\gamma + \lambda_e)$, $(\rho_e + \lambda_e)$ and λ_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 γ, ρ_e and λ_e. Similarly, equations (E.62), (E.64) and (E.65) can be used to identify ρ, γ_n and λ_n simultaneously. The remaining inter-generational persistence parameter, λ is then identified from equation (E.59). Turning to the identification of the child parameters next, we notice that $\sigma^2_{\breve{e}^k}$, $\sigma^2_{\breve{n}^k}$ and $\sigma_{\breve{e}^k,\breve{n}^k}$ can now be identified from equations (E.53), (E.54) and (E.56) respectively. Finally, we note that equations (E.55), (E.57) and (E.58) can be simultaneously used to identify the remaining three idiosyncratic child parameters — $\sigma^2_{\breve{q}^k}$, $\sigma_{\breve{e}^k,\breve{q}^k}$ and $\sigma_{\breve{n}^k,\breve{q}^k}$.

Table 28: Intergenerational Elasticities (Optimal Parental Transfers)

Variables	**Parameters**	**Baseline** (1)	**Observable** (2)
Head Earnings	γ	0.208	0.309
		(0.035)	(0.026)
Other Income	ρ	0.094	0.221
		(0.028)	(0.048)
$\bar{e}^p_f$ on $\bar{n}^k_f$	γ_n	0.175	0.208
		(0.040)	(0.034)
$\bar{n}^p_f$ on $\bar{e}^k_f$	ρ_e	0.052	0.095
		(0.018)	(0.033)
Consumption	λ	0.151	0.448
		(0.033)	(0.047)
Parental Transfers $\left(\bar{c}^p_f\right)$ on $\bar{e}^k_f$	λ_e	0.060	0.100
		(0.065)	(0.052)
Parental Transfers $\left(\bar{c}^p_f\right)$ on $\bar{n}^k_f$	λ_n	0.091	0.172
		(0.066)	(0.079)
Parent-Child Pairs	N	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 28, while the variance-covariance parameters are shown in Table 29. Table 8 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, λ_e and λ_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 29: Variance-Covariance of Idiosyncratic Components (Optimal Parental Transfers)

	Parameters	Baseline (1)	Observable (2)
Variances of Parental Fixed Effects			
Head Earnings	$\sigma^2_{\bar{e}^p}$	0.297	0.095
		(0.021)	(0.005)
Other Income	$\sigma^2_{\bar{n}^p}$	0.805	0.085
		(0.065)	(0.008)
Consumption	$\sigma^2_{\bar{q}^p}$	1.036	0.197
		(0.073)	(0.018)
Variances of Child Idiosyncratic Components			
Head Earnings	$\sigma^2_{\breve{e}^k}$	0.229	0.041
		(0.015)	(0.002)
Other Income	$\sigma^2_{\breve{n}^k}$	0.511	0.062
		(0.037)	(0.004)
Consumption	$\sigma^2_{\breve{q}^k}$	0.734	0.106
		(0.052)	(0.006)
Covariances among Parental Fixed Effects			
Consumption & Head Earnings	$\sigma_{\bar{e}^p,\bar{q}^p}$	-0.274	-0.121
		(0.023)	(0.008)
Consumption & Other Income	$\sigma_{\bar{n}^p,\bar{q}^p}$	-0.817	-0.116
		(0.067)	(0.012)
Head Earnings and Other Income	$\sigma_{\bar{e}^p,\bar{n}^p}$	0.070	0.060
		(0.016)	(0.006)
Covariances among Child Idiosyncratic Components			
Consumption & Head Earnings	$\sigma_{\breve{e}^k,\breve{q}^k}$	-0.250	-0.059
		(0.023)	(0.003)
Consumption & Other Income	$\sigma_{\breve{n}^k,\breve{q}^k}$	-0.525	-0.070
		(0.040)	(0.004)
Head Earnings & Other Income	$\sigma_{\breve{e}^k,\breve{n}^k}$	0.076	0.031
		(0.015)	(0.002)
Parent-Child Pairs	*N*	761	761

Note: See notes to Table 28.

F Appendix to Section 7

F.1 Panel Variation with Persistent and Transitory Shocks

F.1.1 Model: Structure, Moments and Identification

(i) Structure. The general model of intergenerational linkages in individual fixed effects considered in this work is summarized by the following 6 equations. Note that this includes AR(1) persistent shocks and transitory shocks to head earnings, other income and consumption, as well as the full set of cross-elasticities among the two income sources and consumption (γ_n, ρ_e, λ_e and λ_n). Ignoring the consumption cross-elasticities λ_e and λ_n would yield the model presented in Section 2. Similarly, ignoring the shocks will yield the specification estimated in Section 6.3, while eliminating both the shocks and the consumption cross-elasticities simultaneously will deliver our baseline implementation with time-averaged variables and $\lambda_e = \lambda_n = 0$.

$$e^p_{f,t} = \bar{e}^p_f + \mathcal{E}^p_{f,t} + \varepsilon^p_{f,t} \tag{E.1}$$

$$\text{where } \mathcal{E}^p_{f,t} = \alpha^p_e \mathcal{E}^p_{f,t\ 1} + \epsilon^p_{f,t} \text{ with } \epsilon^p_{f,t} \overset{i.i.d.}{\sim} N\left(0, \sigma^2_{\epsilon^p}\right) \text{ and } \varepsilon^p_{f,t} \overset{i.i.d.}{\sim} N\left(0, \sigma^2_{\varepsilon^p}\right)$$

$$n^p_{f,t} = \bar{n}^p_f + \Theta^p_{f,t} + \vartheta^p_{f,t} \tag{E.2}$$

$$\text{where } \Theta^p_{f,t} = \alpha^p_n \Theta^p_{f,t\ 1} + \theta^p_{f,t} \text{ with } \theta^p_{f,t} \overset{i.i.d.}{\sim} N\left(0, \sigma^2_{\theta^p}\right) \text{ and } \vartheta^p_{f,t} \overset{i.i.d.}{\sim} N\left(0, \sigma^2_{\vartheta^p}\right)$$

$$c^p_{f,t} = \bar{q}^p_f + \bar{e}^p_f + \bar{n}^p_f + \Phi^p_{f,t} + \varphi^p_{f,t} + \frac{r\mathcal{E}^p_{f,t}}{1+r-\alpha^p_e} + \frac{r\Theta^p_{f,t}}{1+r-\alpha^p_n} + \frac{r}{1+r}\left(\varepsilon^p_{f,t} + \vartheta^p_{f,t}\right) \tag{E.3}$$

$$\text{where } \Phi^p_{f,t} = \alpha^p_q \Phi^p_{f,t\ 1} + \phi^p_{f,t} \text{ with } \phi^p_{f,t} \overset{i.i.d.}{\sim} N\left(0, \sigma^2_{\phi^p}\right) \text{ and } \varphi^p_{f,t} \overset{i.i.d.}{\sim} N\left(0, \sigma^2_{\varphi^p}\right)$$

$$e^k_{f,t} = (\gamma + \lambda_e)\,\bar{e}^p_f + (\rho_e + \lambda_e)\,\bar{n}^p_f + \lambda_e \bar{q}^p_f + \breve{e}^k_f + \mathcal{E}^k_{f,t} + \varepsilon^k_{f,t} \tag{E.4}$$

$$\text{where } \mathcal{E}^k_{f,t} = \alpha^k_e \mathcal{E}^k_{f,t\ 1} + \epsilon^k_{f,t} \text{ with } \epsilon^k_{f,t} \overset{i.i.d.}{\sim} N\left(0, \sigma^2_{\epsilon^k}\right) \text{ and } \varepsilon^k_{f,t} \overset{i.i.d.}{\sim} N\left(0, \sigma^2_{\varepsilon^k}\right)$$

$$n^k_{f,t} = (\rho + \lambda_n)\,\bar{n}^p_f + (\gamma_n + \lambda_n)\,\bar{e}^p_f + \lambda_n \bar{q}^p_f + \breve{n}^k_f + \Theta^k_{f,t} + \vartheta^k_{f,t} \tag{E.5}$$

$$\text{where } \Theta^k_{f,t} = \alpha^k_n \Theta^k_{f,t\ 1} + \theta^k_{f,t} \text{ with } \theta^k_{f,t} \overset{i.i.d.}{\sim} N\left(0, \sigma^2_{\theta^k}\right) \text{ and } \vartheta^k_{f,t} \overset{i.i.d.}{\sim} N\left(0, \sigma^2_{\vartheta^k}\right)$$

$$\begin{aligned} c^k_{f,t} = {} & (\lambda + \lambda_e + \lambda_n)\,\bar{q}^p_f + (\gamma + \gamma_n + \lambda_e + \lambda_n)\,\bar{e}^p_f + (\rho + \rho_e + \lambda_e + \lambda_n)\,\bar{n}^p_f + \breve{q}^k_f + \breve{e}^k_f + \breve{n}^k_f \\ & + \Phi^k_{f,t} + \varphi^k_{f,t} + \frac{r\mathcal{E}^k_{f,t}}{1+r-\alpha^k_e} + \frac{r\Theta^k_{f,t}}{1+r-\alpha^k_n} + \frac{r}{1+r}\left(\varepsilon^k_{f,t} + \vartheta^k_{f,t}\right) \end{aligned} \tag{E.6}$$

$$\text{where } \Phi^k_{f,t} = \alpha^k_q \Phi^k_{f,t\ 1} + \phi^k_{f,t} \text{ with } \phi^k_{f,t} \overset{i.i.d.}{\sim} N\left(0, \sigma^2_{\phi^k}\right) \text{ and } \varphi^k_{f,t} \overset{i.i.d.}{\sim} N\left(0, \sigma^2_{\varphi^k}\right)$$

(ii) Moment Restrictions. Here we present 75 moment conditions. While deriving expressions for these moment restrictions, we allow the innovations to the contemporaneous AR(1) persistent shocks to be correlated within a generation but later restrict them to be zero for simplification of the estimation procedure. All shocks are assumed to be uncorrelated across generations.

Parental Variance

$$Var\left(e^p_{f,t}\right) = \sigma^2_{\bar{e}^p} + \frac{\sigma^2_{\epsilon^p}}{1-\left(\alpha^p_e\right)^2} + \sigma^2_{\varepsilon^p} \tag{E.7}$$

$$Var\left(n^p_{f,t}\right) = \sigma^2_{\bar{n}^p} + \frac{\sigma^2_{\theta^p}}{1-\left(\alpha^p_n\right)^2} + \sigma^2_{\vartheta^p} \tag{E.8}$$

$$\begin{aligned} Var\left(c^p_{f,t}\right) &= \sigma^2_{\bar{q}^p} + \sigma^2_{\bar{e}^p} + \sigma^2_{\bar{n}^p} + 2\left(\sigma_{\bar{e}^p,\bar{q}^p} + \sigma_{\bar{n}^p,\bar{q}^p} + \sigma_{\bar{e}^p,\bar{n}^p}\right) + \sigma^2_{\varphi^p} \\ &+ \frac{2r\sigma_{\epsilon^p,\phi^p}}{\left(1+r-\alpha^p_e\right)\left(1-\alpha^p_e\alpha^p_q\right)} + \frac{2r\sigma_{\theta^p,\phi^p}}{\left(1+r-\alpha^p_n\right)\left(1-\alpha^p_n\alpha^p_q\right)} + \frac{\sigma^2_{\phi^p}}{1-\left(\alpha^p_q\right)^2} \\ &+ \left(\frac{r}{1+r}\right)^2\left(\sigma^2_{\varepsilon^p} + \sigma^2_{\vartheta^p}\right) + \left(\frac{r}{1+r-\alpha^p_e}\right)^2 \frac{\sigma^2_{\epsilon^p}}{1-\left(\alpha^p_e\right)^2} \\ &+ \left(\frac{r}{1+r-\alpha^p_n}\right)^2 \frac{\sigma^2_{\theta^p}}{1-\left(\alpha^p_n\right)^2} + \left[\frac{2r^2}{\left(1+r-\alpha^p_e\right)\left(1+r-\alpha^p_n\right)}\right]\frac{\sigma_{\epsilon^p,\theta^p}}{1-\alpha^p_e\alpha^p_n} \end{aligned} \tag{E.9}$$

Child Variance

$$\begin{aligned} Var\left(e^k_{f,t}\right) &= \left(\gamma+\lambda_e\right)^2\sigma^2_{\bar{e}^p} + \left(\rho_e+\lambda_e\right)^2\sigma^2_{\bar{n}^p} + \lambda_e^2\sigma^2_{\bar{q}^p} + \sigma^2_{\breve{e}^k} + \frac{\sigma^2_{\epsilon^k}}{1-\left(\alpha^k_e\right)^2} + \sigma^2_{\varepsilon^k} \\ &+ 2\left[\left(\gamma+\lambda_e\right)\left(\rho_e+\lambda_e\right)\sigma_{\bar{e}^p,\bar{n}^p} + \lambda_e\left(\gamma+\lambda_e\right)\sigma_{\bar{e}^p,\bar{q}^p} + \lambda_e\left(\rho_e+\lambda_e\right)\sigma_{\bar{n}^p,\bar{q}^p}\right] \end{aligned} \tag{E.10}$$

$$\begin{aligned} Var\left(n^k_{f,t}\right) &= \left(\gamma_n+\lambda_n\right)^2\sigma^2_{\bar{e}^p} + \left(\rho+\lambda_n\right)^2\sigma^2_{\bar{n}^p} + \lambda_n^2\sigma^2_{\bar{q}^p} + \sigma^2_{\breve{n}^k} + \frac{\sigma^2_{\theta^k}}{1-\left(\alpha^k_n\right)^2} + \sigma^2_{\vartheta^k} \\ &+ 2\left[\left(\gamma_n+\lambda_n\right)\left(\rho+\lambda_n\right)\sigma_{\bar{e}^p,\bar{n}^p} + \lambda_n\left(\gamma_n+\lambda_n\right)\sigma_{\bar{e}^p,\bar{q}^p} + \lambda_n\left(\rho+\lambda_n\right)\sigma_{\bar{n}^p,\bar{q}^p}\right] \end{aligned} \tag{E.11}$$

$$\begin{aligned} Var\left(c^k_{f,t}\right) &= \left(\lambda+\lambda_e+\lambda_n\right)^2\sigma^2_{\bar{q}^p} + \left(\gamma+\gamma_n+\lambda_e+\lambda_n\right)^2\sigma^2_{\bar{e}^p} + \left(\rho+\rho_e+\lambda_e+\lambda_n\right)^2\sigma^2_{\bar{n}^p} \\ &+ 2\left(\gamma+\gamma_n+\lambda_e+\lambda_n\right)\left(\lambda+\lambda_e+\lambda_n\right)\sigma_{\bar{e}^p,\bar{q}^p} + 2\left(\rho+\rho_e+\lambda_e+\lambda_n\right)\left(\lambda+\lambda_e+\lambda_n\right)\sigma_{\bar{n}^p,\bar{q}^p} \\ &+ 2\left(\rho+\rho_e+\lambda_e+\lambda_n\right)\left(\gamma+\gamma_n+\lambda_e+\lambda_n\right)\sigma_{\bar{e}^p,\bar{n}^p} \\ &+ \sigma^2_{\breve{q}^k} + \sigma^2_{\breve{e}^k} + \sigma^2_{\breve{n}^k} + 2\left[\sigma_{\breve{e}^k,\breve{n}^k} + \sigma_{\breve{e}^k,\breve{q}^k} + \sigma_{\breve{n}^k,\breve{q}^k}\right] + \sigma^2_{\varphi^k} \\ &+ \frac{2r\sigma_{\epsilon^k,\phi^k}}{\left(1+r-\alpha^k_e\right)\left(1-\alpha^k_e\alpha^k_q\right)} + \frac{2r\sigma_{\theta^k,\phi^k}}{\left(1+r-\alpha^k_n\right)\left(1-\alpha^k_n\alpha^k_q\right)} + \frac{\sigma^2_{\phi^k}}{1-\left(\alpha^k_q\right)^2} \\ &+ \left(\frac{r}{1+r}\right)^2\left(\sigma^2_{\varepsilon^k} + \sigma^2_{\vartheta^k}\right) + \left(\frac{r}{1+r-\alpha^k_e}\right)^2 \frac{\sigma^2_{\epsilon^k}}{1-\left(\alpha^k_e\right)^2} \\ &+ \left(\frac{r}{1+r-\alpha^k_n}\right)^2 \frac{\sigma^2_{\theta^k}}{1-\left(\alpha^k_n\right)^2} + \left[\frac{2r^2}{\left(1+r-\alpha^k_e\right)\left(1+r-\alpha^k_n\right)}\right]\frac{\sigma_{\epsilon^k,\theta^k}}{1-\alpha^k_e\alpha^k_n} \end{aligned} \tag{E.12}$$

Contemporaneous Parental Covariance

$$
\begin{aligned}
Cov\left(e^p_{f,t}, n^p_{f,t}\right) &= \sigma_{\bar{e}^p,\bar{n}^p} + \frac{\sigma_{\epsilon^p,\theta^p}}{1-\alpha^p_e\alpha^p_n} && \text{(E.13)}\\
Cov\left(e^p_{ft}, c^p_{ft}\right) &= \sigma^2_{\bar{e}^p} + \sigma_{\bar{e}^p,\bar{q}^p} + \sigma_{\bar{e}^p,\bar{n}^p} + \left(\frac{r}{1+r-\alpha^p_e}\right)\frac{\sigma^2_{\epsilon^p}}{1-\left(\alpha^p_e\right)^2}\\
&+ \left(\frac{r}{1+r-\alpha^p_n}\right)\frac{\sigma_{\epsilon^p,\theta^p}}{1-\alpha^p_e\alpha^p_n} + \frac{\sigma_{\epsilon^p,\phi^p}}{1-\alpha^p_e\alpha^p_q} + \frac{r}{1+r}\sigma^2_{\varepsilon^p} && \text{(E.14)}\\
Cov\left(n^p_{f,t}, c^p_{f,t}\right) &= \sigma^2_{\bar{n}^p} + \sigma_{\bar{n}^p,\bar{q}^p} + \sigma_{\bar{e}^p,\bar{n}^p} + \left(\frac{r}{1+r-\alpha^p_n}\right)\frac{\sigma^2_{\theta^p}}{1-\left(\alpha^p_n\right)^2}\\
&+ \left(\frac{r}{1+r-\alpha^p_e}\right)\frac{\sigma_{\epsilon^p,\theta^p}}{1-\alpha^p_e\alpha^p_n} + \frac{\sigma_{\theta^p,\phi^p}}{1-\alpha^p_n\alpha^p_q} + \frac{r}{1+r}\sigma^2_{\vartheta^p} && \text{(E.15)}
\end{aligned}
$$

Contemporaneous Child Covariance

$$
\begin{aligned}
Cov\left(e^k_{f,t}, n^k_{f,t}\right) &= \left(\gamma+\lambda_e\right)\left(\gamma_n+\lambda_n\right)\sigma^2_{\bar{e}^p} + \left(\rho+\lambda_n\right)\left(\rho_e+\lambda_e\right)\sigma^2_{\bar{n}^p} + \lambda_e\lambda_n\sigma^2_{\bar{q}^p} + \sigma_{\breve{e}^k,\breve{n}^k} + \frac{\sigma_{\epsilon^k,\theta^k}}{1-\alpha^k_e\alpha^k_n}\\
&+ \left[\left(\rho+\lambda_n\right)\left(\gamma+\lambda_e\right) + \left(\rho_e+\lambda_e\right)\left(\gamma_n+\lambda_n\right)\right]\sigma_{\bar{e}^p,\bar{n}^p}\\
&+ \left[\lambda_n\left(\gamma+\lambda_e\right) + \lambda_e\left(\gamma_n+\lambda_n\right)\right]\sigma_{\bar{e}^p,\bar{q}^p} + \left[\lambda_n\left(\rho_e+\lambda_e\right) + \lambda_e\left(\rho+\lambda_n\right)\right]\sigma_{\bar{n}^p,\bar{q}^p} && \text{(E.16)}\\
Cov\left(e^k_{f,t}, c^k_{f,t}\right) &= \left(\gamma+\lambda_e\right)\left(\gamma+\gamma_n+\lambda_e+\lambda_n\right)\sigma^2_{\bar{e}^p} + \left(\rho_e+\lambda_e\right)\left(\rho+\rho_e+\lambda_e+\lambda_n\right)\sigma^2_{\bar{n}^p}\\
&+ \lambda_e\left(\lambda+\lambda_e+\lambda_n\right)\sigma^2_{\bar{q}^p} + \left[\left(\gamma+\lambda_e\right)\left(\lambda+\lambda_e+\lambda_n\right) + \lambda_e\left(\gamma+\gamma_n+\lambda_e+\lambda_n\right)\right]\sigma_{\bar{e}^p,\bar{q}^p}\\
&+ \left[\left(\rho_e+\lambda_e\right)\left(\lambda+\lambda_e+\lambda_n\right) + \lambda_e\left(\rho+\rho_e+\lambda_e+\lambda_n\right)\right]\sigma_{\bar{n}^p,\bar{q}^p}\\
&+ \left[\left(\gamma+\lambda_e\right)\left(\rho+\rho_e+\lambda_e+\lambda_n\right) + \left(\rho_e+\lambda_e\right)\left(\gamma+\gamma_n+\lambda_e+\lambda_n\right)\right]\sigma_{\bar{e}^p,\bar{n}^p}\\
&+ \sigma^2_{\breve{e}^k} + \sigma_{\breve{e}^k,\breve{n}^k} + \sigma_{\breve{e}^k,\breve{q}^k} + \frac{\sigma_{\epsilon^k,\phi^k}}{1-\alpha^k_e\alpha^k_q} + \frac{r}{1+r}\sigma^2_{\varepsilon^k}\\
&+ \left(\frac{r}{1+r-\alpha^k_e}\right)\frac{\sigma^2_{\epsilon^k}}{1-\left(\alpha^k_e\right)^2} + \left(\frac{r}{1+r-\alpha^k_n}\right)\frac{\sigma_{\epsilon^k,\theta^k}}{1-\alpha^k_e\alpha^k_n} && \text{(E.17)}\\
Cov\left(n^k_{f,t}, c^k_{f,t}\right) &= \left(\gamma_n+\lambda_n\right)\left(\gamma+\gamma_n+\lambda_e+\lambda_n\right)\sigma^2_{\bar{e}^p} + \left(\rho+\lambda_n\right)\left(\rho+\rho_e+\lambda_e+\lambda_n\right)\sigma^2_{\bar{n}^p}\\
&+ \lambda_n\left(\lambda+\lambda_e+\lambda_n\right)\sigma^2_{\bar{q}^p} + \left[\left(\gamma_n+\lambda_n\right)\left(\lambda+\lambda_e+\lambda_n\right) + \lambda_n\left(\gamma+\gamma_n+\lambda_e+\lambda_n\right)\right]\sigma_{\bar{e}^p,\bar{q}^p}\\
&+ \left[\left(\rho+\lambda_n\right)\left(\lambda+\lambda_e+\lambda_n\right) + \lambda_n\left(\rho+\rho_e+\lambda_e+\lambda_n\right)\right]\sigma_{\bar{n}^p,\bar{q}^p}\\
&+ \left[\left(\gamma_n+\lambda_n\right)\left(\rho+\rho_e+\lambda_e+\lambda_n\right) + \left(\rho+\lambda_n\right)\left(\gamma+\gamma_n+\lambda_e+\lambda_n\right)\right]\sigma_{\bar{e}^p,\bar{n}^p}\\
&+ \sigma^2_{\breve{n}^k} + \sigma_{\breve{e}^k,\breve{n}^k} + \sigma_{\breve{n}^k,\breve{q}^k} + \frac{\sigma_{\theta^k,\phi^k}}{1-\alpha^k_n\alpha^k_q} + \frac{r}{1+r}\sigma^2_{\vartheta^k}\\
&+ \left(\frac{r}{1+r-\alpha^k_n}\right)\frac{\sigma^2_{\theta^k}}{1-\left(\alpha^k_n\right)^2} + \left(\frac{r}{1+r-\alpha^k_e}\right)\frac{\sigma_{\epsilon^k,\theta^k}}{1-\alpha^k_e\alpha^k_n} && \text{(E.18)}
\end{aligned}
$$

Cross-Generation Covariance

$$
\begin{aligned}
Cov\left(e^p_{f,t}, c^k_{f,t}\right) &= (\gamma + \gamma_n + \lambda_e + \lambda_n)\,\sigma^2_{\bar{e}^p} \\
&+ (\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} \qquad (E.19)\\
Cov\left(n^p_{f,t}, c^k_{f,t}\right) &= (\rho + \rho_e + \lambda_e + \lambda_n)\,\sigma^2_{\bar{n}^p} \\
&+ (\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} \qquad (E.20)\\
Cov\left(c^p_{f,t}, e^k_{f,t}\right) &= (\gamma + \lambda_e)\left(\sigma^2_{\bar{e}^p} + \sigma_{\bar{e}^p,\bar{q}^p} + \sigma_{\bar{e}^p,\bar{n}^p}\right) + (\rho_e + \lambda_e)\left(\sigma^2_{\bar{n}^p} + \sigma_{\bar{n}^p,\bar{q}^p} + \sigma_{\bar{e}^p,\bar{n}^p}\right) \\
&+ \lambda_e\left(\sigma^2_{\bar{q}^p} + \sigma_{\bar{e}^p,\bar{q}^p} + \sigma_{\bar{n}^p,\bar{q}^p}\right) \qquad (E.21)\\
Cov\left(c^p_{f,t}, n^k_{f,t}\right) &= (\gamma_n + \lambda_n)\left(\sigma^2_{\bar{e}^p} + \sigma_{\bar{e}^p,\bar{q}^p} + \sigma_{\bar{e}^p,\bar{n}^p}\right) + (\rho + \lambda_n)\left(\sigma^2_{\bar{n}^p} + \sigma_{\bar{n}^p,\bar{q}^p} + \sigma_{\bar{e}^p,\bar{n}^p}\right) \\
&+ \lambda_n\left(\sigma^2_{\bar{q}^p} + \sigma_{\bar{e}^p,\bar{q}^p} + \sigma_{\bar{n}^p,\bar{q}^p}\right) \qquad (E.22)\\
Cov\left(e^p_{f,t}, e^k_{f,t}\right) &= (\gamma + \lambda_e)\,\sigma^2_{\bar{e}^p} + (\rho_e + \lambda_e)\,\sigma_{\bar{e}^p,\bar{n}^p} + \lambda_e\sigma_{\bar{e}^p,\bar{q}^p} \qquad (E.23)\\
Cov\left(n^p_{f,t}, n^k_{f,t}\right) &= (\rho + \lambda_n)\,\sigma^2_{\bar{n}^p} + (\gamma_n + \lambda_n)\,\sigma_{\bar{e}^p,\bar{n}^p} + \lambda_n\sigma_{\bar{n}^p,\bar{q}^p} \qquad (E.24)\\
Cov\left(e^p_{f,t}, n^k_{f,t}\right) &= (\rho + \lambda_n)\,\sigma_{\bar{e}^p,\bar{n}^p} + (\lambda + \lambda_n)\,\sigma^2_{\bar{e}^p} + \lambda_n\sigma_{\bar{e}^p,\bar{q}^p} \qquad (E.25)\\
\mathrm{Cov}\left(n^p_{f,t}, e^k_{f,t}\right) &= (\gamma + \lambda_e)\,\sigma_{\bar{e}^p,\bar{n}^p} + (\rho_e + \lambda_e)\,\sigma^2_{\bar{n}^p} + \lambda_e\sigma_{\bar{n}^p,\bar{q}^p} \qquad (E.26)\\
Cov\left(c^p_{f,t}, c^k_{f,t}\right) &= (\lambda + \lambda_e + \lambda_n)\left(\sigma^2_{\bar{q}^p} + \sigma_{\bar{e}^p,\bar{q}^p} + \sigma_{\bar{n}^p,\bar{q}^p}\right) \\
&+ (\gamma + \gamma_n + \lambda_e + \lambda_n)\left(\sigma^2_{\bar{e}^p} + \sigma_{\bar{e}^p,\bar{q}^p} + \sigma_{\bar{e}^p,\bar{n}^p}\right) \\
&+ (\rho + \rho_e + \lambda_e + \lambda_n)\left(\sigma^2_{\bar{n}^p} + \sigma_{\bar{n}^p,\bar{q}^p} + \sigma_{\bar{e}^p,\bar{n}^p}\right) \qquad (E.27)
\end{aligned}
$$

Non-contemporaneous Covariances (lead 1) for Parent

$$
\begin{aligned}
Cov\left(e^p_{f,t}, e^p_{f,t+1}\right) &= \sigma^2_{\bar{e}^p} + \frac{\alpha^p_e\sigma^2_{\epsilon^p}}{1-\left(\alpha^p_e\right)^2} \qquad (E.28)\\
Cov\left(n^p_{f,t}, n^p_{f,t+1}\right) &= \sigma^2_{\bar{n}^p} + \frac{\alpha^p_n\sigma^2_{\theta^p}}{1-\left(\alpha^p_n\right)^2} \qquad (E.29)\\
Cov\left(c^p_{f,t}, c^p_{f,t+1}\right) &= \sigma^2_{\bar{q}^p} + \sigma^2_{\bar{e}^p} + \sigma^2_{\bar{n}^p} + 2\left(\sigma_{\bar{e}^p,\bar{q}^p} + \sigma_{\bar{n}^p,\bar{q}^p} + \sigma_{\bar{e}^p,\bar{n}^p}\right) + \frac{\alpha^p_q\sigma^2_{\phi^p}}{1-\left(\alpha^p_q\right)^2} \\
&+ \left(\frac{r}{1+r-\alpha^p_e}\right)\frac{\left(\alpha^p_e+\alpha^p_q\right)\sigma_{\epsilon^p,\phi^p}}{1-\alpha^p_e\alpha^p_q} + \left(\frac{r}{1+r-\alpha^p_n}\right)\frac{\left(\alpha^p_n+\alpha^p_q\right)\sigma_{\theta^p,\phi^p}}{1-\alpha^p_n\alpha^p_q} \\
&+ \left(\frac{r}{1+r-\alpha^p_e}\right)^2\frac{\alpha^p_e\sigma^2_{\epsilon^p}}{1-\left(\alpha^p_e\right)^2} + \left(\frac{r}{1+r-\alpha^p_n}\right)^2\frac{\alpha^p_n\sigma^2_{\theta^p}}{1-\left(\alpha^p_n\right)^2} \\
&+ \left(\frac{r}{1+r-\alpha^p_e}\right)\left(\frac{r}{1+r-\alpha^p_n}\right)\frac{\left(\alpha^p_e+\alpha^p_n\right)\sigma_{\epsilon^p,\theta^p}}{1-\alpha^p_e\alpha^p_n} \qquad (E.30)\\
Cov\left(e^p_{f,t}, n^p_{f,t+1}\right) &= \sigma_{\bar{e}^p,\bar{n}^p} + \frac{\alpha^p_n\sigma_{\epsilon^p,\theta^p}}{1-\alpha^p_e\alpha^p_n} \qquad (E.31)\\
Cov\left(n^p_{f,t}, e^p_{f,t+1}\right) &= \sigma_{\bar{e}^p,\bar{n}^p} + \frac{\alpha^p_e\sigma_{\epsilon^p,\theta^p}}{1-\alpha^p_e\alpha^p_n} \qquad (E.32)
\end{aligned}
$$

$$\begin{aligned}
Cov\left(e^p_{f,t}, c^p_{f,t+1}\right) &= \sigma^2_{\bar{e}^p} + \sigma_{\bar{e}^p,\bar{q}^p} + \sigma_{\bar{e}^p,\bar{n}^p} + \frac{\alpha^p_q \sigma_{\epsilon^p,\phi^p}}{1-\alpha^p_e\alpha^p_q} \\
&+ \left(\frac{r}{1+r-\alpha^p_n}\right)\frac{\alpha^p_n \sigma_{\epsilon^p,\theta^p}}{1-\alpha^p_e\alpha^p_n} + \left(\frac{r}{1+r-\alpha^p_e}\right)\frac{\alpha^p_e \sigma^2_{\epsilon^p}}{1-\left(\alpha^p_e\right)^2} \qquad \text{(E.33)} \\
Cov\left(n^p_{f,t}, c^p_{f,t+1}\right) &= \sigma^2_{\bar{n}^p} + \sigma_{\bar{n}^p,\bar{q}^p} + \sigma_{\bar{e}^p,\bar{n}^p} + \frac{\alpha^p_q \sigma_{\theta^p,\phi^p}}{1-\alpha^p_n\alpha^p_q} \\
&+ \left(\frac{r}{1+r-\alpha^p_e}\right)\frac{\alpha^p_e \sigma_{\epsilon^p,\theta^p}}{1-\alpha^p_e\alpha^p_n} + \left(\frac{r}{1+r-\alpha^p_n}\right)\frac{\alpha^p_n \sigma^2_{\theta^p}}{1-\left(\alpha^p_n\right)^2} \qquad \text{(E.34)} \\
Cov\left(c^p_{f,t}, e^p_{f,t+1}\right) &= \sigma^2_{\bar{e}^p} + \sigma_{\bar{e}^p,\bar{q}^p} + \sigma_{\bar{e}^p,\bar{n}^p} + \frac{\alpha^p_e \sigma_{\epsilon^p,\phi^p}}{1-\alpha^p_e\alpha^p_q} \\
&+ \left(\frac{r}{1+r-\alpha^p_n}\right)\frac{\alpha^p_e \sigma_{\epsilon^p,\theta^p}}{1-\alpha^p_e\alpha^p_n} + \left(\frac{r}{1+r-\alpha^p_e}\right)\frac{\alpha^p_e \sigma^2_{\epsilon^p}}{1-\left(\alpha^p_e\right)^2} \qquad \text{(E.35)} \\
Cov\left(c^p_{f,t}, n^p_{f,t+1}\right) &= \sigma^2_{\bar{n}^p} + \sigma_{\bar{q}^p,\bar{n}^p} + \sigma_{\bar{e}^p,\bar{n}^p} + \frac{\alpha^p_n \sigma_{\theta^p,\phi^p}}{1-\alpha^p_n\alpha^p_q} \\
&+ \left(\frac{r}{1+r-\alpha^p_e}\right)\frac{\alpha^p_n \sigma_{\epsilon^p,\theta^p}}{1-\alpha^p_e\alpha^p_n} + \left(\frac{r}{1+r-\alpha^p_n}\right)\frac{\alpha^p_n \sigma^2_{\theta^p}}{1-\left(\alpha^p_n\right)^2} \qquad \text{(E.36)}
\end{aligned}$$

Non-contemporaneous Covariances (lead 1) for Child

$$\begin{aligned}
Cov\left(e^k_{f,t}, e^k_{f,t+1}\right) &= \left(\gamma+\lambda_e\right)^2\sigma^2_{\bar{e}^p} + \left(\rho_e+\lambda_e\right)^2\sigma^2_{\bar{n}^p} + \lambda^2_e\sigma^2_{\bar{q}^p} + \sigma^2_{\breve{e}^k} + \frac{\alpha^k_e\sigma^2_{\epsilon^k}}{1-\left(\alpha^k_e\right)^2} \\
&+ 2\lambda_e\left[\left(\gamma+\lambda_e\right)\sigma_{\bar{e}^p,\bar{q}^p} + \left(\rho_e+\lambda_e\right)\sigma_{\bar{n}^p,\bar{q}^p}\right] \\
&+ 2\left(\gamma+\lambda_e\right)\left(\rho_e+\lambda_e\right)\sigma_{\bar{e}^p,\bar{n}^p} \qquad \text{(E.37)} \\
Cov\left(n^k_{f,t}, n^k_{f,t+1}\right) &= \left(\gamma_n+\lambda_n\right)^2\sigma^2_{\bar{e}^p} + \left(\rho+\lambda_n\right)^2\sigma^2_{\bar{n}^p} + \lambda^2_n\sigma^2_{\bar{q}^p} + \sigma^2_{\breve{n}^k} + \frac{\alpha^k_n\sigma^2_{\theta^k}}{1-\left(\alpha^k_n\right)^2} \\
&+ 2\lambda_n\left[\left(\gamma_n+\lambda_n\right)\sigma_{\bar{e}^p,\bar{q}^p} + \left(\rho+\lambda_n\right)\sigma_{\bar{n}^p,\bar{q}^p}\right] \\
&+ 2\left(\gamma_n+\lambda_n\right)\left(\rho+\lambda_n\right)\sigma_{\bar{e}^p,\bar{n}^p} \qquad \text{(E.38)} \\
Cov\left(e^k_{f,t}, n^k_{f,t+1}\right) &= \left(\gamma+\lambda_e\right)\left(\gamma_n+\lambda_n\right)\sigma^2_{\bar{e}^p} + \left(\rho+\lambda_n\right)\left(\rho_e+\lambda_e\right)\sigma^2_{\bar{n}^p} + \lambda_e\lambda_n\sigma^2_{\bar{q}^p} + \sigma_{\breve{e}^k,\breve{n}^k} + \frac{\alpha^k_n\sigma_{\epsilon^k,\theta^k}}{1-\alpha^k_e\alpha^k_n} \\
&+ \left[\left(\rho+\lambda_n\right)\left(\gamma+\lambda_e\right) + \left(\rho_e+\lambda_e\right)\left(\gamma_n+\lambda_n\right)\right]\sigma_{\bar{e}^p,\bar{n}^p} \\
&+ \left[\lambda_n\left(\gamma+\lambda_e\right) + \lambda_e\left(\gamma_n+\lambda_n\right)\right]\sigma_{\bar{e}^p,\bar{q}^p} + \left[\lambda_n\left(\rho_e+\lambda_e\right) + \lambda_e\left(\rho+\lambda_n\right)\right]\sigma_{\bar{n}^p,\bar{q}^p} \qquad \text{(E.39)} \\
Cov\left(n^k_{f,t}, e^k_{f,t+1}\right) &= \left(\gamma+\lambda_e\right)\left(\gamma_n+\lambda_n\right)\sigma^2_{\bar{e}^p} + \left(\rho+\lambda_n\right)\left(\rho_e+\lambda_e\right)\sigma^2_{\bar{n}^p} + \lambda_e\lambda_n\sigma^2_{\bar{q}^p} + \sigma_{\breve{e}^k,\breve{n}^k} + \frac{\alpha^k_e\sigma_{\epsilon^k,\theta^k}}{1-\alpha^k_e\alpha^k_n} \\
&+ \left[\left(\rho+\lambda_n\right)\left(\gamma+\lambda_e\right) + \left(\rho_e+\lambda_e\right)\left(\gamma_n+\lambda_n\right)\right]\sigma_{\bar{e}^p,\bar{n}^p} \\
&+ \left[\lambda_n\left(\gamma+\lambda_e\right) + \lambda_e\left(\gamma_n+\lambda_n\right)\right]\sigma_{\bar{e}^p,\bar{q}^p} + \left[\lambda_n\left(\rho_e+\lambda_e\right) + \lambda_e\left(\rho+\lambda_n\right)\right]\sigma_{\bar{n}^p,\bar{q}^p} \qquad \text{(E.40)}
\end{aligned}$$

$$
\begin{aligned}
Cov\left(c_{f,t}^{k}, c_{f,t+1}^{k}\right) &= (\lambda+\lambda_e+\lambda_n)^2\,\sigma^2_{\bar{q}^p} + (\gamma+\gamma_n+\lambda_e+\lambda_n)^2\,\sigma^2_{\bar{e}^p} + (\rho+\rho_e+\lambda_e+\lambda_n)^2\,\sigma^2_{\bar{n}^p} \\
&+ 2\left(\gamma+\gamma_n+\lambda_e+\lambda_n\right)\left(\lambda+\lambda_e+\lambda_n\right)\sigma_{\bar{e}^p,\bar{q}^p} \\
&+ 2\left(\rho+\rho_e+\lambda_e+\lambda_n\right)\left(\lambda+\lambda_e+\lambda_n\right)\sigma_{\bar{n}^p,\bar{q}^p} \\
&+ 2\left(\rho+\rho_e+\lambda_e+\lambda_n\right)\left(\gamma+\gamma_n+\lambda_e+\lambda_n\right)\sigma_{\bar{e}^p,\bar{n}^p} \\
&+ \sigma^2_{\breve{q}^k} + \sigma^2_{\breve{e}^k} + \sigma^2_{\breve{n}^k} + 2\left[\sigma_{\breve{e}^k,\breve{n}^k} + \sigma_{\breve{e}^k,\breve{q}^k} + \sigma_{\breve{n}^k,\breve{q}^k}\right] + \frac{\alpha_q^k\sigma^2_{\phi^k}}{1-\left(\alpha_q^k\right)^2} \\
&+ \left(\frac{r}{1+r-\alpha_e^k}\right)\frac{\left(\alpha_e^k+\alpha_q^k\right)\sigma_{\epsilon^k,\phi^k}}{1-\alpha_e^k\alpha_q^k} + \left(\frac{r}{1+r-\alpha_n^k}\right)\frac{\left(\alpha_n^k+\alpha_q^k\right)\sigma_{\theta^k,\phi^k}}{1-\alpha_n^k\alpha_q^k} \\
&+ \left(\frac{r}{1+r-\alpha_e^k}\right)^2\frac{\alpha_e^k\sigma^2_{\epsilon^k}}{1-\left(\alpha_e^k\right)^2} + \left(\frac{r}{1+r-\alpha_n^k}\right)^2\frac{\alpha_n^k\sigma^2_{\theta^k}}{1-\left(\alpha_n^k\right)^2} \\
&+ \left(\frac{r}{1+r-\alpha_e^k}\right)\left(\frac{r}{1+r-\alpha_n^k}\right)\frac{\left(\alpha_e^k+\alpha_n^k\right)\sigma_{\epsilon^k,\theta^k}}{1-\alpha_e^k\alpha_n^k} \qquad \text{(E.41)}
\end{aligned}
$$

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

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

$$
\begin{aligned}
Cov\left(c_{f,t}^{k}, e_{f,t+1}^{k}\right) &= \left(\gamma+\lambda_{e}\right)\left(\gamma+\gamma_{n}+\lambda_{e}+\lambda_{n}\right)\sigma_{\bar{e}^{p}}^{2}+\left(\rho_{e}+\lambda_{e}\right)\left(\rho+\rho_{e}+\lambda_{e}+\lambda_{n}\right)\sigma_{\bar{n}^{p}}^{2}+\frac{\alpha_{e}^{k}\sigma_{\epsilon^{k},\phi^{k}}}{1-\alpha_{e}^{k}\alpha_{q}^{k}} \\
&+ \lambda_{e}\left(\lambda+\lambda_{e}+\lambda_{n}\right)\sigma_{\bar{q}^{p}}^{2}+\sigma_{\breve{e}^{k}}^{2}+\sigma_{\breve{e}^{k},\breve{n}^{k}}+\sigma_{\breve{e}^{k},\breve{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}} \\
&+ \left[\left(\gamma+\lambda_{e}\right)\left(\lambda+\lambda_{e}+\lambda_{n}\right)+\lambda_{e}\left(\gamma+\gamma_{n}+\lambda_{e}+\lambda_{n}\right)\right]\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-\left(\alpha_{e}^{k}\right)^{2}} \\
&+ \left[\left(\rho_{e}+\lambda_{e}\right)\left(\lambda+\lambda_{e}+\lambda_{n}\right)+\lambda_{e}\left(\rho+\rho_{e}+\lambda_{e}+\lambda_{n}\right)\right]\sigma_{\bar{n}^{p},\bar{q}^{p}} \\
&+ \left[\left(\gamma+\lambda_{e}\right)\left(\rho+\rho_{e}+\lambda_{e}+\lambda_{n}\right)+\left(\rho_{e}+\lambda_{e}\right)\left(\gamma+\gamma_{n}+\lambda_{e}+\lambda_{n}\right)\right]\sigma_{\bar{e}^{p},\bar{n}^{p}} \qquad \text{(E.44)} \\
Cov\left(c_{f,t}^{k}, n_{f,t+1}^{k}\right) &= \left(\gamma_{n}+\lambda_{n}\right)\left(\gamma+\gamma_{n}+\lambda_{e}+\lambda_{n}\right)\sigma_{\bar{e}^{p}}^{2}+\left(\rho+\lambda_{n}\right)\left(\rho+\rho_{e}+\lambda_{e}+\lambda_{n}\right)\sigma_{\bar{n}^{p}}^{2}+\frac{\alpha_{n}^{k}\sigma_{\theta^{k},\phi^{k}}}{1-\alpha_{n}^{k}\alpha_{q}^{k}} \\
&+ \lambda_{n}\left(\lambda+\lambda_{e}+\lambda_{n}\right)\sigma_{\bar{q}^{p}}^{2}+\sigma_{\breve{n}^{k}}^{2}+\sigma_{\breve{e}^{k},\breve{n}^{k}}+\sigma_{\breve{n}^{k},\breve{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}} \\
&+ \left[\left(\gamma_{n}+\lambda_{n}\right)\left(\lambda+\lambda_{e}+\lambda_{n}\right)+\lambda_{n}\left(\gamma+\gamma_{n}+\lambda_{e}+\lambda_{n}\right)\right]\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-\left(\alpha_{n}^{k}\right)^{2}} \\
&+ \left[\left(\rho+\lambda_{n}\right)\left(\lambda+\lambda_{e}+\lambda_{n}\right)+\lambda_{n}\left(\rho+\rho_{e}+\lambda_{e}+\lambda_{n}\right)\right]\sigma_{\bar{n}^{p},\bar{q}^{p}} \\
&+ \left[\left(\gamma_{n}+\lambda_{n}\right)\left(\rho+\rho_{e}+\lambda_{e}+\lambda_{n}\right)+\left(\rho+\lambda_{n}\right)\left(\gamma+\gamma_{n}+\lambda_{e}+\lambda_{n}\right)\right]\sigma_{\bar{e}^{p},\bar{n}^{p}} \qquad \text{(E.45)}
\end{aligned}
$$

Non-contemporaneous Covariances (lead 2) for Parent

$$Cov\left(e_{f,t}^{p}, e_{f,t+2}^{p}\right) = \sigma_{\bar{e}^{p}}^{2}+\frac{\left(\alpha_{e}^{p}\right)^{2}\sigma_{\epsilon^{p}}^{2}}{1-\left(\alpha_{e}^{p}\right)^{2}} \qquad \text{(E.46)}$$

$$Cov\left(n_{f,t}^{p}, n_{f,t+2}^{p}\right) = \sigma_{\bar{n}^{p}}^{2}+\frac{\left(\alpha_{n}^{p}\right)^{2}\sigma_{\theta^{p}}^{2}}{1-\left(\alpha_{n}^{p}\right)^{2}} \qquad \text{(E.47)}$$

$$
\begin{aligned}
Cov\left(c_{f,t}^{p}, c_{f,t+2}^{p}\right) &= \sigma_{\bar{q}^{p}}^{2}+\sigma_{\bar{e}^{p}}^{2}+\sigma_{\bar{n}^{p}}^{2}+2\left(\sigma_{\bar{q}^{p},\bar{e}^{p}}+\sigma_{\bar{q}^{p},\bar{n}^{p}}+\sigma_{\bar{e}^{p},\bar{n}^{p}}\right)+\frac{\left(\alpha_{q}^{p}\right)^{2}\sigma_{\phi^{p}}^{2}}{1-\left(\alpha_{q}^{p}\right)^{2}} \\
&+ \left(\frac{r}{1+r-\alpha_{e}^{p}}\right)\frac{\left(\left(\alpha_{e}^{p}\right)^{2}+\left(\alpha_{q}^{p}\right)^{2}\right)\sigma_{\epsilon^{p},\phi^{p}}}{1-\alpha_{e}^{p}\alpha_{q}^{p}}+\left(\frac{r}{1+r-\alpha_{n}^{p}}\right)\frac{\left(\left(\alpha_{n}^{p}\right)^{2}+\left(\alpha_{q}^{p}\right)^{2}\right)\sigma_{\theta^{p},\phi^{p}}}{1-\alpha_{n}^{p}\alpha_{q}^{p}} \\
&+ \left(\frac{r}{1+r-\alpha_{e}^{p}}\right)^{2}\frac{\left(\alpha_{e}^{p}\right)^{2}\sigma_{\epsilon^{p}}^{2}}{1-\left(\alpha_{e}^{p}\right)^{2}}+\left(\frac{r}{1+r-\alpha_{n}^{p}}\right)^{2}\frac{\left(\alpha_{n}^{p}\right)^{2}\sigma_{\theta^{p}}^{2}}{1-\left(\alpha_{n}^{p}\right)^{2}} \\
&+ \left(\frac{r}{1+r-\alpha_{e}^{p}}\right)\left(\frac{r}{1+r-\alpha_{n}^{p}}\right)\frac{\left(\left(\alpha_{e}^{p}\right)^{2}+\left(\alpha_{n}^{p}\right)^{2}\right)\sigma_{\epsilon^{p},\theta^{p}}}{1-\alpha_{e}^{p}\alpha_{n}^{p}} \qquad \text{(E.48)}
\end{aligned}
$$

$$Cov\left(e_{f,t}^{p}, n_{f,t+2}^{p}\right) = \sigma_{\bar{e}^{p},\bar{n}^{p}}+\frac{\left(\alpha_{n}^{p}\right)^{2}\sigma_{\epsilon^{p},\theta^{p}}}{1-\alpha_{e}^{p}\alpha_{n}^{p}} \qquad \text{(E.49)}$$

$$Cov\left(n_{f,t}^{p}, e_{f,t+2}^{p}\right) = \sigma_{\bar{e}^{p},\bar{n}^{p}}+\frac{\left(\alpha_{e}^{p}\right)^{2}\sigma_{\epsilon^{p},\theta^{p}}}{1-\alpha_{e}^{p}\alpha_{n}^{p}} \qquad \text{(E.50)}$$

$$Cov\left(e^p_{f,t},c^p_{f,t+2}\right) = \sigma^2_{\bar{e}^p}+\sigma_{\bar{e}^p,\bar{q}^p}+\sigma_{\bar{e}^p,\bar{n}^p}+\frac{\left(\alpha^p_q\right)^2\sigma_{\epsilon^p,\phi^p}}{1-\alpha^p_e\alpha^p_q} + \left(\frac{r}{1+r-\alpha^p_n}\right)\frac{\left(\alpha^p_n\right)^2\sigma_{\epsilon^p,\theta^p}}{1-\alpha^p_e\alpha^p_n}+\left(\frac{r}{1+r-\alpha^p_e}\right)\frac{\left(\alpha^p_e\right)^2\sigma^2_{\epsilon^p}}{1-\left(\alpha^p_e\right)^2} \quad (E.51)$$

$$Cov\left(n^p_{f,t},c^p_{f,t+2}\right) = \sigma^2_{\bar{n}^p}+\sigma_{\bar{n}^p,\bar{q}^p}+\sigma_{\bar{e}^p,\bar{n}^p}+\frac{\left(\alpha^p_q\right)^2\sigma_{\theta^p,\phi^p}}{1-\alpha^p_n\alpha^p_q} + \left(\frac{r}{1+r-\alpha^p_e}\right)\frac{\left(\alpha^p_e\right)^2\sigma_{\epsilon^p,\theta^p}}{1-\alpha^p_e\alpha^p_n}+\left(\frac{r}{1+r-\alpha^p_n}\right)\frac{\left(\alpha^p_n\right)^2\sigma^2_{\theta^p}}{1-\left(\alpha^p_n\right)^2} \quad (E.52)$$

$$Cov\left(c^p_{f,t},e^p_{f,t+2}\right) = \sigma^2_{\bar{e}^p}+\sigma_{\bar{e}^p,\bar{q}^p}+\sigma_{\bar{e}^p,\bar{n}^p}+\frac{\left(\alpha^p_e\right)^2\sigma_{\epsilon^p,\phi^p}}{1-\alpha^p_e\alpha^p_q} + \left(\frac{r}{1+r-\alpha^p_n}\right)\frac{\left(\alpha^p_e\right)^2\sigma_{\epsilon^p,\theta^p}}{1-\alpha^p_e\alpha^p_n}+\left(\frac{r}{1+r-\alpha^p_e}\right)\frac{\left(\alpha^p_e\right)^2\sigma^2_{\epsilon^p}}{1-\left(\alpha^p_e\right)^2} \quad (E.53)$$

$$Cov\left(c^p_{f,t},n^p_{f,t+2}\right) = \sigma^2_{\bar{n}^p}+\sigma_{\bar{q}^p,\bar{n}^p}+\sigma_{\bar{e}^p,\bar{n}^p}+\frac{\left(\alpha^p_n\right)^2\sigma_{\theta^p,\phi^p}}{1-\alpha^p_n\alpha^p_q} + \left(\frac{r}{1+r-\alpha^p_e}\right)\frac{\left(\alpha^p_n\right)^2\sigma_{\epsilon^p,\theta^p}}{1-\alpha^p_e\alpha^p_n}+\left(\frac{r}{1+r-\alpha^p_n}\right)\frac{\left(\alpha^p_n\right)^2\sigma^2_{\theta^p}}{1-\left(\alpha^p_n\right)^2} \quad (E.54)$$

Non-contemporaneous Covariances (lead 2) for Child

$$Cov\left(e^k_{f,t},e^k_{f,t+2}\right) = (\gamma+\lambda_e)^2\sigma^2_{\bar{e}^p}+(\rho_e+\lambda_e)^2\sigma^2_{\bar{n}^p}+\lambda_e^2\sigma^2_{\bar{q}^p}+\sigma^2_{\breve{e}^k}+\frac{\left(\alpha^k_e\right)^2\sigma^2_{\epsilon^k}}{1-\left(\alpha^k_e\right)^2} + 2\lambda_e\left[(\gamma+\lambda_e)\sigma_{\bar{e}^p,\bar{q}^p}+(\rho_e+\lambda_e)\sigma_{\bar{n}^p,\bar{q}^p}\right] + 2(\gamma+\lambda_e)(\rho_e+\lambda_e)\sigma_{\bar{e}^p,\bar{n}^p} \quad (E.55)$$

$$Cov\left(n^k_{f,t},n^k_{f,t+2}\right) = (\gamma_n+\lambda_n)^2\sigma^2_{\bar{e}^p}+(\rho+\lambda_n)^2\sigma^2_{\bar{n}^p}+\lambda_n^2\sigma^2_{\bar{q}^p}+\sigma^2_{\breve{n}^k}+\frac{\left(\alpha^k_n\right)^2\sigma^2_{\theta^k}}{1-\left(\alpha^k_n\right)^2} + 2\lambda_n\left[(\gamma_n+\lambda_n)\sigma_{\bar{e}^p,\bar{q}^p}+(\rho+\lambda_n)\sigma_{\bar{n}^p,\bar{q}^p}\right] + 2(\gamma_n+\lambda_n)(\rho+\lambda_n)\sigma_{\bar{e}^p,\bar{n}^p} \quad (E.56)$$

$$Cov\left(e^k_{f,t},n^k_{f,t+2}\right) = (\gamma+\lambda_e)(\gamma_n+\lambda_n)\sigma^2_{\bar{e}^p}+(\rho+\lambda_n)(\rho_e+\lambda_e)\sigma^2_{\bar{n}^p}+\lambda_e\lambda_n\sigma^2_{\bar{q}^p}+\sigma_{\breve{e}^k,\breve{n}^k}+\frac{\left(\alpha^k_n\right)^2\sigma_{\epsilon^k,\theta^k}}{1-\alpha^k_e\alpha^k_n} + \left[(\rho+\lambda_n)(\gamma+\lambda_e)+(\rho_e+\lambda_e)(\gamma_n+\lambda_n)\right]\sigma_{\bar{e}^p,\bar{n}^p} + \left[\lambda_n(\gamma+\lambda_e)+\lambda_e(\gamma_n+\lambda_n)\right]\sigma_{\bar{e}^p,\bar{q}^p}+\left[\lambda_n(\rho_e+\lambda_e)+\lambda_e(\rho+\lambda_n)\right]\sigma_{\bar{n}^p,\bar{q}^p} \quad (E.57)$$

$$Cov\left(n^k_{f,t},e^k_{f,t+2}\right) = (\gamma+\lambda_e)(\gamma_n+\lambda_n)\sigma^2_{\bar{e}^p}+(\rho+\lambda_n)(\rho_e+\lambda_e)\sigma^2_{\bar{n}^p}+\lambda_e\lambda_n\sigma^2_{\bar{q}^p}+\sigma_{\breve{e}^k,\breve{n}^k}+\frac{\left(\alpha^k_e\right)^2\sigma_{\epsilon^k,\theta^k}}{1-\alpha^k_e\alpha^k_n} + \left[(\rho+\lambda_n)(\gamma+\lambda_e)+(\rho_e+\lambda_e)(\gamma_n+\lambda_n)\right]\sigma_{\bar{e}^p,\bar{n}^p} + \left[\lambda_n(\gamma+\lambda_e)+\lambda_e(\gamma_n+\lambda_n)\right]\sigma_{\bar{e}^p,\bar{q}^p}+\left[\lambda_n(\rho_e+\lambda_e)+\lambda_e(\rho+\lambda_n)\right]\sigma_{\bar{n}^p,\bar{q}^p} \quad (E.58)$$

$$
\begin{aligned}
Cov\left(c_{f,t}^{k}, c_{f,t+2}^{k}\right) &= (\lambda+\lambda_e+\lambda_n)^2\,\sigma_{\bar{q}^p}^2 + (\gamma+\gamma_n+\lambda_e+\lambda_n)^2\,\sigma_{\bar{e}^p}^2 + (\rho+\rho_e+\lambda_e+\lambda_n)^2\,\sigma_{\bar{n}^p}^2 \\
&+ 2\left(\gamma+\gamma_n+\lambda_e+\lambda_n\right)\left(\lambda+\lambda_e+\lambda_n\right)\sigma_{\bar{e}^p,\bar{q}^p} \\
&+ 2\left(\rho+\rho_e+\lambda_e+\lambda_n\right)\left(\lambda+\lambda_e+\lambda_n\right)\sigma_{\bar{n}^p,\bar{q}^p} \\
&+ 2\left(\rho+\rho_e+\lambda_e+\lambda_n\right)\left(\gamma+\gamma_n+\lambda_e+\lambda_n\right)\sigma_{\bar{e}^p,\bar{n}^p} \\
&+ \sigma_{\breve{q}^k}^2 + \sigma_{\breve{e}^k}^2 + \sigma_{\breve{n}^k}^2 + 2\left[\sigma_{\breve{e}^k,\breve{n}^k} + \sigma_{\breve{e}^k,\breve{q}^k} + \sigma_{\breve{n}^k,\breve{q}^k}\right] + \frac{\left(\alpha_q^k\right)^2\sigma_{\phi^k}^2}{1-\left(\alpha_q^k\right)^2} \\
&+ \left(\frac{r}{1+r-\alpha_e^k}\right)\frac{\left(\left(\alpha_e^k\right)^2+\left(\alpha_q^k\right)^2\right)\sigma_{\epsilon^k,\phi^k}}{1-\alpha_e^k\alpha_q^k} + \left(\frac{r}{1+r-\alpha_n^k}\right)\frac{\left(\left(\alpha_n^k\right)^2+\left(\alpha_q^k\right)^2\right)\sigma_{\theta^k,\phi^k}}{1-\alpha_n^k\alpha_q^k} \\
&+ \left(\frac{r}{1+r-\alpha_e^k}\right)^2\frac{\left(\alpha_e^k\right)^2\sigma_{\epsilon^k}^2}{1-\left(\alpha_e^k\right)^2} + \left(\frac{r}{1+r-\alpha_n^k}\right)^2\frac{\left(\alpha_n^k\right)^2\sigma_{\theta^k}^2}{1-\left(\alpha_n^k\right)^2} \\
&+ \left(\frac{r}{1+r-\alpha_e^k}\right)\left(\frac{r}{1+r-\alpha_n^k}\right)\frac{\left(\left(\alpha_e^k\right)^2+\left(\alpha_n^k\right)^2\right)\sigma_{\epsilon^k,\theta^k}}{1-\alpha_e^k\alpha_n^k} \qquad \text{(E.59)}
\end{aligned}
$$

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

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

$$
\begin{aligned}
Cov\left(c_{f,t}^{k}, e_{f,t+2}^{k}\right) &= (\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{\left(\alpha_e^k\right)^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_{\breve{e}^k}^2 + \sigma_{\breve{e}^k,\breve{n}^k} + \sigma_{\breve{e}^k,\breve{q}^k} + \left(\frac{r}{1+r-\alpha_n^k}\right)\frac{\left(\alpha_e^k\right)^2\sigma_{\xi^k,\eta^k}}{1-\alpha_e^k\alpha_n^k} \\
&+ \left[(\gamma+\lambda_e)(\lambda+\lambda_e+\lambda_n)+\lambda_e(\gamma+\lambda+\lambda_e+\lambda_n)\right]\sigma_{\bar{e}^p,\bar{q}^p} + \left(\frac{r}{1+r-\alpha_e^p}\right)\frac{\left(\alpha_e^k\right)^2\sigma_{\epsilon^k}^2}{1-\left(\alpha_e^k\right)^2} \\
&+ \left[(\rho_e+\lambda_e)(\lambda+\lambda_e+\lambda_n)+\lambda_e(\rho+\rho_e+\lambda_e+\lambda_n)\right]\sigma_{\bar{n}^p,\bar{q}^p} \\
&+ \left[(\gamma+\lambda_e)(\rho+\rho_e+\lambda_e+\lambda_n)+(\rho_e+\lambda_e)(\gamma+\gamma_n+\lambda_e+\lambda_n)\right]\sigma_{\bar{e}^p,\bar{n}^p} \qquad \text{(E.62)} \\
Cov\left(c_{f,t}^{k}, n_{f,t+2}^{k}\right) &= (\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{\left(\alpha_n^k\right)^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_{\breve{n}^k}^2 + \sigma_{\breve{e}^k,\breve{n}^k} + \sigma_{\breve{n}^k,\breve{q}^k} + \left(\frac{r}{1+r-\alpha_e^k}\right)\frac{\left(\alpha_n^k\right)^2\sigma_{\epsilon^k,\theta^k}}{1-\alpha_e^k\alpha_n^k} \\
&+ \left[(\lambda+\lambda_n)(\lambda+\lambda_e+\lambda_n)+\lambda_n(\gamma+\gamma_n+\lambda_e+\lambda_n)\right]\sigma_{\bar{e}^p,\bar{q}^p} + \left(\frac{r}{1+r-\alpha_n^k}\right)\frac{\left(\alpha_n^k\right)^2\sigma_{\theta^k}^2}{1-\left(\alpha_n^k\right)^2} \\
&+ \left[(\rho+\lambda_n)(\lambda+\lambda_e+\lambda_n)+\lambda_n(\rho+\rho_e+\lambda_e+\lambda_n)\right]\sigma_{\bar{n}^p,\bar{q}^p} \\
&+ \left[(\gamma_n+\lambda_n)(\rho+\rho_e+\lambda_e+\lambda_n)+(\rho+\lambda_n)(\gamma+\gamma_n+\lambda_e+\lambda_n)\right]\sigma_{\bar{e}^p,\bar{n}^p} \qquad \text{(E.63)}
\end{aligned}
$$

Non-contemporaneous Covariances (lead 3) for Parent

$$
\begin{aligned}
Cov\left(e_{f,t}^{p}, e_{f,t+3}^{p}\right) &= \sigma_{\bar{e}^p}^2 + \frac{\left(\alpha_e^p\right)^3\sigma_{\epsilon^p}^2}{1-\left(\alpha_e^p\right)^2} \qquad \text{(E.64)} \\
Cov\left(n_{f,t}^{p}, n_{f,t+6}^{p}\right) &= \sigma_{\bar{n}^p}^2 + \frac{\left(\alpha_n^p\right)^3\sigma_{\theta^p}^2}{1-\left(\alpha_n^p\right)^2} \qquad \text{(E.65)} \\
Cov\left(c_{f,t}^{p}, c_{f,t+3}^{p}\right) &= \sigma_{\bar{q}^p}^2 + \sigma_{\bar{e}^p}^2 + \sigma_{\bar{n}^p}^2 + 2\left(\sigma_{\bar{e}^p,\bar{q}^p} + \sigma_{\bar{n}^p,\bar{q}^p} + \sigma_{\bar{e}^p,\bar{n}^p}\right) + \frac{\left(\alpha_q^p\right)^3\sigma_{\phi^p}^2}{1-\left(\alpha_q^p\right)^2} \\
&+ \left(\frac{r}{1+r-\alpha_e^p}\right)\frac{\left(\left(\alpha_e^p\right)^3+\left(\alpha_q^p\right)^3\right)\sigma_{\epsilon^p,\phi^p}}{1-\alpha_e^p\alpha_q^p} + \left(\frac{r}{1+r-\alpha_n^p}\right)\frac{\left(\left(\alpha_n^p\right)^3+\left(\alpha_q^p\right)^3\right)\sigma_{\theta^p,\phi^p}}{1-\alpha_n^p\alpha_q^p} \\
&+ \left(\frac{r}{1+r-\alpha_e^p}\right)^2\frac{\left(\alpha_e^p\right)^3\sigma_{\epsilon^p}^2}{1-\left(\alpha_e^p\right)^2} + \left(\frac{r}{1+r-\alpha_n^p}\right)^2\frac{\left(\alpha_n^p\right)^3\sigma_{\theta^p}^2}{1-\left(\alpha_n^p\right)^2} \\
&+ \left(\frac{r}{1+r-\alpha_e^p}\right)\left(\frac{r}{1+r-\alpha_n^p}\right)\frac{\left(\left(\alpha_e^p\right)^3+\left(\alpha_n^p\right)^3\right)\sigma_{\epsilon^p,\theta^p}}{1-\alpha_e^p\alpha_n^p} \qquad \text{(E.66)} \\
Cov\left(e_{f,t}^{p}, n_{f,t+3}^{p}\right) &= \sigma_{\bar{e}^p,\bar{n}^p} + \frac{\left(\alpha_n^p\right)^3\sigma_{\epsilon^p,\theta^p}}{1-\alpha_e^p\alpha_n^p} \qquad \text{(E.67)} \\
Cov\left(n_{f,t}^{p}, e_{f,t+3}^{p}\right) &= \sigma_{\bar{e}^p,\bar{n}^p} + \frac{\left(\alpha_e^p\right)^3\sigma_{\epsilon^p,\theta^p}}{1-\alpha_e^p\alpha_n^p} \qquad \text{(E.68)}
\end{aligned}
$$

$$Cov\left(e^p_{f,t},c^p_{f,t+6}\right) = \sigma^2_{\bar{e}^p}+\sigma_{\bar{e}^p,\bar{q}^p}+\sigma_{\bar{e}^p,\bar{n}^p}+\frac{\left(\alpha^p_q\right)^3\sigma_{\epsilon^p,\phi^p}}{1-\alpha^p_e\alpha^p_q} + \left(\frac{r}{1+r-\alpha^p_n}\right)\frac{\left(\alpha^p_n\right)^3\sigma_{\epsilon^p,\theta^p}}{1-\alpha^p_e\alpha^p_n}+\left(\frac{r}{1+r-\alpha^p_e}\right)\frac{\left(\alpha^p_e\right)^3\sigma^2_{\epsilon^p}}{1-\left(\alpha^p_e\right)^2} \quad (E.69)$$

$$Cov\left(n^p_{f,t},c^p_{f,t+3}\right) = \sigma^2_{\bar{n}^p}+\sigma_{\bar{n}^p,\bar{q}^p}+\sigma_{\bar{e}^p,\bar{n}^p}+\frac{\left(\alpha^p_q\right)^3\sigma_{\theta^p,\phi^p}}{1-\alpha^p_n\alpha^p_q} + \left(\frac{r}{1+r-\alpha^p_e}\right)\frac{\left(\alpha^p_e\right)^3\sigma_{\epsilon^p,\theta^p}}{1-\alpha^p_e\alpha^p_n}+\left(\frac{r}{1+r-\alpha^p_n}\right)\frac{\left(\alpha^p_n\right)^3\sigma^2_{\theta^p}}{1-\left(\alpha^p_n\right)^2} \quad (E.70)$$

$$Cov\left(c^p_{f,t},e^p_{f,t+3}\right) = \sigma^2_{\bar{e}^p}+\sigma_{\bar{e}^p,\bar{q}^p}+\sigma_{\bar{e}^p,\bar{n}^p}+\frac{\left(\alpha^p_e\right)^3\sigma_{\epsilon^p,\phi^p}}{1-\alpha^p_e\alpha^p_q} + \left(\frac{r}{1+r-\alpha^p_n}\right)\frac{\left(\alpha^p_e\right)^3\sigma_{\epsilon^p,\theta^p}}{1-\alpha^p_e\alpha^p_n}+\left(\frac{r}{1+r-\alpha^p_e}\right)\frac{\left(\alpha^p_e\right)^3\sigma^2_{\epsilon^p}}{1-\left(\alpha^p_e\right)^2} \quad (E.71)$$

$$Cov\left(c^p_{f,t},n^p_{f,t+3}\right) = \sigma^2_{\bar{n}^p}+\sigma_{\bar{q}^p,\bar{n}^p}+\sigma_{\bar{e}^p,\bar{n}^p}+\frac{\left(\alpha^p_n\right)^3\sigma_{\theta^p,\phi^p}}{1-\alpha^p_n\alpha^p_q} + \left(\frac{r}{1+r-\alpha^p_e}\right)\frac{\left(\alpha^p_n\right)^3\sigma_{\epsilon^p,\theta^p}}{1-\alpha^p_e\alpha^p_n}+\left(\frac{r}{1+r-\alpha^p_e}\right)\frac{\left(\alpha^p_n\right)^3\sigma^2_{\theta^p}}{1-\left(\alpha^p_n\right)^2} \quad (E.72)$$

Non-contemporaneous Covariances (lead 3) for Child

$$Cov\left(e^k_{f,t},e^k_{f,t+3}\right) = (\gamma+\lambda_e)^2\sigma^2_{\bar{e}^p}+(\rho_e+\lambda_e)^2\sigma^2_{\bar{n}^p}+\lambda_e^2\sigma^2_{\bar{q}^p}+\sigma^2_{\breve{e}^k}+\frac{\left(\alpha^k_e\right)^3\sigma^2_{\epsilon^k}}{1-\left(\alpha^k_e\right)^2} + 2\left[(\gamma+\lambda_e)(\rho_e+\lambda_e)\sigma_{\bar{e}^p,\bar{n}^p}+\lambda_e(\gamma+\lambda_e)\sigma_{\bar{e}^p,\bar{q}^p}+\lambda_e(\rho_e+\lambda_e)\sigma_{\bar{n}^p,\bar{q}^p}\right] \quad (E.73)$$

$$Cov\left(n^k_{f,t},n^k_{f,t+3}\right) = (\gamma_n+\lambda_n)^2\sigma^2_{\bar{e}^p}+(\rho+\lambda_n)^2\sigma^2_{\bar{n}^p}+\lambda_n^2\sigma^2_{\bar{q}^p}+\sigma^2_{\breve{n}^k}+\frac{\left(\alpha^k_n\right)^3\sigma^2_{\theta^k}}{1-\left(\alpha^k_n\right)^2} + 2\left[(\gamma_n+\lambda_n)(\rho+\lambda_n)\sigma_{\bar{e}^p,\bar{n}^p}+\lambda_n(\gamma_n+\lambda_n)\sigma_{\bar{e}^p,\bar{q}^p}+\lambda_n(\rho+\lambda_n)\sigma_{\bar{n}^p,\bar{q}^p}\right] \quad (E.74)$$

$$Cov\left(e^k_{f,t},n^k_{f,t+3}\right) = (\gamma+\lambda_e)(\gamma_n+\lambda_n)\sigma^2_{\bar{e}^p}+(\rho+\lambda_n)(\rho_e+\lambda_e)\sigma^2_{\bar{n}^p}+\lambda_e\lambda_n\sigma^2_{\bar{q}^p}+\sigma_{\breve{e}^k,\breve{n}^k}+\frac{\left(\alpha^k_n\right)^3\sigma_{\epsilon^k,\theta^k}}{1-\alpha^k_e\alpha^k_n} + \left[(\rho+\lambda_n)(\gamma+\lambda_e)+(\rho_e+\lambda_e)(\gamma_n+\lambda_n)\right]\sigma_{\bar{e}^p,\bar{n}^p} + \left[\lambda_n(\gamma+\lambda_e)+\lambda_e(\gamma_n+\lambda_n)\right]\sigma_{\bar{e}^p,\bar{q}^p}+\left[\lambda_n(\rho_e+\lambda_e)+\lambda_e(\rho+\lambda_n)\right]\sigma_{\bar{n}^p,\bar{q}^p} \quad (E.75)$$

$$Cov\left(n^k_{f,t},e^k_{f,t+3}\right) = (\gamma+\lambda_e)(\gamma_n+\lambda_n)\sigma^2_{\bar{e}^p}+(\rho+\lambda_n)(\rho_e+\lambda_e)\sigma^2_{\bar{n}^p}+\lambda_e\lambda_n\sigma^2_{\bar{q}^p}+\sigma_{\breve{e}^k,\breve{n}^k}+\frac{\left(\alpha^k_e\right)^3\sigma_{\epsilon^k,\theta^k}}{1-\alpha^k_e\alpha^k_n} + \left[(\rho+\lambda_n)(\gamma+\lambda_e)+(\rho_e+\lambda_e)(\gamma_n+\lambda_n)\right]\sigma_{\bar{e}^p,\bar{n}^p} + \left[\lambda_n(\gamma+\lambda_e)+\lambda_e(\gamma_n+\lambda_n)\right]\sigma_{\bar{e}^p,\bar{q}^p}+\left[\lambda_n(\rho_e+\lambda_e)+\lambda_e(\rho+\lambda_n)\right]\sigma_{\bar{n}^p,\bar{q}^p} \quad (E.76)$$

$$
\begin{aligned}
Cov\left(c_{f,t}^k, c_{f,t+3}^k\right) &= \left(\lambda+\lambda_e+\lambda_n\right)^2 \sigma_{\bar{q}^p}^2+\left(\gamma+\gamma_n+\lambda_e+\lambda_n\right)^2 \sigma_{\bar{e}^p}^2+\left(\rho+\rho_e+\lambda_e+\lambda_n\right)^2 \sigma_{\bar{n}^p}^2 \\
&+ 2\left(\gamma+\gamma_n+\lambda_e+\lambda_n\right)\left(\lambda+\lambda_e+\lambda_n\right) \sigma_{\bar{q}^p, \bar{e}^p} \\
&+ 2\left(\rho+\rho_e+\lambda_e+\lambda_n\right)\left(\lambda+\lambda_e+\lambda_n\right) \sigma_{\bar{q}^p, \bar{n}^p} \\
&+ 2\left(\rho+\rho_e+\lambda_e+\lambda_n\right)\left(\gamma+\gamma_n+\lambda_e+\lambda_n\right) \sigma_{\bar{e}^p, \bar{n}^p} \\
&+ \sigma_{\breve{q}^k}^2+\sigma_{\breve{e}^k}^2+\sigma_{\breve{n}^k}^2+2\left[\sigma_{\breve{e}^k, \breve{n}^k}+\sigma_{\breve{e}^k, \breve{q}^k}+\sigma_{\breve{n}^k, \breve{q}^k}\right] \\
&+ \left(\frac{r}{1+r-\alpha_e^k}\right) \frac{\left(\left(\alpha_e^k\right)^3+\left(\alpha_q^k\right)^3\right) \sigma_{\xi^k, \omega^k}}{1-\alpha_e^k \alpha_q^k}+\left(\frac{r}{1+r-\alpha_n^k}\right) \frac{\left(\left(\alpha_n^k\right)^3+\left(\alpha_q^k\right)^3\right) \sigma_{\theta^k, \phi^k}}{1-\alpha_n^k \alpha_q^k} \\
&+ \left(\frac{r}{1+r-\alpha_e^k}\right)^2 \frac{\left(\alpha_e^k\right)^3 \sigma_{\epsilon^k}^2}{1-\left(\alpha_e^k\right)^2}+\left(\frac{r}{1+r-\alpha_n^k}\right)^2 \frac{\left(\alpha_n^k\right)^3 \sigma_{\theta^k}^2}{1-\left(\alpha_n^k\right)^2}+\frac{\left(\alpha_q^k\right)^3 \sigma_{\phi^k}^2}{1-\left(\alpha_q^k\right)^2} \\
&+ \left(\frac{r}{1+r-\alpha_e^k}\right)\left(\frac{r}{1+r-\alpha_n^k}\right) \frac{\left(\left(\alpha_e^k\right)^3+\left(\alpha_n^k\right)^3\right) \sigma_{\epsilon^k, \theta^k}}{1-\alpha_e^k \alpha_n^k} \qquad (E.77)
\end{aligned}
$$

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

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

$$
\begin{aligned}
Cov\left(c_{f,t}^{k}, e_{f,t+3}^{k}\right) &= (\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{\left(\alpha_e^k\right)^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_{\breve{e}^k}^2 + \sigma_{\breve{e}^k,\breve{n}^k} + \sigma_{\breve{e}^k,\breve{q}^k} + \left(\frac{r}{1+r-\alpha_n^k}\right)\frac{\left(\alpha_e^k\right)^3\sigma_{\epsilon^k,\theta^k}}{1-\alpha_e^k\alpha_n^k} \\
&+ \left[(\gamma+\lambda_e)(\lambda+\lambda_e+\lambda_n)+\lambda_e(\gamma+\gamma_n+\lambda_e+\lambda_n)\right]\sigma_{\bar{e}^p,\bar{q}^p} + \left(\frac{r}{1+r-\alpha_e^k}\right)\frac{\left(\alpha_e^k\right)^3\sigma_{\epsilon^k}^2}{1-\left(\alpha_e^k\right)^2} \\
&+ \left[(\rho_e+\lambda_e)(\lambda+\lambda_e+\lambda_n)+\lambda_e(\rho+\rho_e+\lambda_e+\lambda_n)\right]\sigma_{\bar{n}^p,\bar{q}^p} \\
&+ \left[(\gamma+\lambda_e)(\rho+\rho_e+\lambda_e+\lambda_n)+(\rho_e+\lambda_e)(\gamma+\gamma_n+\lambda_e+\lambda_n)\right]\sigma_{\bar{e}^p,\bar{n}^p} \qquad \text{(E.80)} \\
Cov\left(c_{f,t}^{k}, n_{f,t+3}^{k}\right) &= (\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{\left(\alpha_n^k\right)^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_{\breve{n}^k}^2 + \sigma_{\breve{e}^k,\breve{n}^k} + \sigma_{\breve{n}^k,\breve{q}^k} + \left(\frac{r}{1+r-\alpha_e^k}\right)\frac{\left(\alpha_n^k\right)^3\sigma_{\epsilon^k,\theta^k}}{1-\alpha_e^k\alpha_n^k} \\
&+ \left[(\gamma_n+\lambda_n)(\lambda+\lambda_e+\lambda_n)+\lambda_n(\gamma+\gamma_n+\lambda_e+\lambda_n)\right]\sigma_{\bar{e}^p,\bar{q}^p} + \left(\frac{r}{1+r-\alpha_n^k}\right)\frac{\left(\alpha_n^k\right)^3\sigma_{\theta^k}^2}{1-\left(\alpha_n^k\right)^2} \\
&+ \left[(\rho+\lambda_n)(\lambda+\lambda_e+\lambda_n)+\lambda_n(\rho+\rho_e+\lambda_e+\lambda_n)\right]\sigma_{\bar{n}^p,\bar{q}^p} \\
&+ \left[(\gamma_n+\lambda_n)(\rho+\rho_e+\lambda_e+\lambda_n)+(\rho+\lambda_n)(\gamma+\gamma_n+\lambda_e+\lambda_n)\right]\sigma_{\bar{e}^p,\bar{n}^p} \qquad \text{(E.81)}
\end{aligned}
$$

(iii) Identification. There are 43 parameters to identify from 75 equations - (E.7) through (E.81). We will proceed with the identification argument in the following nine groups of parameters:

(i) $\left[\boldsymbol{\alpha_e^p, \alpha_n^p, \sigma_{\epsilon^p}^2, \sigma_{\theta^p}^2, \sigma_{\varepsilon^p}^2, \sigma_{\vartheta^p}^2}\right]$: Consider the following four equations: (E.7), (E.28), (E.46) and (E.64). We can take the following three differences of those four moment conditions:

$$
\begin{aligned}
Var\left(e_{f,t}^p\right) - Cov\left(e_{f,t}^p, e_{f,t+2}^p\right) &= \sigma_{\epsilon^p}^2 + \sigma_{\varepsilon^p}^2 \qquad \text{(E.82)} \\
Cov\left(e_{f,t}^p, e_{f,t+1}^p\right) - Cov\left(e_{f,t}^p, e_{f,t+2}^p\right) &= \frac{\alpha_e^p\sigma_{\epsilon^p}^2}{1+\alpha_e^p} \qquad \text{(E.83)} \\
Cov\left(e_{f,t}^p, e_{f,t+1}^p\right) - Cov\left(e_{f,t}^p, e_{f,t+3}^p\right) &= \alpha_e^p\sigma_{\epsilon^p}^2 \qquad \text{(E.84)}
\end{aligned}
$$

Combining (E.83) and (E.84), we identify α_e^p as $\left[\frac{Cov\left(e_{f,t}^p, e_{f,t+1}^p\right)\ \ Cov\left(e_{f,t}^p, e_{f,t+3}^p\right)}{Cov\left(e_{f,t}^p, e_{f,t+1}^p\right)\ \ Cov\left(e_{f,t}^p, e_{f,t+2}^p\right)} - 1\right]$. Once α_e^p is identified, equation (E.84) can be used to identify $\sigma_{\epsilon^p}^2$, and consequently $\sigma_{\varepsilon^p}^2$ is identified from equation (E.82). This exact sequence of arguments to identify the three parameters related to parental earnings process — α_e^p, $\sigma_{\epsilon^p}^2$ and $\sigma_{\varepsilon^p}^2$, can be repeated for identifying the three parameters pertaining to parental other income process — α_n^p, $\sigma_{\theta^p}^2$ and $\sigma_{\vartheta^p}^2$ using the following four moment conditions: (E.8), (E.29), (E.47) and (E.65).

(ii) $\left[\boldsymbol{\alpha_e^k, \alpha_n^k, \sigma_{\epsilon^k}^2, \sigma_{\theta^k}^2, \sigma_{\varepsilon^k}^2, \sigma_{\vartheta^k}^2}\right]$: Proceeding just like in point (i) above, one can identify the set of parameters, $\left\{\alpha_e^k, \sigma_{\epsilon^k}^2, \sigma_{\varepsilon^k}^2\right\}$ using the following four moment conditions: (E.10), (E.37), (E.55) and (E.73), and the set of parameters, $\left\{\alpha_n^k, \sigma^2_{\theta^k}, \sigma^2_{\vartheta^k}\right\}$ using the following four moment conditions: (E.11), (E.38), (E.56) and (E.74).

(iii) $\left[\boldsymbol{\sigma^2_{\bar{e}^p}, \sigma^2_{\bar{n}^p}, \sigma_{\bar{e}^p,\bar{n}^p}, \sigma_{\epsilon^p,\theta^p}, \sigma_{\epsilon^k,\theta^k}}\right]$: One can identify $\sigma^2_{\bar{e}^p}$ and $\sigma^2_{\bar{n}^p}$ from equations (E.7) and (E.8) respectively. Next, considering the equations (E.31) and (E.32) simultaneously, one can identify the two parameters $\sigma_{\bar{e}^p,\bar{n}^p}$ and $\sigma_{\epsilon^p,\theta^p}$. Finally, subtracting equation (E.39) from equation (E.40), we notice that the difference is a function of only one so-far unidentified parameter, $\sigma_{\epsilon^k,\theta^k}$.

(iv) $\left[\boldsymbol{\alpha^p_q, \sigma_{\epsilon^p,\phi^p}, \sigma_{\bar{e}^p,\bar{q}^p}}\right]$: Consider equation (E.33). Collect all the so-far identified parameters and the empirical moment to one side of the equation and define it as A. Then $A = z + \frac{x.y}{1\ ax}$, where $a \equiv \alpha^p_e$, $x \equiv \alpha^p_q$, $y \equiv \sigma_{\epsilon^p,\phi^p}$ and $z \equiv \sigma_{\bar{e}^p,\bar{q}^p}$. Similarly, equation (E.35) can be re-arranged as $B = z + \frac{ay}{1\ ax}$, equation (E.51) can be re-arranged as $C = z + \frac{x^2y}{1\ ax}$ and equation (E.53) can be re-arranged as $D = z + \frac{a^2y}{1\ ax}$. Note that $\{x, y, z\}$ needs to be identified while $\{a, A, B, C, D\}$ is already identified. Then, $\frac{C\ \ D}{A\ \ B} - a = \frac{\frac{x^2y\ \ a^2y}{1\ ax}}{\frac{xy\ \ ay}{1\ ax}} - a = \frac{x^2\ \ a^2}{x\ \ a} - a = (x + a) - a = x$, implying α^p_q 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) $\left[\boldsymbol{\sigma_{\theta^p,\phi^p}, \sigma_{\bar{n}^p,\bar{q}^p}, \sigma^2_{\bar{q}^p}, \sigma^2_{\phi^p}}\right]$: The two equations (E.34) and (E.36) can be simultaneously used to identify the parameters $\sigma_{\bar{n}^p,\bar{q}^p}$ and σ_{θ^p,ϕ^p}. This leaves $\sigma^2_{\bar{q}^p}$ and $\sigma^2_{\phi^p}$ to be identified from equations (E.30) and (E.48).

(vi) $\boldsymbol{[\gamma, \rho, \gamma_n, \rho_e, \lambda, \lambda_e, \lambda_n]}$: Considering equations (E.21), (E.23) and (E.26) together, we notice that these are 3 equations in 3 unknown parameter combinations — $(\gamma + \lambda_e)$, $(\rho_e + \lambda_e)$ and λ_e, because the rest of the parameters in these equations have already been identified above. Therefore, these equations can be used to simultaneously identify γ, ρ_e and λ_e. Similarly, equations (E.22), (E.24) and (E.25) can be used to identify ρ, γ_n and λ_n simultaneously. The remaining inter-generational persistence parameter, λ is then identified from equation (E.19).

(vii) $\left[\boldsymbol{\alpha^k_q, \sigma_{\epsilon^k,\phi^k}}\right]$: Consider equation (E.42). Collect all the so-far identified parameters and the empirical moment to one side of the equation and define it as A^0. Then, $A^0 = z^0 + \frac{x^0y^0}{1\ a^0x^0}$, where $a^0 \equiv \alpha^k_e$, $x^0 \equiv \alpha^k_q$, $y^0 \equiv \sigma_{\epsilon^k,\phi^k}$ and $z^0 \equiv \left(\sigma^2_{\breve{e}^k} + \sigma_{\breve{e}^k,\breve{n}^k} + \sigma_{\breve{e}^k,\breve{q}^k}\right)$. Similarly, equation (E.44) can be re-arranged as $B^0 = z^0 + \frac{a^0y^0}{1\ a^0x^0}$, equation (E.60) can be re-arranged as $C^0 = z^0 + \frac{x^{02}y^0}{1\ a^0x^0}$ and equation (E.62) can be re-arranged as $D^0 = z^0 + \frac{a^{02}y^0}{1\ a^0x^0}$. Note that $\{x^0, y^0, z^0\}$ needs to be identified while $\{a^0, A^0, B^0, C^0, D^0\}$ is already identified. However, we do not intend to identify z^0 as it is a function of multiple parameters of our model. Then, $\frac{C^0\ \ D^0}{A^0\ \ B^0} - a^0 = \frac{\frac{x^{02}y^0\ \ a^{02}y^0}{1\ a^0x^0}}{\frac{x^0y^0\ \ a^0y^0}{1\ a^0x^0}} - a^0 = \frac{x^{02}\ \ a^{02}}{x^0\ \ a^0} - a^0 = (x^0 + a^0) - a^0 = x^0$, implying α^k_q is now identified. Consequently, $y^0 = \frac{(A^0\ \ B^0)(1\ \ a^0x^0)}{x^0\ \ a^0}$, implying $\sigma_{\epsilon^k,\phi^k}$ is also identified.

(viii) $\left[\boldsymbol{\sigma_{\breve{e}^k,\breve{n}^k}, \sigma_{\theta^k,\phi^k}, \sigma^2_{\phi^k}}\right]$: $\sigma_{\breve{e}^k,\breve{n}^k}$ can be directly identified from equation (E.40). Subtracting equation (E.43) from equation (E.45), we notice that the difference is a function of only one so-far unidentified parameter, σ_{θ^k,ϕ^k}, ensuring its identification. Subtracting equation (E.59) from equation (E.41), we notice that the difference is a function of only one so-far unidentified parameter, $\sigma^2_{\phi^k}$, ensuring its identification.

(ix) $\left[\boldsymbol{\sigma^2_{\breve{e}^k}, \sigma^2_{\breve{n}^k}, \sigma_{\breve{e}^k,\breve{q}^k}, \sigma_{\breve{n}^k,\breve{q}^k}, \sigma^2_{\breve{q}^k}, \sigma^2_{\varphi^p}, \sigma^2_{\varphi^k}}\right]$: Equations (E.37) and (E.38) directly identify $\sigma^2_{\breve{e}^k}$ and

$\sigma^2_{\breve{n}^k}$ respectively. This leaves $\sigma_{\breve{e}^k,\breve{q}^k}$ and $\sigma_{\breve{n}^k,\breve{q}^k}$ to be identified from equations (E.42) and (E.43) respectively. Finally, $\sigma^2_{\breve{q}^k}$ is identified from equation (E.41), and equations (E.9) and (E.12) can be used to directly identify $\sigma^2_{\varphi^p}$ and $\sigma^2_{\varphi^k}$ respectively.

F.1.2 Estimation

The model presented in Section F.1.1 above has 43 parameters to estimate from the 75 moment conditions (for 761 parent-child pairs). Given the limited sample size and the large number of parameters, we proceed in steps. First, we estimate the parameters of the shock processes; second, we perform the GMM estimation of the remaining parameters holding the shock process parameters fixed. Results are shown in Tables 30 and 32.

We assume that innovations to the AR(1) shock processes are uncorrelated with each other; that is, we posit $\sigma_{\epsilon^g,\theta^g}, \sigma_{\epsilon^g,\phi^g}, \sigma_{\theta^g,\phi^g} = 0$ for each generation $g \in \{p, k\}$. Below we detail the estimation steps to recover the parameters of the shock processes.

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) $S^{e,g}_{f,t} = \mathcal{E}^g_{f,t} + \varepsilon^g_{f,t}$ for earnings,
(ii) $S^{n,g}_{f,t} = \Theta^g_{f,t} + \vartheta^g_{f,t}$ for other income, and
(iii) $S^{c,g}_{f,t} = \Phi^g_{f,t} + \varphi^g_{f,t} + \frac{r.\mathsf{E}^g_{f,t}}{1+r \quad \alpha^g_e} + \frac{r.\Theta^g_{f,t}}{1+r \quad \alpha^g_n} + \frac{r}{1+r}\left(\varepsilon^g_{f,t} + \vartheta^g_{f,t}\right)$ 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) $Var\left(S^{e,g}\right) = \sigma^2_{\mathsf{E}^g} + \sigma^2_{\varepsilon^g}$,
(b) $Var\left(S^{n,g}\right) = \sigma^2_{\Theta^g} + \sigma^2_{\vartheta^g}$, and
(c) $Var\left(S^{c,g}\right) = \sigma^2_{\Phi^g} + \sigma^2_{\varphi^g} + \left(\frac{r}{1+r \quad \alpha^g_e}\right)^2 \sigma^2_{\mathsf{E}^g} + \left(\frac{r}{1+r \quad \alpha^g_n}\right)^2 \sigma^2_{\Theta^g} + \left(\frac{r}{1+r}\right)^2 (\sigma^2_{\varepsilon^g} + \sigma^2_{\vartheta^g})$.
Note that we can calculate the variances of the total shocks, $Var\left(S^{x,g}\right)$ 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, $\sigma^2_{\varepsilon^g} = 0.05 * Var\left(\bar{e}^g_f\right)$, $\sigma^2_{\vartheta^g} = 0.05 * Var\left(\bar{n}^g_f\right)$ and $\sigma^2_{\varphi^g} + \left(\frac{r}{1+r}\right)^2 (\sigma^2_{\varepsilon^g} + \sigma^2_{\vartheta^g}) = 0.05 * Var\left(\bar{c}^g_f\right)$, 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 $Var\left(\bar{x}^g_f\right)$ for each $x \in \{e, n, c\}$, implying we can get estimates of $\sigma^2_{\varepsilon^g}$, $\sigma^2_{\vartheta^g}$ and $\sigma^2_{\varphi^g}$, for any given value of r. We assume $r = 0.04$. Subtracting the estimates of $\sigma^2_{\varepsilon^g}$ and $\sigma^2_{\vartheta^g}$ from the estimates of $Var\left(S^{e,g}\right)$ and $Var\left(S^{n,g}\right)$ respectively in Step 1, we can get values for $\sigma^2_{\mathcal{E}^g}$ and $\sigma^2_{\Theta^g}$.

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

Step 4: From Step 1, we note that $\sigma^2_{\Phi^g} = \mathrm{Var}\left(S^{c,g}\right) - \sigma^2_{\varphi^g} - \left(\frac{r}{1+r-\alpha^g_e}\right)^2 \sigma^2_{\mathcal{E}^g} - \left(\frac{r}{1+r-\alpha^g_n}\right)^2 \sigma^2_{\Theta^g} - \left(\frac{r}{1+r}\right)^2 \left(\sigma^2_{\varepsilon^g} + \sigma^2_{\vartheta^g}\right)$, where all terms on the right hand side have already been identified in the previous steps. Hence, $\sigma^2_{\Phi^g}$ is now estimated.

Step 5: The derivation for α^g_q follows the same principle as in Step 3:

$$\alpha^{S,g}_{c}.Var\left(S^{c,g}\right) = Cov\left(\Phi^{g}_{f,t}, \Phi^{g}_{f,t-1}\right) + \left(\frac{r}{1+r-\alpha^g_e}\right)^2 Cov\left(\mathcal{E}^{g}_{f,t}, \mathcal{E}^{g}_{f,t-1}\right) + \left(\frac{r}{1+r-\alpha^g_n}\right)^2 Cov\left(\Theta^{g}_{f,t}, \Theta^{g}_{f,t-1}\right)$$

$$\implies \alpha^g_q = \frac{1}{\sigma^2_{\Phi^g}}\left[\alpha^{S,g}_{c}.Var\left(S^{c,g}\right) - \left(\frac{r}{1+r-\alpha^g_e}\right)^2 \alpha^g_e \sigma^2_{\mathcal{E}^g} - \left(\frac{r}{1+r-\alpha^g_n}\right)^2 \alpha^g_n \sigma^2_{\Theta^g}\right].$$

Note that all terms on the right hand side is pre-determined and thus α^g_q 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 α's should be interpreted as estimates for the case when $\sigma_{\epsilon^g,\theta^g}, \sigma_{\epsilon^g,\phi^g}, \sigma_{\theta^g,\phi^g} = 0$ 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 ϵ, θ and ϕ within each generation.

Step 6: To get the variances of the innovations to the AR(1) persistent shocks, we note that $\sigma^2_{\epsilon^g} = \sigma^2_{\mathcal{E}^g}\left(1 - \left(\alpha^g_e\right)^2\right)$, $\sigma^2_{\theta^g} = \sigma^2_{\Theta^g}\left(1 - \left(\alpha^g_n\right)^2\right)$ and $\sigma^2_{\phi^g} = \sigma^2_{\Phi^g}\left(1 - \left(\alpha^g_q\right)^2\right)$, $\forall g \in \{p, k\}$.

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. 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.

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

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

(c) Persistence of AR(1) Shocks — $\alpha^p_e = 0.386$, $\alpha^p_n = 0.318$ and $\alpha^p_q = 0.095$ are the persistence of the AR(1) shocks to earnings, other income and consumption 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 30: Estimates: Intergenerational Elasticities (75 Moments)

Variables	Parameters	Full Model (1)	$\boldsymbol{\lambda_e, \lambda_n = 0}$ (2)	No AR(1) Shock (3)	No AR(1) Shock; $\boldsymbol{\lambda_e, \lambda_n = 0}$ (4)
Head Earnings	γ	0.423	0.403	0.384	0.378
		(0.082)	(0.059)	(0.073)	(0.045)
Other Income	ρ	0.106	0.116	0.102	0.112
		(0.068)	(0.064)	(0.056)	(0.066)
$\bar{e}_f^p$ on $\bar{n}_f^k$	γ_n	0.130	0.172	0.123	0.163
		(0.137)	(0.074)	(0.097)	(0.077)
$\bar{n}_f^p$ on $\bar{e}_f^k$	ρ_e	0.076	0.072	0.075	0.074
		(0.055)	(0.057)	(0.046)	(0.049)
Consumption	λ	0.203	0.204	0.197	0.199
		(0.080)	(0.084)	(0.071)	(0.081)
Parental Transfers $\left(\bar{c}_f^p\right)$ on $\bar{e}_f^k$	λ_e	-0.049	0	-0.019	0
		(0.151)		(0.141)	
Parental Transfers $\left(\bar{c}_f^p\right)$ on $\bar{n}_f^k$	λ_n	0.102	0	0.104	0
		(0.187)		(0.146)	
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 31: Parental Importance for Child Inequality (75 Moments)

Variables	Full Model (1)	$\boldsymbol{\lambda_e, \lambda_n = 0}$ (2)	No AR(1) Shock (3)	No AR(1) Shock; $\boldsymbol{\lambda_e, \lambda_n = 0}$ (4)
Head Earnings	12.4%	12.2%	11.7%	11.7%
Other Income	1.7%	1.7%	1.6%	1.7%
Consumption	22.3%	22.0%	20.9%	20.4%

Note: All numbers are based on parameter estimates in Tables 30 and 32.

The numbers for parental importance for explaining heterogeneity in the child outcomes in Table 31 reveals two observations - first, shutting off the direct channel of parental consumption on child income processes matter very little, and second, ignoring AR(1) persistent shocks in the model (i.e., having only transitory shocks alongside individual fixed effects) underestimates the parental importance slightly.

Table 32: Estimates: Idiosyncratic Fixed Effects (75 Moments)

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

Note: See notes to Table 30.

F.1.3 Sensitivity Checks

(i) Using Short-Lead Auto-covariances Only. Tables 30 through 32 use 75 moments to estimate the parameters. However, once all the shock parameters are calibrated externally, or when AR(1) shocks are not considered, we do not require the long-lead 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 33 the parental importance numbers corresponding to parameter estimates obtained by using only 39 moments, from (E.7) through (E.45). Restricting the use of long-lead auto-covariances implies a slight decrease in the parental importance for explaining heterogeneity in child outcomes.

Table 33: Parental Impact on Variance of Child Outcomes (39 Moments)

Variables	**Full Model**	$\boldsymbol{\lambda_e, \lambda_n = 0}$	**No AR(1) Shock**	**No AR(1) Shock;** $\boldsymbol{\lambda_e, \lambda_n = 0}$
	(1)	(2)	(3)	(4)
Head Earnings	11.7%	11.5%	10.5%	10.6%
Other Income	1.6%	1.6%	1.5%	1.5%
Consumption	21.7%	21.4%	19.1%	18.3%

Note: All estimates correspond to 761 parent-child pairs using 39 moment restrictions.

(ii) Variance of Transitory Shocks. 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.

Table 34: Parental Impact on Variance of Child Outcomes: Robustness to Transitory Shock Variance

Variable	**Transitory Shock Variance**		
	5% of CSV	**10% of CSV**	**20% of CSV**
	(1)	(2)	(3)
Head Earnings	12.4%	12.5%	12.6%
Other Income	1.7%	1.7%	1.7%
Consumption	22.3%	22.4%	22.7%

Note: CSV refers to Cross-Sectional Variance of the corresponding variable in each generation. All estimates correspond to 761 parent-child pairs. Column (1) is the same as column (1) in Table 31. Column (2) 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 — $\sigma^2_{\epsilon^p} = 0.091$, $\sigma^2_{\theta^p} = 0.279$, $\sigma^2_{\phi^p} = 0.070$, $\sigma^2_{\epsilon^k} = 0.083$, $\sigma^2_{\theta^k} = 0.293$, $\sigma^2_{\phi^k} = 0.087$; and the variances of the transitory shocks — $\sigma^2_{\varepsilon^p} = 0.029$, $\sigma^2_{\vartheta^p} = 0.081$, $\sigma^2_{\varphi^p} = 0.009$, $\sigma^2_{\varepsilon^k} = 0.025$, $\sigma^2_{\vartheta^k} = 0.053$, $\sigma^2_{\varphi^k} = 0.011$. 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 — $\sigma^2_{\epsilon^p} = 0.054$, $\sigma^2_{\theta^p} = 0.185$, $\sigma^2_{\phi^p} = 0.060$, $\sigma^2_{\epsilon^k} = 0.054$, $\sigma^2_{\theta^k} = 0.231$, $\sigma^2_{\phi^k} = 0.076$; and the variances of the transitory shocks — $\sigma^2_{\varepsilon^p} = 0.058$, $\sigma^2_{\vartheta^p} = 0.161$, $\sigma^2_{\varphi^p} = 0.019$, $\sigma^2_{\varepsilon^k} = 0.050$, $\sigma^2_{\vartheta^k} = 0.107$, $\sigma^2_{\varphi^k} = 0.023$.

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 34, 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.

(iii) Persistence of AR(1) Shocks. In Table 35, 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 Impact on Variance of Child Outcomes: Robustness to Persistence of AR(1) Shocks

Variables	**Estimated α's** (1)	$\boldsymbol{\alpha^0 s = 0.75}$ (2)	$\boldsymbol{\alpha^0 s = 0.50}$ (3)	$\boldsymbol{\alpha^0 s = 0.25}$ (4)	$\boldsymbol{\alpha^0 s = 0.10}$ (5)
Head Earnings	12.4%	15.5%	13.2%	12.0%	11.6%
Other Income	1.7%	2.5%	1.9%	1.7%	1.6%
Consumption	22.3%	26.2%	22.9%	21.8%	21.4%

Note: All estimates correspond to 761 parent-child pairs. Each column uses a different set of calibrated values for the persistent shock parameters (not reported here for brevity) but the transitory shock parameters are held constant at the values used in column (1).

F.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 7.2 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.

F.2.1 Moment Conditions

Parent Variance

$$Var\left(\Delta e^p_{f,t}\right) = \sigma^2_{\epsilon^p} + 2\sigma^2_{\varepsilon^p} \tag{E.85}$$
$$Var\left(\Delta n^p_{f,t}\right) = \sigma^2_{\theta^p} + 2\sigma^2_{\vartheta^p} \tag{E.86}$$
$$Var\left(\Delta c^p_{f,t}\right) = \omega^2_{e^p}\sigma^2_{\epsilon^p} + \omega^2_{n^p}\sigma^2_{\theta^p} + \psi^2_{e^p}\sigma^2_{\varepsilon^p} + \psi^2_{n^p}\sigma^2_{\vartheta^p} + \sigma^2_{\xi^p} \tag{E.87}$$

Child Variance

$$Var\left(\Delta e^k_{f,t}\right) = \gamma^2_{\Delta}\sigma^2_{\epsilon^p} + \sigma^2_{\breve{\epsilon}^k} + 2\sigma^2_{\varepsilon^k} \tag{E.88}$$
$$Var\left(\Delta n^k_{f,t}\right) = \rho^2_{\Delta}\sigma^2_{\theta^p} + \sigma^2_{\breve{\theta}^k} + 2\sigma^2_{\vartheta^k} \tag{E.89}$$
$$\begin{aligned} Var\left(\Delta c^k_{f,t}\right) &= \omega^2_{e^k}\left(\gamma^2_{\Delta}\sigma^2_{\epsilon^p} + \sigma^2_{\breve{\epsilon}^k}\right) + \psi^2_{e^k}\sigma^2_{\varepsilon^k} \\ &+ \omega^2_{n^k}\left(\rho^2_{\Delta}\sigma^2_{\theta^p} + \sigma^2_{\breve{\theta}^k}\right) + \psi^2_{n^k}\sigma^2_{\vartheta^k} \\ &+ \lambda^2_{\Delta}\sigma^2_{\xi^p} + \sigma^2_{\breve{\xi}^k} \end{aligned} \tag{E.90}$$

Contemporaneous Parent Covariance

$$Cov\left(\Delta e^p_{f,t}, \Delta c^p_{f,t}\right) = \omega_{e^p}\sigma^2_{\epsilon^p} + \psi_{e^p}\sigma^2_{\varepsilon^p} \tag{E.91}$$
$$Cov\left(\Delta n^p_{f,t}, \Delta c^p_{f,t}\right) = \omega_{n^p}\sigma^2_{\theta^p} + \psi_{n^p}\sigma^2_{\vartheta^p} \tag{E.92}$$

Contemporaneous Child Covariance

$$Cov\left(\Delta e^k_{f,t}, \Delta c^k_{f,t}\right) = \gamma^2_{\Delta}\omega_{e^k}\sigma^2_{\epsilon^p} + \omega_{e^k}\sigma^2_{\breve{\epsilon}^k} + \psi_{e^k}\sigma^2_{\varepsilon^k} \tag{E.93}$$
$$Cov\left(\Delta n^k_{f,t}, \Delta c^k_{f,t}\right) = \rho^2_{\Delta}\omega_{n^k}\sigma^2_{\theta^p} + \omega_{n^k}\sigma^2_{\breve{\theta}^k} + \psi_{n^k}\sigma^2_{\vartheta^k} \tag{E.94}$$

Contemporaneous Cross-Generation Covariance

$$Cov\left(\Delta e^{p}_{f,t}, \Delta e^{k}_{f,t}\right) = \gamma_{\Delta}\sigma^{2}_{\epsilon^{p}} \tag{E.95}$$
$$Cov\left(\Delta n^{p}_{f,t}, \Delta n^{k}_{f,t}\right) = \rho_{\Delta}\sigma^{2}_{\theta^{p}} \tag{E.96}$$
$$Cov\left(\Delta c^{p}_{f,t}, \Delta c^{k}_{f,t}\right) = \gamma_{\Delta}\omega_{e^{p}}\omega_{e^{k}}\sigma^{2}_{\epsilon^{p}} + \rho_{\Delta}\omega_{n^{p}}\omega_{n^{k}}\sigma^{2}_{\theta^{p}} + \lambda_{\Delta}\sigma^{2}_{\xi^{p}} \tag{E.97}$$
$$Cov\left(\Delta e^{p}_{f,t}, \Delta c^{k}_{f,t}\right) = \gamma_{\Delta}\omega_{e^{k}}\sigma^{2}_{\epsilon^{p}} \tag{E.98}$$
$$Cov\left(\Delta n^{p}_{f,t}, \Delta c^{k}_{f,t}\right) = \rho_{\Delta}\omega_{n^{k}}\sigma^{2}_{\theta^{p}} \tag{E.99}$$
$$Cov\left(\Delta c^{p}_{f,t}, \Delta e^{k}_{f,t}\right) = \gamma_{\Delta}\omega_{e^{p}}\sigma^{2}_{\epsilon^{p}} \tag{E.100}$$
$$Cov\left(\Delta c^{p}_{f,t}, \Delta n^{k}_{f,t}\right) = \rho_{\Delta}\omega_{n^{p}}\sigma^{2}_{\theta^{p}} \tag{E.101}$$

Non-contemporaneous Covariances (lead 1) for Parent

$$Cov\left(\Delta e^{p}_{f,t}, \Delta e^{p}_{f,t+1}\right) = -\sigma^{2}_{\varepsilon^{p}} \tag{E.102}$$
$$Cov\left(\Delta n^{p}_{f,t}, \Delta n^{p}_{f,t+1}\right) = -\sigma^{2}_{\vartheta^{p}} \tag{E.103}$$
$$Cov\left(\Delta c^{p}_{f,t}, \Delta e^{p}_{f,t+1}\right) = -\psi_{e^{p}}\sigma^{2}_{\varepsilon^{p}} \tag{E.104}$$
$$Cov\left(\Delta c^{p}_{f,t}, \Delta n^{p}_{f,t+1}\right) = -\psi_{n^{p}}\sigma^{2}_{\vartheta^{p}} \tag{E.105}$$

Non-contemporaneous Covariances (lead 1) for Child

$$Cov\left(\Delta e^{k}_{f,t}, \Delta e^{k}_{f,t+1}\right) = -\sigma^{2}_{\varepsilon^{k}} \tag{E.106}$$
$$Cov\left(\Delta n^{k}_{f,t}, \Delta n^{k}_{f,t+1}\right) = -\sigma^{2}_{\vartheta^{k}} \tag{E.107}$$
$$Cov\left(\Delta c^{k}_{f,t}, \Delta e^{k}_{f,t+1}\right) = -\psi_{e^{k}}\sigma^{2}_{\varepsilon^{k}} \tag{E.108}$$
$$Cov\left(\Delta c^{k}_{f,t}, \Delta n^{k}_{f,t+1}\right) = -\psi_{n^{k}}\sigma^{2}_{\vartheta^{k}} \tag{E.109}$$

F.2.2 Identification

There are 21 parameters to be identified from 25 moment conditions. It is straightforward to see the identification of $\sigma^2_{\varepsilon^p}$, $\sigma^2_{\vartheta^p}$, ψ_{e^p}, ψ_{n^p}, $\sigma^2_{\varepsilon^k}$, $\sigma^2_{\vartheta^k}$, ψ_{e^k} and ψ_{n^k} from equations (E.102) through (E.109). Subsequently, $\sigma^2_{\epsilon^p}$ and $\sigma^2_{\theta^p}$ can be identified from equations (E.85) and (E.86). This allows identification of γ_Δ and ρ_Δ from equations (E.95) and (E.96); and consequently ω_{e^k}, ω_{n^k}, ω_{e^p} and ω_{n^p} from equations (E.98) through (E.101) respectively. Now, equations (E.87), (E.88) and (E.89) can identify $\sigma^2_{\xi^p}$, $\sigma^2_{\breve{\epsilon}^k}$ and $\sigma^2_{\breve{\theta}^k}$ respectively. Finally, λ_Δ is identified from equation (E.97), which leaves $\sigma^2_{\breve{\xi}^k}$ to be identified from (E.90).

F.2.3 Results and Empirical Moments

The PSID becomes biennial from 1998 onwards. To maintain parity throughout our sample period, we use two calender year differences to measure the time-differences denoted by Δ 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 36: Intergenerational Growth Elasticities

	Parameters	**Imputed** (1)	**Food** (2)
Head Earnings Growth	γ_Δ	0.242	0.257
		(0.160)	(0.173)
Other Income Growth	ρ_Δ	0.097	0.099
		(0.071)	(0.078)
Consumption Growth	λ_Δ	0.007	0.043
		(0.048)	(0.072)
Parent-Child Pairs	*N*	761	761

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

Table 36 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 37 and 38. 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 37 shows that we estimate higher value of consumption insurance when using food expenditures rather than imputed consumption data.

Table 37: Partial Insurance Parameters

	Parameters	Imputed (1)	Food (2)
Parents			
Permanent Head Earnings	ω_e^p	0.229	0.108
		(0.040)	(0.077)
Permanent Other Income	ω_n^p	0.068	0.030
		(0.013)	(0.027)
Transitory Head Earnings	ψ_e^p	0.150	0.058
		(0.041)	(0.076)
Transitory Other Income	ψ_n^p	0.035	-0.044
		(0.040)	(0.051)
Children			
Permanent Head Earnings	ω_e^k	0.232	0.029
		(0.054)	(0.175)
Permanent Other Income	ω_n^k	0.150	0.088
		(0.030)	(0.031)
Transitory Head Earnings	ψ_e^k	0.203	0.028
		(0.039)	(0.073)
Transitory Other Income	ψ_n^k	0.037	-0.029
		(0.023)	(0.043)
Parent-Child Pairs	*N*	761	761

Note: See note to 36.

Table 38: Variances of Shocks

	Parameters	Imputed (1)	Food (2)
Parental Shocks			
Transitory Earnings	$\sigma^2_{\varepsilon^p}$	0.048	0.048
		(0.005)	(0.005)
Transitory Other Income	$\sigma^2_{\vartheta^p}$	0.068	0.068
		(0.015)	(0.015)
Permanent Earnings	$\sigma^2_{\epsilon^p}$	0.066	0.066
		(0.007)	(0.007)
Permanent Other Income	$\sigma^2_{\theta^p}$	0.218	0.217
		(0.025)	(0.029)
Consumption Growth	$\sigma^2_{\xi^p}$	0.036	0.141
		(0.002)	(0.009)
Child Shocks			
Transitory Earnings	$\sigma^2_{\varepsilon^k}$	0.048	0.049
		(0.005)	(0.006)
Transitory Other Income	$\sigma^2_{\vartheta^k}$	0.111	0.112
		(0.029)	(0.032)
Idiosyncratic Permanent Earnings	$\sigma^2_{\tilde{\epsilon}^k}$	0.049	0.047
		(0.008)	(0.012)
Idiosyncratic Permanent Other Income	$\sigma^2_{\tilde{\theta}^k}$	0.161	0.161
		(0.027)	(0.028)
Idiosyncratic Consumption Growth	$\sigma^2_{\tilde{\xi}^k}$	0.033	0.176
		(0.002)	(0.012)
Parent-Child Pairs	*N*	761	761

Note: See note to Table 36.

Table 39: Empirical Moments

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

Note: These empirical moments are used to generate the parameter estimates in Tables 36, 37 and 38 through GMM. Bootstrap standard errors are reported in parentheses. Δ refers to change over 2 calendar years and $t+1$ implies 2-calendar-year lead.

F.3 No Income Cross-Effects, Random Match, Imputed Consumption & No Marital Status Restriction

Table 40: Robustness: Variance-Covariance of Idiosyncratic Components

Parameters	Baseline (1)	Random Match (2)	$\gamma_n = \rho_e = 0$ (3)	Imputed Consumption (4)	All Marital Status (5)
Variances of Parental Fixed Effects					
Head Earnings: $\sigma^2_{\bar{e}^p}$	0.296	0.291	0.290	0.292	0.298
	(0.020)	(0.022)	(0.021)	(0.021)	(0.014)
Other Income: $\sigma^2_{\bar{n}^p}$	0.805	0.808	0.805	0.805	0.775
	(0.058)	(0.071)	(0.063)	(0.069)	(0.048)
Consumption: $\sigma^2_{\bar{q}^p}$	1.027	1.032	1.049	0.859	1.014
	(0.064)	(0.073)	(0.073)	(0.067)	(0.055)
Variances of Child Idiosyncratic Components					
Head Earnings: $\sigma^2_{\breve{e}^k}$	0.229	0.247	0.215	0.226	0.273
	(0.014)	(0.015)	(0.013)	(0.012)	(0.015)
Other Income $\sigma^2_{\breve{n}^k}$	0.511	0.533	0.523	0.508	1.120
	(0.041)	(0.048)	(0.043)	(0.040)	(0.073)
Consumption: $\sigma^2_{\breve{q}^k}$	0.733	0.752	0.745	0.576	1.779
	(0.058)	(0.069)	(0.059)	(0.044)	(0.102)
among Parental Fixed Effects					
Consumption & Head Earnings: $\sigma_{\bar{e}^p,\bar{q}^p}$	-0.270	-0.263	-0.278	-0.222	-0.285
	(0.026)	(0.028)	(0.026)	(0.023)	(0.019)
Consumption & Other Income: $\sigma_{\bar{n}^p,\bar{q}^p}$	-0.816	-0.821	-0.831	-0.767	-0.791
	(0.060)	(0.069)	(0.065)	(0.068)	(0.050)
Head Earnings and Other Income: $\sigma_{\bar{e}^p,\bar{n}^p}$	0.069	0.067	0.084	0.067	0.082
	(0.017)	(0.017)	(0.018)	(0.017)	(0.013)
Covariances among Child Idiosyncratic Components					
Consumption & Head Earnings: $\sigma_{\breve{e}^k,\breve{q}^k}$	-0.250	-0.263	-0.256	-0.216	-0.422
	(0.024)	(0.025)	(0.024)	(0.018)	(0.031)
Consumption & Other Income: $\sigma_{\breve{n}^k,\breve{q}^k}$	-0.523	-0.542	-0.533	-0.481	-1.307
	(0.046)	(0.055)	(0.047)	(0.042)	(0.082)
Head Earnings & Other Income: $\sigma_{\breve{e}^k,\breve{n}^k}$	0.076	0.095	0.093	0.073	0.194
	(0.017)	(0.019)	(0.017)	(0.015)	(0.021)
Parent-Child Pairs	761	761	761	761	1038

Note: See notes to Tables 10 and 11.

Table 41: Robustness: Role of Cross-Effects in Parental Importance for Child Heterogeneity

Variable	**Parental Influence in Alternative Models**			
	Baseline	**Baseline;** $\gamma_n = \rho_e = 0$	**Model B**	**Model B;** $\gamma_n = \rho_e = 0$
	459 Pairs	459 Pairs	459 Pairs	459 Pairs
	(1)	(2)	(3)	(4)
Head Earnings	10.6%	14.4%	14.6%	17.9%
	[4.8%, 16.4%]	[8.3%, 20.6%]	[1.1%, 10.4%]	[11.4%, 24.5%]
Wife Earnings	-	-	8.1%	5.0%
			[2.7%, 13.4%]	[1.2%, 8.8%]
Wife Earnings + Transfer Income	3.5%	1.5%	-	-
	[1.4%, 7.4%]	[-0.9%, 3.9%]		
Consumption	24.6%	17.0%	22.8%	14.2%
	[14.0%, 35.2%]	[9.5%, 24.5%]	[12.6%, 33.0%]	[8.7%, 19.7%]

Note: Baseline model uses the sum of wife earnings and transfer income as the measure of other income. Model B uses wife earnings only as the measure of other income. Both models use food expenditure as the measure of consumption, and use only cross-sectional variation in time-averaged variables. Numbers in parentheses are 95% confidence intervals, calculated using bootstrap standard errors with 100 repetitions.

F.4 Effect of Income Tax

Table 42: Effect of Income Tax: Parental Influence on Variance of Child Outcomes.

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%]
Parent-Child Pairs	755	755	755	700

Note: Results are based on parameter estimates in Tables 43 and 44 of Appendix F.4. 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.

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.

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

Table 43: Effect of Federal Income Tax: Intergenerational Elasticities

Variables	**Parameters**	**Pre-tax** (1)	**Case A** (2)	**Case B** (3)	**Case C** (4)
Head Earnings	γ	0.229	0.167	0.225	0.268
		(0.026)	(0.029)	(0.026)	(0.032)
Other Income	ρ	0.097	0.115	0.091	0.098
		(0.027)	(0.033)	(0.028)	(0.038)
$\bar{e}_f^p$ on $\bar{n}_f^k$	γ_n	0.203	0.223	0.199	0.097
		(0.034)	(0.034)	(0.039)	(0.041)
$\bar{n}_f^p$ on $\bar{e}_f^k$	ρ_e	0.052	0.048	0.044	0.019
		(0.017)	(0.016)	(0.014)	(0.022)
Consumption	λ	0.150	0.127	0.119	0.122
		(0.035)	(0.039)	(0.033)	(0.037)
Parent-Child Pairs	*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 44: Effect of Federal Income Tax: Estimates of Variances and Covariances of Fixed Effects

	Parameters	Pre-tax	Case A	Case B	Case C
		(1)	(2)	(3)	(4)
Variances of Parental Fixed Effects					
Head Earnings	$\sigma^2_{\bar{e}^p}$	0.294	0.251	0.231	0.250
		(0.021)	(0.017)	(0.017)	(0.015)
Other Income	$\sigma^2_{\bar{n}^p}$	0.806	0.800	0.734	0.861
		(0.063)	(0.072)	(0.061)	(0.097)
Consumption	$\sigma^2_{\bar{q}^p}$	1.031	0.871	0.862	0.996
		(0.071)	(0.069)	(0.065)	(0.088)
Variances of Child Idiosyncratic Components					
Head Earnings	$\sigma^2_{\breve{e}^k}$	0.222	0.198	0.179	0.190
		(0.010)	(0.013)	(0.010)	(0.011)
Other Income	$\sigma^2_{\breve{n}^k}$	0.505	0.500	0.458	0.547
		(0.040)	(0.046)	(0.037)	(0.042)
Consumption	$\sigma^2_{\breve{q}^k}$	0.712	0.573	0.571	0.693
		(0.053)	(0.046)	(0.042)	(0.050)
Covariances among Parental Fixed Effects					
Consumption & Head Earnings	$\sigma_{\bar{e}^p,\bar{q}^p}$	-0.271	-0.171	-0.177	-0.213
		(0.024)	(0.022)	(0.020)	(0.024)
Consumption & Other Income	$\sigma_{\bar{n}^p,\bar{q}^p}$	-0.819	-0.734	-0.714	-0.823
		(0.066)	(0.069)	(0.062)	(0.089)
Head Earnings and Other Income	$\sigma_{\bar{e}^p,\bar{n}^p}$	0.071	-0.008	0.024	0.030
		(0.015)	(0.014)	(0.014)	(0.018)
Covariances among Child Idiosyncratic Components					
Consumption & Head Earnings	$\sigma_{\breve{e}^k,\breve{q}^k}$	-0.239	-0.156	-0.161	-0.169
		(0.018)	(0.014)	(0.014)	(0.019)
Consumption & Other Income	$\sigma_{\breve{n}^k,\breve{q}^k}$	-0.511	-0.435	-0.429	-0.529
		(0.043)	(0.044)	(0.039)	(0.043)
Head Earnings & Other Income	$\sigma_{\breve{e}^k,\breve{n}^k}$	0.071	-0.001	0.028	0.030
		(0.012)	(0.011)	(0.012)	(0.013)
Parent-Child Pairs	*N*	755	755	755	700

Note: See note to Table 43.

F.5 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 7.8 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 45: Intergenerational Elasticity by Child Cohort (Age: 30-40)

	Parameters	**1960s & 1970s Cohorts**	**1960s Cohort**	**1970s Cohort**
		(1)	(2)	(3)
Head Earnings	γ	0.212	0.252	0.197
		(0.056)	(0.071)	(0.096)
Other Income	ρ	0.042	-0.006	0.100
		(0.047)	(0.057)	(0.090)
$\bar{e}_f^p$ on $\bar{n}_f^k$	γ_n	0.212	0.201	0.236
		(0.073)	(0.113)	(0.129)
$\bar{n}_f^p$ on $\bar{e}_f^k$	ρ_e	0.040	0.009	0.079
		(0.027)	(0.044)	(0.042)
Consumption	λ	0.076	-0.029	0.201
		(0.070)	(0.088)	(0.119)
Parent-Child Pairs	*N*	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 46: Variance-Covariance of Idiosyncratic Components by Child Cohort (Age: 30-40)

	Parameters	**1960s & 1970s Cohorts**	**1960s Cohort**	**1970s Cohort**
		(1)	(2)	(3)
Variances of Parental Fixed Effects				
Head Earnings	$\sigma^2_{\bar{e}^p}$	0.200	0.172	0.225
		(0.018)	(0.018)	(0.030)
Other Income	$\sigma^2_{\bar{n}^p}$	0.844	0.946	0.749
		(0.112)	(0.163)	(0.129)
Consumption	$\sigma^2_{\bar{q}^p}$	0.909	0.978	0.835
		(0.114)	(0.150)	(0.162)
Variances of Child Idiosyncratic Components				
Head Earnings	$\sigma^2_{\breve{e}^k}$	0.240	0.232	0.244
		(0.018)	(0.028)	(0.029)
Other Income	$\sigma^2_{\breve{n}^k}$	0.659	0.561	0.749
		(0.070)	(0.092)	(0.108)
Consumption	$\sigma^2_{\breve{q}^k}$	0.875	0.817	0.911
		(0.086)	(0.115)	(0.129)
Covariances among Parental Fixed Effects				
Consumption & Head Earnings	$\sigma_{\bar{e}^p,\bar{q}^p}$	-0.126	-0.060	-0.186
		(0.033)	(0.039)	(0.058)
Consumption & Other Income	$\sigma_{\bar{n}^p,\bar{q}^p}$	-0.796	-0.887	-0.707
		(0.111)	(0.155)	(0.136)
Head Earnings and Other Income	$\sigma_{\bar{e}^p,\bar{n}^p}$	-0.007	-0.045	0.028
		(0.023)	(0.032)	(0.045)
Covariances among Child Idiosyncratic Components				
Consumption & Head Earnings	$\sigma_{\breve{e}^k,\breve{q}^k}$	-0.233	-0.269	-0.189
		(0.025)	(0.039)	(0.037)
Consumption & Other Income	$\sigma_{\breve{n}^k,\breve{q}^k}$	-0.657	-0.584	-0.720
		(0.077)	(0.103)	(0.116)
Head Earnings & Other Income	$\sigma_{\breve{e}^k,\breve{n}^k}$	0.048	0.078	0.014
		(0.024)	(0.028)	(0.037)
Parent-Child Pairs	N	337	166	171

Note: See notes to Table 45 for details.