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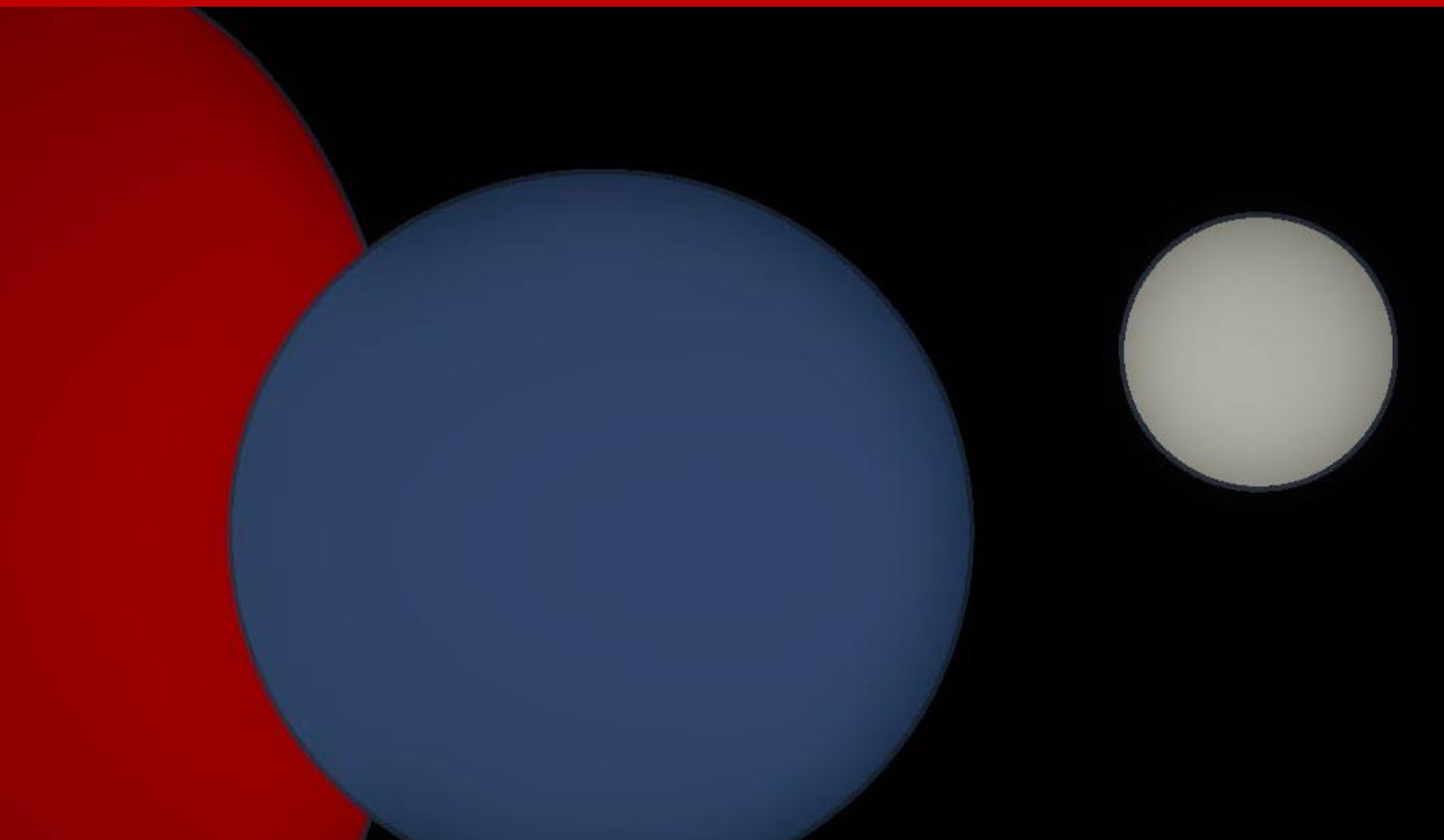

# Consumption and Income Inequality across Generations*

Giovanni Gallipoli† Hamish Low‡ Aruni Mitra§

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**Abstract**

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

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

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# 1 Introduction

Parents influence their children's life-cycle outcomes in many ways. Economists often quantify these influences using measures of intergenerational persistence along dimensions of heterogeneity such as earnings, wealth, or consumption.[1] The various channels of family influence are inter-related as parents can affect their children's outcomes in complex ways: through choices about education, through transmission of ability and preferences, by providing income-enhancing opportunities, as well as through inter-vivos and bequest transfers affecting wealth and consumption.[2] Further, these mechanisms may be substitutes: investing in a child's education to increase their earnings potential may imply less transfers of wealth. Several studies have looked at either income or consumption in isolation, mostly focusing on the estimation of intergenerational pass-through parameters. In this paper we pursue a different approach and develop a parsimonious model of the *joint* persistence of expenditures, earnings and other income. Rather than focusing on persistence alone, our focus is on understanding the importance of different aspects of family heterogeneity, compared to idiosyncratic life-cycle events, for the evolution of income and consumption inequality. Our work has two main objectives: first, to estimate the diverse ways parental influences shape children's economic outcomes in a unified framework; second, to quantify how much of the inequality observed in a particular generation can be attributed to parental factors.

To assess the importance of parental heterogeneity, we model intergenerationally linked households that make consumption and saving choices in an environment where persistent shocks shape permanent income. In the baseline model, the distribution of endogenous expenditures is characterized alongside a standard income process. The intergenerational linkages stem from intra-family persistence of earned income as well as from savings and transfer decisions. Specifically, we allow parents to influence outcomes of children in three ways: through earned income, through other sources of income such as transfers, and through consumption. An advantage of this approach is that we can assess the influence of parental heterogeneity on inequality in the next generation, and contrast the importance of family background with the impact of idiosyncratic variation which is independent of parents. The extent to which inequality among parents is passed through to inequality among children depends on intergenerational elasticities; however, the relative importance of family factors for inequality among children also depends on the magnitude of idiosyncratic

[1]Research linking 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, Danzinger, Li, and Schoeni, 2014) and occupations (Corak and Piraino, 2010; Bello and Morchio, 2016). Boar (2017) documents parental precautionary motives geared to insure children.

[2]For the role of transfers, see Daruich and Kozlowski (2016) and Abbott, Gallipoli, Meghir, and Violante (2019). Restuccia and Urrutia (2004), Cunha, Heckman, and Schennach (2010), Carneiro, Lopez Garcia, Salvanes, and Tominey (2015), Lee and Seshadri (2019) and Caucutt and Lochner (2019) examine parental investments and credit constraints at different stages of the life-cycle.

(family-independent) variation. Hence, a decomposition of observed inequality requires estimates of intergenerational pass-through parameters, estimates of inequality among parents and estimates of idiosyncratic sources of heterogeneity. To this purpose we use a method-of-moments approach, which delivers estimates of the parameters determining each of these elements. The model implies restrictions on the variances of earnings, other income and consumption of parents and their adult children, and on their covariation across generations. These moments jointly identify the parameters dictating intergenerational linkages, as well as the responses of income and consumption to life-cycle shocks. Then, through the model, we can quantify the contribution of parental factors to children's outcomes and to inequality.

For estimation we employ data from the Panel Study of Income Dynamics (PSID) covering birth-cohorts of individuals born between the early 1950s and the late 1970s. We link household income, expenditures and other family characteristics across generations in a long panel format.[3] To avoid the selection issues associated with women's labour force participation, we focus on a sample of father-son pairs to characterize earnings persistence; however, we include women's labour earnings within our measure of other income. The availability of expenditure data varies across survey waves; for this reason, we can either use food expenditure for the full sample period (Waldkirch, Ng, and Cox, 2004) or restrict attention to the period since 1997 for which extensive consumption records are available (Charles, Danzinger, Li, and Schoeni, 2014). Our baseline estimation uses information about the higher moments of measured food consumption going back to the late 1960s; then, in a set of robustness checks, we document the robustness of our findings by replicating the analysis for sample periods that have detailed expenditure records for most categories and also by using imputed measures of total household outlays in the full-length sample (see, Attanasio and Pistaferri, 2014).

We find that intergenerational persistence is highest for earnings, with an elasticity of 0.23. We also estimate a significant pass-through in consumption expenditures from parent to child, albeit slightly below the elasticity of earnings. Of course, consumption persistence operates also indirectly through other channels. The intra-family elasticity for other income is only 0.10 and mostly reflects similarities in spousal earnings across generations. This spousal selection emphasizes an important trait of family influences, as men tend to marry women who have similar economic outcomes as their mothers (see also Fernandez, Fogli, and Olivetti, 2004). In addition, better parental earnings are associated with higher unearned income among kids, with a cross-elasticity of 0.21. This suggests that higher parental earnings is associated with higher spousal earnings among children. We show that ignoring this cross-elasticity leads to substantial under-estimates of the parental influences on

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

consumption inequality. Taken together, our estimates of the intergenerational pass-through are consistent with the view that persistence is driven largely by associations in the lifetime earnings of both spouses as well as by family preferences for consumption, with persistence in observable characteristics like educational attainment playing a crucial role.[4]

The central question that we address in the debate on the role of family background for life-cycle outcomes is whether observed within-generation inequality would be much different if heterogeneity among parents were removed. The model delivers a transparent setting to perform inequality accounting exercises and quantify the contribution of parental factors: these exercises consistently indicate that idiosyncratic heterogeneity over the life-cycle, rather than family background, accounts for the bulk of cross-sectional dispersion in income and expenditures. The largest impact of parental factors is on consumption inequality, as our baseline estimates imply that roughly one third of within-generation consumption inequality can be attributed to family characteristics. Further examination shows that the relatively larger role of family heterogeneity on consumption follows from the interaction of (i) cross-sectional insurance reducing the impact of idiosyncratic income risk on expenditures, and (ii) the direct and indirect parental influences that are reflected into consumption choices, notably the intergenerational transmission of saving propensities and marital sorting.

Whether or not insurance increases or decreases cross-sectional inequality depends on the source of the insurance. If richer parents are better able to insure their own children through different types of transfer, then this insurance may exacerbate ex-post inequality. This would arise because similar ability children without access to parental transfers would be in a very different situation from those that do. By contrast, government provided insurance within a generation will mitigate the extent of cross-sectional inequality. Our analysis captures both channels of insurance: estimates show that the net effect of the different channels is that consumption inequality is much lower than inequality in earnings and in other income.

Our model can help reconcile the somewhat puzzling observation that intergenerational persistence is fairly stable (Hertz, 2007; Lee and Solon, 2009), while inequality within generations is growing (Heathcote, Perri, and Violante, 2010; Attanasio and Pistaferri, 2016). Mechanically, a negative association between economic inequality and mobility arises in the model with stronger intergenerational pass-through channels, which in turn induce greater income dispersion in the childrens' generation. Such an association would be consistent with the empirical observation that more unequal societies exhibit lower earnings mobility across generations, a relationship often dubbed the 'Great Gatsby' curve (see Krueger, 2012; Corak, 2013; Rauh, 2017).However, our estimates of intergenerational persistence are not large enough to support this explanation of increased inequal-

[4]See Landersø and Heckman (2017) and Gayle, Golan, and Soytas (2018) for evidence on the importance of education and human capital for intergenerational persistence. For a discussion of causal effects of parental traits see, among others, Carneiro and Heckman (2003); Black and Devereux (2011); Lefgren, Sims, and Lindquist (2012).

ity. The observed negative correlation between inequality and intergenerational mobility does not imply that a decline in mobility is either necessary or sufficient for the rise in inequality. In fact, while inequality has increased in the U.S. over the past few decades, we document that mobility is little changed, and this implies that a rise in uninsurable life-cycle risk was a more important driver of growing dispersion in the younger generation than intra-family linkages. The point we stress is that growing parental disparities are not, all else equal, sufficient to trigger substantially greater inequality in the absence of much larger inter-generational elasticities.[5]

In Section 2 we introduce the benchmark consumption model with intergenerational linkages. Section 3 discusses parameter identification and the estimation approach. Results are presented in Section 4 while in Section 5 we explore the implications of our estimates for the evolution of cross-sectional inequality. Various robustness checks are reported in Section 6.

## 2 Framework of Intergenerational Inequality

We develop an estimable consumption model of heterogeneous and intergenerationally linked households. The model features multiple parent-child linkages and is designed to examine the joint behaviour of earnings, other income and expenditures.

To motivate these linkages, we begin by establishing stylized facts about the evolution of intra-family persistence in the U.S. over recent decades. In Appendix A we report reduced-form estimates of the intergenerational pass-through of earnings and consumption since 1990, obtained using the method popularized by Lee and Solon (2009) in their analysis of the gender-specific evolution of earnings persistence. Like those authors, we find little evidence of changes in the intergenerational elasticity of labour earnings over time, with similar patterns holding for expenditures. To corroborate this evidence, we also compute mobility matrices and intergenerational flows across quartiles of the distributions of earnings and expenditures.[6] This analysis, also shown in Appendix A, emphasizes that persistence is more intense at the tails of the distribution and that the inter-generational pass-through was remarkably stable over the past decades. These findings are consistent with evidence in Chetty, Hendren, Kline, Saez, and Turner (2014), who examine large administrative U.S. earning records and conclude that measures of "...intergenerational mobility have remained extremely stable for the 1971-1993 birth cohorts". For these reasons we maintain the assumption of stationarity in the baseline analysis. However, among the robustness checks of Section 6, we explore potential cross-cohort differences in the cross-generation pass-through parameters and the variances of the idiosyncratic risk processes.

[5] See Cordoba, Liu, and Ripoll (2016) for a model of long-run inequality and mobility with endogenous fertility.

[6] Mobility matrices deliver the conditional probability of a child being placed in a certain quartile of the distribution given the quartile of his/her family.

## 2.1 Baseline Model

The building blocks of our analysis are the time series processes for earnings and other income of parents and children, along with a mechanism mapping them into distributions of family outcomes. Households optimally choose consumption expenditures to maximize discounted expected utility subject to a budget constraint. Households receive income from labour earnings of the head (usually the husband for couples in the PSID) and from other income, including transfers and earnings of the spouse. We allow for each of labour earnings, other income, and consumption to exhibit persistence across generations.

**Earnings and Other Income.** We denote a time period (a year) by $t$. Parent and child are identified by superscripts $p$ and $k$. A parent-child pair is denoted by the family subscript $f$. Head's earnings, other income and consumption expenditures (all logged) are denoted by $e$, $n$ and $c$, respectively. Our baseline specification of the parents' earning process features a fixed effect and an additive transitory shock. The fixed effect is invariant over the working-life of the individual. In Section 6.6 we also consider robustness to an alternative model specification that focuses on growth rates. The latter allows for period-specific permanent innovations that are correlated across generations. We find no evidence in support of this alternative specification of parent-child linkages.

In year $t$ the parent in family $f$ has earnings $e^p_{f,t}$ consisting of an individual fixed effect, $\bar{e}^p_f$, and an independent mean-zero transitory shock, $\zeta^p_{f,t}$, with variance $\sigma^2_{\zeta^p}$. Similarly, the process for other income, $n^p_{f,t}$, comprises a fixed effect, $\bar{n}^p_f$, and a transitory mean-zero component, $u^p_{f,t}$, with variance $\sigma^2_{u^p}$,

$$\begin{aligned} e^p_{f,t} &= \bar{e}^p_f + \zeta^p_{f,t} & (1) \\ n^p_{f,t} &= \bar{n}^p_f + u^p_{f,t}. & (2) \end{aligned}$$

The income process of children has a similar structure; that is, $e^k_{f,t} = \bar{e}^k_f + \zeta^k_{f,t}$ and $n^k_{f,t} = \bar{n}^k_f + u^k_{f,t}$ (where $\zeta^k_{f,t}$ and $u^k_{f,t}$ are mean zero i.i.d. innovations with variances $\sigma^2_{\zeta^k}$ and $\sigma^2_{u^k}$ respectively). Crucially, fixed effects in the children generation depend on both parental permanent components and on idiosyncratic random variables that are independent of the family. Thus, for the children of family $f$ this structure results in the following income components:

$$\begin{aligned} e^k_{f,t} &= \underbrace{\gamma\bar{e}^p_f + \theta\bar{n}^p_f + \delta^k_f}_{\bar{e}^k_f} + \zeta^k_{f,t} & (3) \\ n^k_{f,t} &= \underbrace{\rho\bar{n}^p_f + \lambda\bar{e}^p_f + \varepsilon^k_f}_{\bar{n}^k_f} + u^k_{f,t} & (4) \end{aligned}$$

where $\varepsilon_f^k$ and $\delta_f^k$ are idiosyncratic permanent shocks with variances $\sigma^2_{\varepsilon^k}$ and $\sigma^2_{\delta^k}$, respectively. We allow for the most general dependence structure across generations: alongside a direct channel from parental earnings to child earnings, and a direct channel from other income of parents to other income of children, the specification features cross effects so that parental earnings can influence other income of children, while other income of parents can affect earnings of children. For example, higher parental lifetime earnings influence child earnings through the persistence parameter $\gamma$, but also change a child's unearned income as captured by the parameter $\lambda$.

**Consumption.** With the income processes in place, we set-up the dynamic life-cycle problem that delivers consumption policy rules. 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 consumption problem of a member of family $f$, written in levels, is given by:

$$\begin{aligned} \max_{\{C_{f,\tau}\}_{\tau=t}^{T}} \quad & \mathbb{E}_t \quad \sum_{j=0}^{T-t} \beta^j u(C_{f,t+j}) \\ & s.t. \\ A_{f,t+1} \quad = \quad & (1+r)\left(A_{f,t} + E_{f,t} + N_{f,t} - C_{f,t}\right), \end{aligned} \tag{5}$$

where $\beta$ is the discount factor, $r$ is the real interest rate, $A_{f,t}$ is assets at the start of the period, $E_{f,t}$ is the value of the male household head's labour earnings, and $N_{f,t}$ is the value of other household income, which is defined as a sum of spousal earnings and total transfer income of the husband and wife. The representation in equation (5) does not explicitly specify an altruistic, paternalistic or accidental motive for parents to make transfers to their children. However, the empirical framework can accommodate flexibly a variety of linkages between the components of the budget constraint.[7]

The optimization problem in equation (5) yields consumption $C_{f,t}$ for any individual as the annuity value of total lifetime resources.[8] Then, the approximate log-consumption process for a parent can be represented as,

$$c^p_{f,t} = q^p_{f,t} + \bar{e}^p_f + \bar{n}^p_f + \alpha\left(r\right)\left(u^p_{f,t} + \zeta^p_{f,t}\right).$$

The term $\alpha\left(r\right)$ is an annuitization factor which tends to $r/(1+r)$ as the time horizon becomes larger. The variable $q^p_{f,t}$ denotes an idiosyncratic consumption shifter, subsuming unobserved income from savings and possible heterogeneity in preferences over the timing of consumption. Like other consumption shifters, $q^p_{f,t}$ comprises both a permanent and a transitory component so that

[7] For an analysis of altruistically linked households using PSID data see Altonji, Hayashi, and Kotlikoff (1997).

[8] See Appendix A for the analytical solution of the optimal consumption path under the assumption of (i) a quadratic utility function or (ii) a first-order Taylor approximation of the Euler equation under CRRA utility.

$q^p_{f,t} = \bar{q}^p_f + v^p_{f,t}$. Combining these processes, the log-consumption of the parent can be written as:

$$c^p_{f,t} = \bar{q}^p_f + \bar{e}^p_f + \bar{n}^p_f + v^p_{f,t} + \alpha(r)\left(u^p_{f,t} + \zeta^p_{f,t}\right) \tag{6}$$

and analogously for the child. Parents influence the consumption of their children through family persistence in both earnings and other income, as described in (3) and (4). In addition, we allow for the possibility of a direct transmission channel through the consumption shifter $\bar{q}^k_f$, which comprises an inherited component and a child-specific component: $\bar{q}^k_f = \phi\bar{q}^p_f + \psi^k_f$.

Substituting the intra-family transmission mechanisms into the log-consumption process for children, we obtain:

$$\begin{aligned} c^k_{f,t} &= \phi\bar{q}^p_f + (\gamma+\lambda)\,\bar{e}^p_f + (\rho+\theta)\,\bar{n}^p_f \\ &+ \varepsilon^k_f + \psi^k_f + \delta^k_f + v^k_{f,t} + \alpha(r)\left(u^k_{f,t} + \zeta^k_{f,t}\right). \end{aligned} \tag{7}$$

There are, therefore, three ways in which parents can affect the consumption process of their children: (i) the earnings channel; (ii) the channel operating through other household income; and (iii) inherited consumption shifters.

One issue with taking these equations to the data is that our measures of the various components are imperfect. In particular, our measure of transfer income, $n^p_{f,t}$, contains only transfers into the household and we do not have transfers out. This means we are not able to replicate exactly the budget constraint in equation (5). A second issue is whether to use pre- or post-tax earnings. The advantage of using post-tax earnings is that we get closer to the budget constraint. On the other hand, we cannot satisfy the budget constraint because we are missing key components, such as part of spending, wealth and the taxes related to it. Further, post-tax earnings already include substantial insurance, which may confound the contribution that parents make. Omitted components from the budget constraint will be captured by $q_{f,t}$.

## 2.2 Cross-sectional Dispersion and Intergenerational Smoothing

The presence of an intergenerational correlation in the consumption shifter $q_{f,t}$ reflects the accrual of different family influences. In particular, heterogeneity in $q_{f,t}$ may capture family-specific consumption preferences that shape saving behaviour. As we show in Appendix A, linear approximations of the Euler equation for general concave utility functions (say, CRRA) lead to omitted higher-order preference terms being loaded onto the unobserved $q_{f,t}$ shifter.[9] Accounting for the co-dependence between consumption propensities and income turns out to be quantitatively important (see Alan,

[9] Higher order preference terms may co-move with earnings and with other income. Moreover, if individuals with low permanent income are credit-constrained, a precautionary saving motive may generate a negative correlation between $q_{f,t}$ and permanent income.

Browning, and Ejrnæs, 2018). In the estimation, we find evidence of strong negative covariance between consumption shifters $\bar{q}_f$ and measures of income. One interpretation of this negative correlation is that households with higher income tend to save proportionally more. This behaviour acts as a force towards reducing the cross-sectional dispersion of expenditures.

**Breaking down inequality.** Equations (1) through (4), and (6) and (7) specify the complete set of conditions that characterize intergenerational dependence in this economy, linking earned income, other income and consumption across generations. These relationships characterise inequality among parents and children and highlight how family heterogeneity translates into inequality. Equations (1), (2) and (6) describe the processes (in levels) for parents and can be mapped into cross-sectional variances:

$$\begin{aligned} \text{Var}\left(e_f^p\right) &= \sigma^2_{\bar{e}^p} && (8)\\ \text{Var}\left(n_f^p\right) &= \sigma^2_{\bar{n}^p} && (9)\\ \text{Var}\left(c_f^p\right) &= \sigma^2_{\bar{q}^p} + \sigma^2_{\bar{e}^p} + \sigma^2_{\bar{n}^p} + 2\left(\sigma_{\bar{q}^p,\bar{e}^p} + \sigma_{\bar{q}^p,\bar{n}^p} + \sigma_{\bar{e}^p,\bar{n}^p}\right). && (10) \end{aligned}$$

The latter equations highlight how consumption inequality among parents depends not only on inequality in earnings and other income, but also on their covariances. To the extent that insurance implies that other income is negatively correlated with earnings, then consumption inequality may be lower than earnings inequality.

Similarly, equations (3), (4) and (7) describe the key processes (in levels) for children and how inequality among children depends on inequality among parents:

$$\begin{aligned} \text{Var}\left(e_f^k\right) &= \gamma^2\sigma^2_{\bar{e}^p} + \theta^2\sigma^2_{\bar{n}^p} + 2\gamma\theta\sigma_{\bar{e}^p,\bar{n}^p} + \sigma^2_{\delta^k} && (11)\\ \text{Var}\left(n_f^k\right) &= \rho^2\sigma^2_{\bar{n}^p} + \lambda^2\sigma^2_{\bar{e}^p} + 2\rho\lambda\sigma_{\bar{e}^p,\bar{n}^p} + \sigma^2_{\varepsilon^k} && (12)\\ \text{Var}\left(c_f^k\right) &= \phi^2\sigma^2_{\bar{q}^p} + (\gamma+\lambda)^2\sigma^2_{\bar{e}^p} + (\rho+\theta)^2\sigma^2_{\bar{n}^p} \\ &\quad +2\left[(\gamma+\lambda)\phi\sigma_{\bar{q}^p,\bar{e}^p} + (\rho+\theta)\phi\sigma_{\bar{q}^p,\bar{n}^p} + (\rho+\theta)(\gamma+\lambda)\sigma_{\bar{e}^p,\bar{n}^p}\right] \\ &\quad +\sigma^2_{\varepsilon^k} + \sigma^2_{\psi^k} + \sigma^2_{\delta^k} + 2\left[\sigma_{\psi^k,\varepsilon^k} + \sigma_{\psi^k,\delta^k} + \sigma_{\delta^k,\varepsilon^k}\right]. && (13) \end{aligned}$$

Earnings inequality among children responds to: (i) the magnitude of earnings inequality among parents ($\sigma^2_{\bar{e}^p}$); and (ii), the intensity of the intergenerational pass-through ($\gamma$). It follows that the pass-through parameter alone is not sufficient to determine the role of parental influences on inequality in subsequent generations. For expenditures, the first two rows of equation (13) describe how family heterogeneity drives differences among their offspring: the first row captures the direct effects of inequality among parents being transmitted into inequality among children; the second row describes the covariances which may offset these direct effects. Finally, the last row captures the drivers of inequality among children that are independent of parents.

# 3 Identification and Estimation

In our baseline specification, we abstract from transitory components of income and consumption, and use time-averaged observations for each individual. This also mitigates concerns about measurement error. We revisit the role of transitory components in Section 6 where we document the robustness of baseline estimates to the inclusion of yearly variation.

## 3.1 Identification

Identification proceeds in three steps. First, we use cross-sectional moments for parents and identify variances and covariances between their sources of income and consumption. Second, given these estimates and inter-generational covariances, we recover parent-child persistence parameters. Lastly, information from the previous two steps is used alongside second moments from the cross-section of children to identify the forces driving inequality among children. In what follows we overview how specific moments identify key elements of the model.

**(a) Cross-sectional variation among parents.** To identify the variance-covariance structure in the parents' cross-section we rely on (8), (9) and on the relationship:

$$\operatorname{Cov}\left(e_f^p, n_f^p\right) = \sigma_{\bar{e}^p,\bar{n}^p}. \tag{14}$$

These equations deliver $\sigma^2_{\bar{e}^p}$, $\sigma^2_{\bar{n}^p}$ and $\sigma_{\bar{e}^p,\bar{n}^p}$. Then, the covariances $\sigma_{\bar{q}^p,\bar{e}^p}$ and $\sigma_{\bar{q}^p,\bar{n}^p}$ are identified from:

$$\begin{aligned} \operatorname{Cov}\left(e_f^p, c_f^p\right) &= \sigma^2_{\bar{e}^p} + \sigma_{\bar{q}^p,\bar{e}^p} + \sigma_{\bar{e}^p,\bar{n}^p} && (15)\\ \operatorname{Cov}\left(n_f^p, c_f^p\right) &= \sigma^2_{\bar{n}^p} + \sigma_{\bar{q}^p,\bar{n}^p} + \sigma_{\bar{e}^p,\bar{n}^p}. && (16) \end{aligned}$$

Finally, equation (10) can be used to recover the dispersion of consumption shifters $\sigma^2_{\bar{q}^p}$.

**(b) Intergenerational persistence.** The intergenerational elasticity parameters $(\gamma, \theta, \rho, \lambda, \phi)$ are identified using within-family covariation. From equation (14) we recover $\sigma_{\bar{e}^p,\bar{n}^p}$ and through (8) we identify $\sigma^2_{\bar{e}^p}$; it follows that equations (17) and (20) jointly identify the intergenerational earnings pass-through $\gamma$ and $\theta$. Similarly, the pass-through parameters for other income, $\rho$ and $\lambda$, are identified from (18) and (19). This leaves the persistence of consumption shifters $\phi$ to be identified from (21). Appendix B reports further details about the identification of pass-through parameters, including a discussion of the over-identifying restrictions.

$$\begin{aligned}
\text{Cov}\left(e_f^p, e_f^k\right) &= \gamma\sigma_{\bar{e}^p}^2 + \theta\sigma_{\bar{e}^p,\bar{n}^p} && (17)\\
\text{Cov}\left(n_f^p, n_f^k\right) &= \rho\sigma_{\bar{n}^p}^2 + \lambda\sigma_{\bar{e}^p,\bar{n}^p} && (18)\\
\text{Cov}\left(e_f^p, n_f^k\right) &= \rho\sigma_{\bar{e}^p,\bar{n}^p} + \lambda\sigma_{\bar{e}^p}^2 && (19)\\
\text{Cov}\left(n_f^p, e_f^k\right) &= \gamma\sigma_{\bar{e}^p,\bar{n}^p} + \theta\sigma_{\bar{n}^p}^2 && (20)\\
\text{Cov}\left(c_f^p, c_f^k\right) &= \phi\left(\sigma_{\bar{q}^p}^2 + \sigma_{\bar{q}^p,\bar{e}^p} + \sigma_{\bar{q}^p,\bar{n}^p}\right) + (\gamma+\lambda)\left(\sigma_{\bar{e}^p}^2 + \sigma_{\bar{q}^p,\bar{e}^p} + \sigma_{\bar{e}^p,\bar{n}^p}\right)\\
&\quad + (\rho+\theta)\left(\sigma_{\bar{n}^p}^2 + \sigma_{\bar{q}^p,\bar{n}^p} + \sigma_{\bar{e}^p,\bar{n}^p}\right) && (21)
\end{aligned}$$

**(c) Cross-sectional variation among children.** Finally, we employ estimates from the previous steps to identify the parameters for the cross-sectional distribution of children. The variances of idiosyncratic permanent shocks, $\sigma_{\delta^k}^2$ and $\sigma_{\varepsilon^k}^2$, are identified from (11) and (12), respectively. Identification of the remaining child-specific parameters follows from combining the covariances of income, earnings and consumption among children (see Appendix B.1) as well as from the variance of consumption expenditures in equation (13).

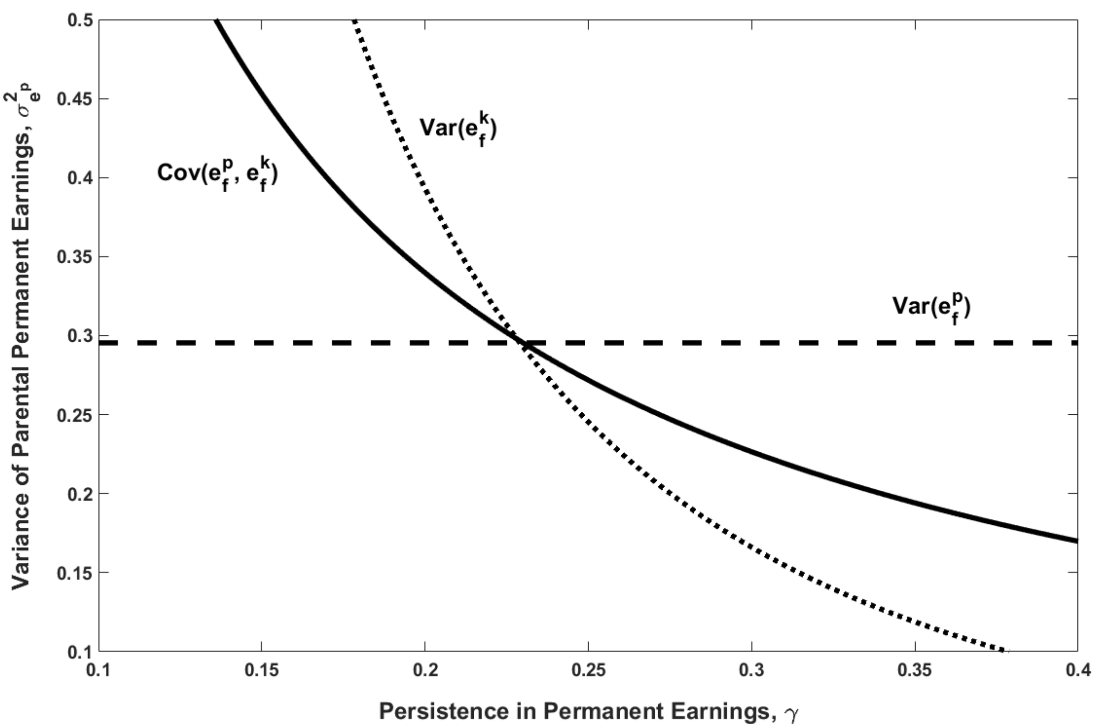


Figure 1: Identification of Persistence and Dispersion Parameters

**Identification: A graphical example.** One insight of the 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 1 where the y-axis measures the parental permanent earnings variance, $\sigma^2_{\bar{e}^p}$, and the x-axis represents the intergenerational earnings persistence, $\gamma$. To identify this pair of parameters we only use three empirical moments: $Var(e^p_f)$, $Cov(e^p_f, e^k_f)$ and $Var(e^k_f)$.

From moment condition (8), the variance of parental earnings ($\sigma^2_{\bar{e}^p}$) is uniquely identified by $\text{Var}\left(e^p_f\right)$: its value is shown as the horizontal dashed line in Figure 1. The moment condition (11) captures the tradeoff between $\gamma$ and $\sigma^2_{\bar{e}^p}$, holding constant other persistence and variance parameters (i.e., $\theta, \sigma^2_{\bar{n}^p}, \sigma_{\bar{e}^p,\bar{n}^p}$ and $\sigma^2_{\delta^k}$). This is plotted as the negatively sloped dotted line in Figure 1. The intersection of the dotted line with the dashed line uniquely identifies the persistence parameter, $\gamma$. However, our model features an additional restriction: the exact location of the pair $(\gamma, \sigma^2_{\bar{e}^p})$ needs to be consistent with the moment condition (17), imposing an additional tradeoff between the two parameters (shown by the solid line). That is, $\sigma^2_{\bar{e}^p}$ and $\gamma$ must be such that both the solid and the dotted lines intersect the dashed line at a common location. One can verify that the location where all three moment conditions hold in Figure 1 corresponds to the baseline parameter estimates presented in Section 4.

## 3.2 Estimation

We estimate model parameters 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 biases associated with using a full variance-covariance matrix featuring higher-order moments (see Altonji and Segal, 1996). Data on earnings, other income and consumption is used to calculate the empirical moments, after removing time and birth-cohort effects. Empirical moments are constructed using the residuals of a log-linear regression of the variables on a full set of year and cohort dummies. This is done separately for the parent and child generations. In Appendix C, we further break down total variation into a component explained by observable characteristics and a residual component representing unobserved heterogeneity.

## 3.3 Data

We use data from the Panel Study of Income Dynamics (PSID). This dataset is often used in the analysis of intergenerational persistence of economic outcomes because the offspring of original sample members become part of the survey sample when they establish independent 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. To reduce noise due to weak labour market attachment and variation in marital status, we sample married households with a male head and at least 5 years of observations.[10] We also restrict the sample to families with non-negative labour earnings and total income, that work no more than 5,840 hours in a year, and with wages at least half of the federal minimum wage. Finally, we select out households that experience annual earnings growth of more than 400%. Baseline results focus on intergenerational linkages between fathers and sons.[11] For each generation, we consider income and expenditures from age 25 onwards, with a maximum sample age of 65, to avoid confounding effects related to retirement. By design, the income and consumption information of parents refers to later stages of the life-cycle. In our baseline sample of 760 unique father-son pairs, the average parental age is 47 years while children's average age is 37. Details about data and sampling restrictions are in Appendix B.

Labour earnings data for the household head and his spouse are readily available for all survey waves of the PSID. Data about transfers from public and private sources for the husband and the wife are also available for most years. In contrast, the consumption expenditure data can be sparse, and not presented as a single variable in the PSID. Expenditures on food are the only category that is observed almost consistently since the earliest 1968 wave, and we use food outlays as the consumption measure for the baseline estimation. In Section 6, we examine the robustness of our findings to an alternative consumption measure, suggested by Attanasio and Pistaferri (2014), that relies on 11 major categories of consumption outlays that are reported from 1999 onwards. This approach measures total consumption expenditure at the household level by estimating a simple demand system using data for the years in which all 11 consumption expenditures were available in the PSID; then, by inverting the demand system, one can recover total expenditures for the years before 1999. The method relies on the theory of consumer demand and two-stage budgeting: the allocation of resources spent in a given period over different commodities is assumed to depend on relative prices, taste-shifters (demographic and socioeconomic variables) and total expenditure. Details about the variables, their availability in the survey and the demand system estimation procedure are reported in Appendix B. We adjust household-level expenditures using the OECD adult equivalence scale.

[10] The restriction to married households is helpful but not inconsequential, as intergenerational insurance may come into play exactly at the time of relationship breakdown (Fisher and Low, 2015).

[11] Our focus on father-son linkages also avoids some sample issues associated with the structure of the PSID (see Hryshko and Manovskii, 2019).

# 4 Results

## 4.1 Baseline Results

Table 1 reports the variances of earnings, other income and consumption expenditures for parents and children.[12] These variances, along with the empirical moments reported in Figure 4 of Appendix C, are used in the baseline implementation to estimate intergenerational persistence parameters and the underlying variance-covariance structure of permanent income and consumption for each generation. We summarize the within-sample fit of the model in Figure 4 of Appendix C.

Table 1: Variances

| **Variable** | **Parent** | **Child** |
|---|---|---|
| Earnings | 0.291 | 0.248 |
| Other Income | 0.808 | 0.534 |
| Consumption | 0.097 | 0.114 |

The two lifetime-income sources are much more dispersed than expenditures in both generations, indicating the presence of cross-sectional consumption smoothing mechanisms. This may occur through taxes and transfers as well as through heterogeneity in saving and spending behaviour of households. Amongst income sources, labour earnings are less dispersed than other family income. In Table 14 of Appendix C we show that the higher dispersion of other income is due to the uneven distribution of transfers while spousal earnings are significantly less dispersed. The relative magnitudes of earnings and consumption dispersion reported in Table 1 are consistent with those found in studies by Krueger and Perri (2006) and Attanasio and Pistaferri (2014). Figure 3 in Appendix B shows the evolution of cross-sectional earnings and consumption inequality in our sample over the last four decades.

The age range used to calculate these variances is wider for parents than it is for children since parents are observed for a longer period of time in PSID data. Therefore, differences in the magnitude of variances of parents and children, shown in Table 1, do not imply a decline in income inequality across generations. Rather, these differences reflect shocks accruing at different stages of the life-cycle. Table 7 in Section 5 reports variances based on samples where the ages of both parents and children are restricted between 30 and 40. These variances illustrate the evolution of inequality across generations, showing a relative increase in inequality among children that is consistent with the well-established notion of increasing income U.S. inequality over the

[12] In Appendix Table 17, we decompose each statistic into the variance due to observable characteristics and the residual variance due to unobservable factors.

past decades. The age restriction, however, substantially reduces sample size and in the baseline analysis, we use the wider age range for parents in order to obtain more accurate estimates of parental permanent income. Since we do not observe children in the later part of their working lives, our estimates reflect how parental heterogeneity impacts dispersion among children in the earlier decades of their adult lives.

**Intergenerational elasticities.** Table 2 reports estimates of intergenerational persistence parameters. The elasticity is highest for earnings, with the pass-through $\gamma$ estimated at 0.23; in contrast, the elasticity for other household income, $\rho$, is 0.10 and that for consumption, $\phi$, is 0.15.

Table 2: Estimates: Intergenerational Elasticities

| **Variables** | **Parameters** | **Estimates** |
|---|---|---|
| | | (1) |
| Earnings | $\gamma$ | 0.230 |
| | | (0.027) |
| Other Income | $\rho$ | 0.100 |
| | | (0.023) |
| $\bar{e}_f^p$ on $\bar{n}_f^k$ | $\lambda$ | 0.206 |
| | | (0.032) |
| $\bar{n}_f^p$ on $\bar{e}_f^k$ | $\theta$ | 0.055 |
| | | (0.019) |
| Consumption Shifters | $\phi$ | 0.154 |
| | | (0.032) |
| *No. of Parent-Child Pairs* | $N$ | 760 |

**Note:** Bootstrap standard errors (100 repetitions) in parentheses. Data is purged of year and birth-cohort effects. The average age for parents in the sample is 47 years; that of children is 37 years.

It is important to emphasize that the significant covariation in idiosyncratic expenditure shifters $q$ across generations, captured by the parameter $\phi$, contributes to consumption inequality over and above any effects working through the earnings and other income channels. That is, family influences on consumption expenditures build up through three inter-dependent channels: earnings, other household income, and persistence in consumption and saving propensities.

Higher parental earnings are associated with higher levels of other income among offspring, with the cross-elasticity $\lambda$ equal to 0.21: this positive covariation holds for both transfers and spousal earnings among children (see Section 4.2.2). On the other hand, other household income has little effect on children's earnings, with the elasticity $\theta$ estimated to be small albeit statistically significant. Explicitly accounting for these cross-effects between different dimensions of intergenerational pass-through (namely, male head earnings, wife earnings and transfer income) turns out to be an important contribution of our approach over the standard reduced-form analysis of intergenerational persistence. As we show in Section 6, ignoring these cross-effects may lead to misleading inference about the role of family influences for cross-sectional inequality in the children's generation.

We show that the pass-through parameters in Table 2 are largely driven by persistence in observable characteristics (see Appendix C). In particular, we document that education accounts for a significant component of the earnings pass-through across generations, corroborating evidence from previous studies (see for example, Landersø and Heckman, 2017; Lefgren, Sims, and Lindquist, 2012).

**Permanent income and consumption.** All estimates of variances and covariances for the permanent components of earnings, other income and consumption are reported in Table 3. The importance of jointly estimating income and consumption processes becomes apparent when examining these estimates. To illustrate how covariations are key to account for data patterns, we note that the variance of the permanent consumption components, $\sigma_{\bar{q}}$ is larger than that of permanent earnings in both generations; however, we know that consumption expenditures are much less dispersed than earnings. This apparent discrepancy highlights the role of the negative covariation between permanent earnings and idiosyncratic consumption shifters. Estimates of this covariance are -0.27 for the parents' generation (see $\sigma_{\bar{e},\bar{q}}$) and exhibit a similar magnitude in the child's generation. In addition, the permanent component of other income exhibits even stronger negative covariation with lifetime consumption shifters (see $\sigma_{\bar{e},\bar{q}}$).

The negative covariation between the permanent components of consumption and income mitigates the impact of income inequality on consumption inequality; that is, the negative covariances compress the distribution of log consumption and drive its overall variance below the variance of income. Moreover, these estimates suggest that higher-income families save proportionally more and have, on average, a lower propensity to consume.[13] Such traits are passed across generations, which reinforces their mitigating influence on consumption dispersion.

[13] See Straub (2018) and Abbott and Gallipoli (2019) for recent evidence of high saving rates among the rich. Fan (2006) suggests that this may be motivated by bequest motives. De Nardi, French, and Jones (2016) argue that other non-bequest motives, like healthcare expenditure, can account for this excess savings.

Table 3: Estimates: Variances and Covariances of Idiosyncratic Components

| | Parameters | Estimates (1) |
|---|---|---|
| **Parental Outcomes: Variances** | | |
| Permanent Earnings | $\sigma^2_{\bar{e}^p}$ | 0.295 |
| | | (0.021) |
| Permanent Other Income | $\sigma^2_{\bar{n}^p}$ | 0.806 |
| | | ( 0.06) |
| Permanent Consumption Shifters | $\sigma^2_{\bar{q}^p}$ | 1.031 |
| | | (0.065) |
| **Child Idiosyncratic Heterogeneity: Variances** | | |
| Permanent Earnings | $\sigma^2_{\delta^k}$ | 0.228 |
| | | (0.011) |
| Permanent Other Income | $\sigma^2_{\varepsilon^k}$ | 0.511 |
| | | (0.043) |
| Permanent Consumption Shifters | $\sigma^2_{\psi^k}$ | 0.730 |
| | | (0.056) |
| **Parental Outcomes: Covariances** | | |
| Consumption Shifters & Earnings | $\sigma_{\bar{q}^p,\bar{e}^p}$ | -0.271 |
| | | (0.024) |
| Consumption Shifters & Other Income | $\sigma_{\bar{q}^p,\bar{n}^p}$ | -0.818 |
| | | (0.061) |
| Earnings and Other Income | $\sigma_{\bar{e}^p,\bar{n}^p}$ | 0.070 |
| | | (0.013) |
| **Child Idiosyncratic Heterogeneity: Covariances** | | |
| Consumption Shifters & Earnings | $\sigma_{\psi^k,\delta^k}$ | -0.247 |
| | | (0.018) |
| Consumption Shifters & Other Income | $\sigma_{\psi^k,\varepsilon^k}$ | -0.522 |
| | | (0.048) |
| Earnings & Other Income | $\sigma_{\delta^k,\varepsilon^k}$ | 0.075 |
| | | (0.013) |
| *No. of Parent-Child Pairs* | $N$ | 760 |

**Note:** Bootstrap standard errors (100 repetitions) in parentheses. Data is purged of year and birth-cohort effects. The average age for parents in the sample is 47 years; that of children is 37 years.

## 4.2 Role of Parental Heterogeneity

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

### 4.2.1 Variance Accounting

Table 4 summarizes the impact of parental heterogeneity on the variance of children outcomes. Let $\text{Var}[y^k(p)]$ measure the offspring variance that is explained by parental factors for variable $y \in \{e, n, c\}$, while $\text{Var}[y^k]$ denotes the total cross-sectional variance in the kids' generation. The ratio $\frac{\text{Var}[y^k(p)]}{\text{Var}[y^k]}$ quantifies the share of total variation attributed to parental heterogeneity. For an illustration of all the calculations involved, see Appendix C.

Table 4: Breaking Up Child Inequality: Parental versus Idiosyncratic Heterogeneity

| **Variables** | **Child Variance** | **Variance due to Parents** | **Idiosyncratic Variance** |
|---|---|---|---|
| | (1) | (2) | (3) |
| Earnings | 0.248 | 0.020 (8.1%) | 0.228 (91.9%) |
| Other Income | 0.534 | 0.024 (4.4%) | 0.510 (95.6%) |
| Consumption | 0.114 | 0.034 (29.8%) | 0.080 (70.2%) |

**Note:** Numbers obtained using parameter estimates from Tables 2 and 3.

Combining the estimates in Tables 2 and 3, we are able to break down the relative contributions of parental and idiosyncratic heterogeneity to the cross-sectional dispersion of child outcomes (see Table 4). By far the largest impact of parental heterogeneity is on consumption dispersion, as it accounts for almost 30% of total variation among offspring. Parental factors account for much less of the variation in income — 8% and 4% for earnings and other income, respectively. As discussed before, this is consistent with the observation that intergenerational transmission of consumption and saving behaviours, after accounting for the level of income, is an important channel of intra-family persistence in consumption expenditures. Since the cross-sectional distribution of expenditures is more compressed than its counterparts for earnings and other income, parental influences end up explaining a much larger share of this lower variance. Nevertheless, it is clear that idiosyncratic heterogeneity accruing over the life-cycle accounts for most of the dispersion of income and consumption outcomes in the younger generation.[14]

Lastly, it is important to emphasize that a significant share of parental influence on consumption dispersion can only be identified if one allows for non-zero cross-elasticities $\lambda$ and $\theta$ between earnings and other income in the two generations. Restricting these cross-elasticities to zero not only diminishes the quantitative contribution of parental heterogeneity to consumption dispersion but also artificially boosts the parental importance for earnings heterogeneity. This highlights again the co-dependence of these processes and the biases that are introduced by ignoring this codependence. The mechanism behind these biases is discussed in Section 6.2 where we re-estimate the model after restricting $\lambda = \theta = 0$.

### 4.2.2 Marital Selection

In the baseline model, other income is the sum of transfer income (both public and private transfers) and spousal earnings. In this subsection, we consider the restriction that other income consists only

Table 5: Components of Other Income: Intergenerational Elasticity Estimates

| | **Parameters** | **Just Transfers** (1) | **Spouse Earnings** (2) | **Other Income** (3) |
|---|---|---|---|---|
| Earnings | $\gamma$ | 0.239 | 0.275 | 0.254 |
| | | (0.050) | (0.027) | (0.032) |
| Other Income | $\rho$ | 0.031 | 0.142 | 0.097 |
| | | (0.046) | (0.036) | (0.033) |
| $\bar{e}_f^p$ on $\bar{n}_f^k$ | $\lambda$ | 0.107 | 0.232 | 0.184 |
| | | (0.073) | (0.033) | (0.045) |
| $\bar{n}_f^p$ on $\bar{e}_f^k$ | $\theta$ | -0.007 | 0.144 | 0.086 |
| | | (0.017) | (0.033) | (0.027) |
| Consumption Shifters | $\phi$ | 0.007 | 0.372 | 0.217 |
| | | (0.047) | (0.047) | (0.047) |
| *No. of Parent-Child Pairs* | $N$ | 459 | 459 | 459 |

**Note:** Bootstrap standard errors (100 repetitions) reported in parentheses. Food expenditures used as a measure of consumption. Tables 14 and 15 in Appendix C present estimates of the corresponding variance-covariance parameters. Sample restricted to observations for which both transfers and wife earnings are not missing.

[14] In Table 19 of Appendix C, we document that the explanatory power of parental heterogeneity is mostly due to observable characteristics.

of transfers (column 1) or only of spousal earnings (column 2).[15] In Table 5, we report estimates of intergenerational pass-through elasticities under these different definitions, including our baseline specification for comparison in column 3. We then report in Table 6 the implications for decomposing inequality into inherited and idiosyncratic sources.

By focusing on spousal earnings, column 2 of Table 5 shows the two ways in which parental heterogeneity can impact on children through spousal selection. First, the elasticity $\rho$ captures the persistence of spousal characteristics. The fact that spousal earnings are rather persistent across parent-child pairs (with a $\rho$ elasticity of 0.14) suggests maternal earnings may play a role in marital selection. This is consistent with findings in Fernandez, Fogli, and Olivetti (2004), who document preference formation based on maternal characteristics. Second, the parameter $\lambda$ captures the impact of father's earnings on their son's spousal earnings. The large value of $\lambda$ is indicative of the strength of this further marital selection.

Table 6: Parental versus Idiosyncratic Heterogeneity: Role of Marital Selection

| **Variable** | **Child Variance** | **Variance due to Parents** | **Idiosyncratic Variance** |
|---|---|---|---|
| | (1) | (2) | (3) |
| *Panel A: Other Income = Wife Earnings* | | | |
| Earnings | 0.229 | 0.033 (14.6%) | 0.196 (85.4%) |
| Wife Earnings | 0.322 | 0.026 (8.1%) | 0.296 (91.9%) |
| Consumption | 0.113 | 0.025 (22.5%) | 0.088 (77.5%) |
| *Panel B: Other Income = Transfers* | | | |
| Earnings | 0.229 | 0.016 (7.1%) | 0.213 (92.9%) |
| Transfers | 1.068 | 0.005 (0.4%) | 1.063 (99.6%) |
| Consumption | 0.113 | 0.034 (30.3%) | 0.079 (69.7%) |
| *Panel C: Other Income = Wife Earnings + Transfers* | | | |
| Earnings | 0.229 | 0.024 (10.7%) | 0.205 (89.3%) |
| Other Income | 0.457 | 0.016 (3.5%) | 0.441 (96.5%) |
| Consumption | 0.113 | 0.027 (24.2%) | 0.086 (75.8%) |

**Note:** Numbers are obtained using parameter estimates in Table 5 and Table 15 in Appendix C, based on a sample of 459 unique parent-child pairs for which data on both transfers and wife earnings are not missing.

More generally, when only spousal earnings are used in estimation, all intergenerational elasticity estimates are strongly significant and at least as large as their baseline counterparts. In fact, the point estimates of intergenerational persistence for consumption shifters and other income

[15] In Table 15 of Appendix E we report the associated variance-covariance estimates.

are roughly 50% higher than baseline results. In contrast, when the specification of other income featuring transfers alone, the persistence parameters are low and imprecisely estimated.

Table 6 considers the implications for inequality of breaking down other income into spousal earnings and transfer income. Column 2 shows how the importance of parents varies when using different measures. The contribution of parents to inequality in other income among children is due to spousal earnings rather than transfers. Nonetheless, under all specifications, parents explain about one quarter of the observed consumption inequality.

## 4.3 Counterfactual Cross-Sectional Distributions

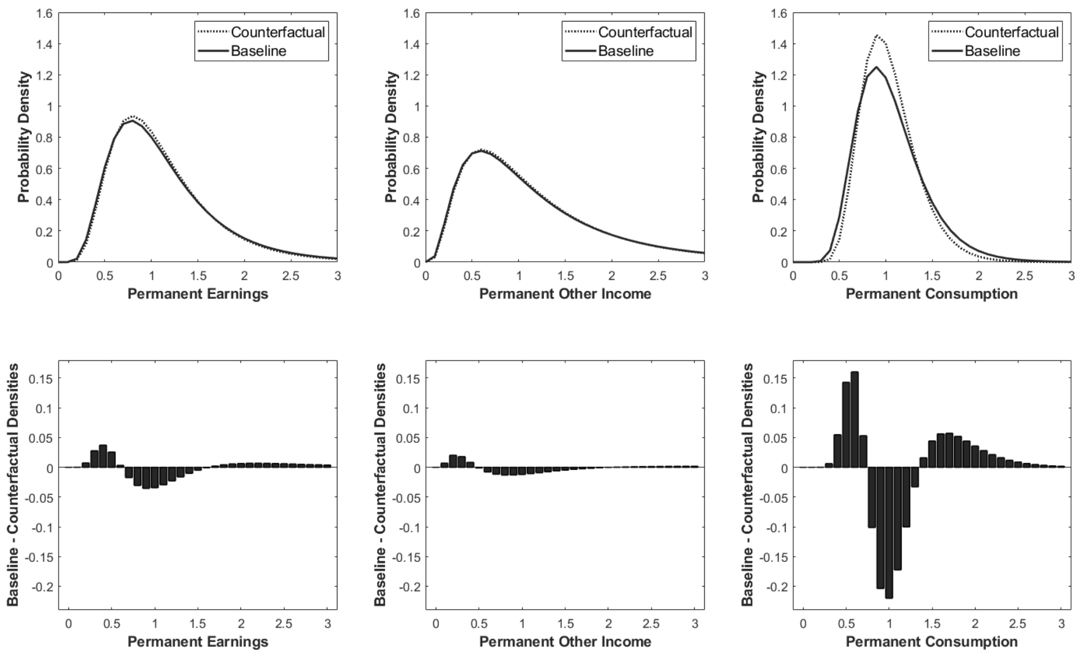


Figure 2: Baseline versus Counterfactual Probability Density Functions

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

The absence of intergenerational transmission is equivalent to a setting with randomly matched parent-child pairs. A simple way of gauging the impact of family background in this setting is to plot the observed and counterfactual cross-sectional distribution of each outcome in the children's generation (top panels of Figure 2) and their local differences, (as measured by the histograms in the bottom panels of Figure 2). The histograms represent, for each interval of the domain, the probability mass of the actual distribution minus the corresponding mass in the counterfactual.[16] The counterfactual distributions are somewhat less dispersed, with the strongest departure from baseline observed for lifetime consumption. In all counterfactuals, the distribution is more compressed. These plots highlight the limited role of family background in understanding the distribution of children's earnings and other income, but more substantial role in understanding consumption inequality. These findings are in line with results in Table 4.

# 5 The Evolution of Inequality across Generations

The magnitudes of the intergenerational pass-through parameters and the variances of idiosyncratic heterogeneity raise questions about the evolution of inequality across generations. A longer data panel would be ideal to identify persistence across multiple generations, since the current span of PSID data covers, at most, the working life of children born between the 1950s and the early 1980s. This makes it hard to obtain direct estimates of the impact of grandparents on grandchildren and generations further apart. However, under a stationarity assumption, one can examine the projected path of inequality by computing a first-order approximation of the expected evolution of the variances of income and consumption starting from current levels.

To examine inequality across generations, we compute the long-run steady-state variances of earnings, other income and consumption. These measures describe the extent of dispersion in income and consumption if, all else equal, the baseline model were allowed sufficient time to converge to its steady state. By comparing current variances to their steady-state values, one can tie changes in cross-sectional inequality to the intergenerational persistence of parental advantage.[17]

**A vector representation of the model.** Earnings, other income and consumption shifters evolve through generations of family $f$ according to the following vector autoregressive process:

$$\begin{bmatrix} \bar{e}_f^{k_t} \\ \bar{n}_f^{k_t} \\ \bar{q}_f^{k_t} \end{bmatrix} = \begin{bmatrix} \gamma & \theta & 0 \\ \lambda & \rho & 0 \\ 0 & 0 & \phi \end{bmatrix} \cdot \begin{bmatrix} \bar{e}_f^{k_{t-1}} \\ \bar{n}_f^{k_{t-1}} \\ \bar{q}_f^{k_{t-1}} \end{bmatrix} + \begin{bmatrix} \delta_f^{k_t} \\ \varepsilon_f^{k_t} \\ \psi_f^{k_t} \end{bmatrix}.$$

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

[16]We assume lognormality of the outcome variables. Appendix C provides a description of the procedure. We use parameter estimates from Tables 2 and 3.

[17]Baseline estimates are based on a larger sample that includes observations for older parents. In this section, we focus on individuals of similar ages in both generations. Since we do not observe children in the second half of their working lives, in this section we restrict the age of both parents and children to be between 30 and 40.

$$\begin{bmatrix} \delta_f^{k_t} \\ \varepsilon_f^{k_t} \\ \psi_f^{k_t} \end{bmatrix} \sim N \left[ \begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma^2_{\delta^k} & \sigma_{\delta^k,\varepsilon^k} & \sigma_{\delta^k,\psi^k} \\ \sigma_{\delta^k,\varepsilon^k} & \sigma^2_{\varepsilon^k} & \sigma_{\varepsilon^k,\psi^k} \\ \sigma_{\delta^k,\psi^k} & \sigma_{\varepsilon^k,\psi^k} & \sigma^2_{\psi^k}. \end{pmatrix} \right]$$

Using parameter estimates, we simulate the VAR forward, iterating until convergence.[18] This delivers simulated data series for $\bar{e}_f^{k_t}$, $\bar{n}_f^{k_t}$, $\bar{q}_f^{k_t}$, $\delta_f^{k_t}$, $\varepsilon_f^{k_t}$ and $\psi_f^{k_t}$. To obtain a series for log consumption, we use the relationship:

$$c_f^{k_t} = \phi q_f^{k_{t-1}} + (\gamma + \lambda)\, e_f^{k_{t-1}} + (\rho + \theta)\, n_f^{k_{t-1}} + \delta_f^{k_t} + \varepsilon_f^{k_t} + \psi_f^{k_t},$$

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

Table 7: Steady-state Inequality versus Current Inequality

| **Variable** | **Parental Variance** | **Child Variance** | **Steady-state Variance** |
|---|---|---|---|
| | (1) | (2) | (3) |
| Earnings | 0.199 | 0.251 | 0.255 |
| Other Income | 0.845 | 0.669 | 0.676 |
| Consumption | 0.097 | 0.118 | 0.127 |

**Note:** Estimates based on sample of 336 unique parent-child pairs. Age restricted between 30 and 40 years.

**Current versus long-term inequality.** Comparing steady-state variances with those observed in data, we see that for earnings and consumption the inequality in the parents' generation is the lowest (see column 1 of Table 7), followed by that in the children's generation (column 2 of Table 7). Steady-state inequality is the largest, suggesting that the variance of lifetime earnings and consumption expenditures might rise further from current levels. For other income, inequality in the children's generation is lower than in their parents' generation and slightly lower than its value in the steady-state. The steady-state variances implied by the baseline model are not far above what is measured in the children's generation. This observation reflects the low value of the

[18] 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 10 and 26. The VAR is simulated over 100,000 generations.

estimated pass-through parameter $\gamma$, meaning that predicted long-run inequality reflects primarily the variance of idiosyncratic shocks.

To illustrate the quantitative importance of intergenerational elasticities in the long-run, we re-estimate the baseline model using a constrained version of the GMM estimator where we hold constant the earnings persistence $\gamma$ at pre-determined values. By exogenously setting larger or smaller values of $\gamma$, we can assess whether, and how much, steady-state inequality might deviate from its initial value. Table 8 shows that for counterfactually high values of $\gamma$, earnings inequality in the children generation (column 4) can be substantially different from long-run model outcomes (column 5). Moreover, a trade-off between inter-generational persistence, $\gamma$ (column 1) and idiosyncratic heterogeneity, $\sigma^2_{\delta^k}$ (column 2) is evident when explaining the total child variance (column 4).[19]

Despite a falling variance for idiosyncratic innovations, $\sigma^2_{\delta^k}$, steady-state inequality in column 5 increases with the magnitude of $\gamma$. Thus, the cross-generational persistence, rather than the innovations variance, emerges as the key determinant of long-run inequality and as the main reason for the similarity of Var $\left(e^k\right)$ and Var $(e^*)$.[20]

These results emphasize that, without any increases in the underlying dispersion of idiosyncratic innovations, one would have to assume implausibly large values of the intergenerational pass-through to induce significantly higher long-run inequality. It follows that intergenerational persistence dictates the proportional impact of parental heterogeneity on inequality. Further evidence of this is in the last column of Table 8, which documents how changes in $\gamma$ lead to significant variation in the contribution of parental factors to cross-sectional earnings inequality. A larger $\gamma$ amplifies the contribution of family background: the parental contribution to inequality swings widely, between 1% and 12% (for values of $\gamma$ between 0.1 and 0.4) even when steady-state earnings dispersion $\widehat{Var(e^*)}$ barely changes.

It is interesting to contrast the values in column 6 of Table 8 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

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

[20]A striking feature of the GMM estimates in Table 8 is that the child variance remains constant and matches exactly the empirical value. In contrast, the observed parental variance is 0.199 and none of the estimates matches this figure exactly. To understand this, consider that the moment estimator has to satisfy equation (17), which implies a direct trade-off between $\gamma$ and $Var(e^p)$. Thus, increasing $\gamma$ tends to decrease $Var(e^p)$. On the other hand, whatever the values for $\gamma$ and $Var(e^p)$, the observed value of $Var(e^k)$ is always matched exactly by choosing the free parameter $\sigma^2_{\delta^k}$, which does not enter any other moment condition.

Table 8: The Importance of Parents: Varying Persistence $\gamma$

| $\gamma$ | $\widehat{\sigma^2_{\delta^k}}$ | $\widehat{Var(e^p)}$ | $\widehat{Var(e^k)}$ | $\widehat{Var(e^*)}$ | $\frac{\gamma^2 \widehat{Var(e^p)}}{\widehat{Var(e^k)}}$ |
|---|---|---|---|---|---|
| (1) | (2) | (3) | (4) | (5) | (6) |
| 0.10 | 0.248 | 0.202 | 0.251 | 0.251 | 1.3% |
| **0.21** | **0.241** | **0.199** | **0.251** | **0.255** | **4.0%** |
| 0.30 | 0.232 | 0.193 | 0.251 | 0.255 | 7.4% |
| 0.40 | 0.221 | 0.182 | 0.251 | 0.263 | 12.2% |
| 0.50 | 0.207 | 0.169 | 0.251 | 0.277 | 17.4% |
| 0.60 | 0.194 | 0.155 | 0.251 | 0.303 | 22.8% |
| 0.70 | 0.181 | 0.141 | 0.251 | 0.354 | 28.1% |
| 0.80 | 0.168 | 0.128 | 0.251 | 0.467 | 33.1% |
| 0.90 | 0.156 | 0.116 | 0.251 | 0.822 | 37.8% |

**Note:** Bold values refer to a specification with $\gamma$ unconstrained and estimated as part of the optimization. The age range for both children and parents is between 30 and 40 years. Estimation is based on 336 unique parent-child pairs for children born in the 1960s and 1970s.

on stationary parameter estimates. For this reason in Appendix D 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.

# 6 Robustness and Extensions

To assess the robustness of these findings we perform several sensitivity checks. First, we consider whether there are differences across cohorts. Second, we assess the importance of the cross-elasticities between earnings and other income by setting $\lambda$ and $\theta$ to zero. Third, we consider a sample of randomly matched parent-child pairs. Fourth, we employ alternative measures of expenditure. Fifth, we target additional moments in the GMM estimation using both cross-sectional and panel variation. Finally, we consider an alternative model of intergenerational persistence, specified in terms of growth rates of the outcome variables. The latter allows us to draw inference about intergenerational persistence between idiosyncratic innovations to income and consumption expenditures.

## 6.1 Estimates by Child Birth-Cohort

We split observations by child birth-cohort and focus on parents and kids aged between 30 and 40 years. Table 9 shows the cross-sectional variances of economic outcomes for the parents and kids for different child-birth cohorts.[21] Table 10 presents estimates of intergenerational pass-through parameters by children's decade of birth. The results are qualitatively similar to the baseline ones.[22] The differences between estimates of the intergenerational pass-through parameters for the 1960s and 1970s cohorts are not statistically significant. In Table 25 of Appendix E we consider whether the importance of parental influence in explaining cross-sectional heterogeneity in the child generation varies by children cohorts. Contrasting the 1960s and 1970s cohorts, the contribution of parental heterogeneity changed only for consumption, dropping from about 38% to 16%. However, cohort-specific sample sizes are small enough to suggest caution when comparing these shares.

Table 9: Variances by Child-Cohort (Age: 30-40 years)

| **Variable** | **Generation** | **All Cohorts** (1) | **1960s Cohort** (2) | **1970s Cohort** (3) |
|---|---|---|---|---|
| **Earnings** | Parent | 0.199 | 0.172 | 0.225 |
| | Child | 0.251 | 0.243 | 0.259 |
| **Other Income** | Parent | 0.845 | 0.945 | 0.752 |
| | Child | 0.669 | 0.568 | 0.770 |
| **Consumption** | Parent | 0.097 | 0.112 | 0.081 |
| | Child | 0.118 | 0.100 | 0.135 |

**Note:** The age range for both children and parents is between 30 and 40 years. Estimation is based on 166 unique parent-child pairs for children born in the 1960s and 170 such pairs for the 1970s cohort.

## 6.2 Restricting Cross-Effects between Income Sources

We consider a restricted version of the baseline model that does not allow parental earnings to affect the other income of the children, nor for parent's other income to affect child's earnings; that is, imposing both $\lambda$ and $\theta$ to be zero. Column 2 in Table 11 reports elasticity estimates under these restrictions. The point estimates of the parameters change significantly, overstating the importance of parents for earnings inequality among children. Most of the difference from

[21] We do not report results for the 1950s cohort as its sample size is small and estimates are quite noisy.

[22] Some of the parameter estimates lose statistical significance, as the age restrictions result in a much smaller sample, weakening the precision of the estimates.

Table 10: Intergenerational Elasticity Estimates by Child Cohort (Age: 30-40)

| | **Parameters** | **All Cohorts** | **1960s Cohort** | **1970s Cohort** |
|---|---|---|---|---|
| | | (1) | (2) | (3) |
| Earnings | $\gamma$ | 0.209 | 0.251 | 0.191 |
| | | (0.069) | (0.087) | (0.106) |
| Other Income | $\rho$ | 0.041 | -0.006 | 0.099 |
| | | (0.058) | (0.068) | (0.093) |
| $\bar{e}_f^p$ on $\bar{n}_f^k$ | $\lambda$ | 0.217 | 0.202 | 0.244 |
| | | (0.079) | (0.131) | ( 0.12) |
| $\bar{n}_f^p$ on $\bar{e}_f^k$ | $\theta$ | 0.040 | 0.009 | 0.079 |
| | | (0.032) | (0.046) | (0.038) |
| Consumption Shifters | $\phi$ | 0.075 | -0.029 | 0.200 |
| | | (0.075) | ( 0.09) | (0.124) |
| *No. of Parent-Child Pairs* | $N$ | 336 | 166 | 170 |

**Note:** Bootstrap standard errors (100 repetitions) in parentheses. Average parental ages in the three child-cohorts are 35, 36 and 35 years. Average ages of the children are 35, 34 and 35 years respectively. '*All Cohorts*' refer to the combined sample of 1960s and 1970s child birth cohorts. Food expenditure is used as proxy measure of consumption. All columns use cross-sectional data variation, net of cohort and year effects. Table 26 in Appendix E reports the estimates for the variance-covariance parameters.

the baseline estimates can be attributed to the restriction that $\lambda = 0$, as in the baseline model $\theta$ is already close to zero. By restricting $\lambda$ to be zero, we effectively decrease its value below the positive baseline estimate. This mechanically pushes up the estimate of $\gamma$ so as to guarantee a fairly constant value of $(\gamma + \lambda)$, the total intergenerational persistence from parental earnings to child outcomes. The exercise highlights the importance of allowing for cross-effects above and beyond the direct channels captured by $\gamma$ and $\rho$ when drawing inference about pass-through parameters.

Column 2 of Table 12 reports the importance of parental heteroegeneity for children's inequality. Parental heterogeneity accounts for a smaller share of cross-sectional consumption dispersion when $\lambda$ and $\theta$ are set to zero. This confirms that while higher parental earnings have a positive direct impact on the earnings and expenditures of children, the consumption distribution is shaped by several other forces and ignoring the indirect effects among different sources of income can lead to incorrect inference.

Table 11: Robustness: Intergenerational Elasticity Estimates

| **Parameters** | **Baseline** (1) | $\boldsymbol{\lambda = \theta = 0}$ (2) | **Random Match** (3) | **Imputation** (4) | **Panel Data** (5) |
|---|---|---|---|---|---|
| Earnings: $\gamma$ | 0.230 | 0.340 | -0.018 | 0.257 | 0.294 |
| | (0.029) | ( 0.02) | (0.028) | (0.029) | (0.041) |
| Other Income: $\rho$ | 0.100 | 0.121 | -0.039 | 0.096 | 0.095 |
| | (0.029) | (0.029) | (0.025) | (0.028) | (0.045) |
| $\bar{e}^p_f$ on $n^k_{f,t}$: $\lambda$ | 0.206 | 0 | -0.007 | 0.236 | 0.107 |
| | (0.038) | (0) | (0.035) | (0.033) | (0.060) |
| $\bar{n}^p_f$ on $e^k_{f,t}$: $\theta$ | 0.055 | 0 | -0.015 | 0.052 | 0.066 |
| | (0.017) | (0) | (0.023) | (0.015) | (0.035) |
| Consumption Shifters: $\phi$ | 0.154 | 0.109 | -0.048 | 0.127 | 0.153 |
| | (0.034) | (0.032) | (0.034) | (0.033) | (0.046) |
| *No. of Parent-Child Pairs: N* | 760 | 760 | 760 | 760 | 760 |

**Note:** Bootstrap standard errors (100 repetitions) in parentheses. Year and cohort effects have been removed.

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

It is conceivable that spurious correlations in the data may affect estimates of parent-child pass-through parameters. To account for this possibility we perform a placebo test using a sample in which parents and children are randomly matched. Estimates based on this sample imply no role

Table 12: Robustness: Importance of Parental Heterogeneity for Child Inequality

| Variables | Baseline | $\lambda = \theta = 0$ | Random Match | Imputation | Panel Data |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Earnings | 8.0 | 13.5 | 0.1 | 9.4 | 12.3 |
| Other Income | 4.4 | 2.2 | 0.2 | 5.0 | 2.1 |
| Consumption | 29.9 | 19.5 | 0.2 | 47.4 | 22.8 |

**Note:** All numbers are percentages (%) and are based on parameter estimates in Table 11 and Table 27 of Appendix E.

of parental heterogeneity for inequality in the children's generation, as seen in column 3 of Table 12. The lack of significance in the randomly matched sample indicates that genuine family linkages, rather than spurious correlations, drive our baseline estimates.

## 6.4 Alternative Measures of Expenditure

Since food consumption is available for most survey years in the PSID, the baseline analysis uses food expenditures as the consumption measure. However, alternative components of consumption might exhibit different properties. We examine the importance of other expenditure categories in two ways. First, we impute total consumption using the procedure suggested by Attanasio and Pistaferri (2014); this approach exploits rich consumption expenditure information available in the PSID after 1997 to approximate households' outlays in the earlier years of the survey. We report results for this alternative consumption measure in column 4 of Tables 11, 12, with underlying parameter estimates in Appendix Table 27. Estimates based on this broader range of expenditures suggest a stronger role of parental heterogeneity for consumption dispersion among children, with roughly half of the total dispersion due to family linkages. This higher estimate of the parental contribution to consumption inequality is arguably an upper bound of their true contribution, as it may reflect latent persistence of observable characteristics used to impute consumption. In a second sensitivity exercise, we restrict the sample to the post-1997 period, when there is no need for imputation of non-food consumption. Estimates from this smaller sample suggest a parental contribution to consumption inequality of roughly 24%, comparable to the baseline estimate.[23]

## 6.5 Using Panel Variation

In the baseline analysis, we average across yearly observations for each sample member and do not account for year-to-year individual variation. Time-averaging significantly reduces the impact of classical measurement error, but it also precludes identification of the variances of mean-zero

[23] Results are available upon request. The smaller size of the post-1997 sample makes estimates less precise.

transitory shocks to earnings, income and consumption. Thus, accounting for panel variation introduces extra parameters due to the need to estimate the variances and covariances of per-period transitory shocks.By the same token, this extra information introduces new moment restrictions. In Appendix E we report the full set of moments and parameters. As shown in column 5 of Tables 11 and 12, modelling period-specific variation makes little difference. However, standard errors are bigger, as one would expect when measurement error becomes more severe.

### 6.6 A Model of Intergenerational Persistence in Growth Rates

In the baseline model, intergenerational persistence arises through the transmission of individual fixed effects in income and consumption. An alternative hypothesis is that these linkages may occur through persistence in growth rates. To examine this possibility, we develop and estimate a model in which the permanent components of both earnings and other income are random walk processes (similar to Blundell, Pistaferri, and Preston, 2008). In this model the contemporaneous permanent innovations to these processes are correlated across parent-child pairs. Appendix E presents details of this alternative specification, along with a discussion of the identification strategy and parameter estimates. We find little or no evidence of intergenerational persistence in permanent innovations to earnings, other income and consumption expenditures.

## 7 Conclusion

This paper examines the importance of family background for understanding income and consumption inequality. We estimate the intergenerational elasticities of earnings, of other income and of consumption, and document their significance for the persistence of inequality across generations. Our main finding is that the quantitative contribution of idiosyncratic heterogeneity to cross-sectional inequality is significantly larger than that of parental effects. In reaching this conclusion, we highlight the importance of jointly estimating the income and expenditure processes, and of accounting for cross-effects between sources of income and consumption.

Parents impact children consumption behaviours both by directly influencing their propensity to spend and, indirectly, through the transmission of earnings and other income. We also find that the intergenerational elasticity of other income is largely due to persistence of spousal characteristics.

Our estimates imply that intergenerational persistence is not, by itself, high enough to induce further large increases in inequality over time and across generations. This emphasizes the prominent role of idiosyncratic heterogeneity, which diffuses and attenuates the impact of family background on the cross-sectional distributions of life-cycle income and consumption.

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# Appendix

There are five appendices, A through E corresponding to Sections 2 through 6 in the main paper respectively.

# A Appendix to Section 2

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

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

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

We are interested in knowing the persistence in permanent earnings and consumption, but we do not directly observe the long-term (permanent) earnings and consumption of any individual. An adult child's earnings are observed only over a limited range of ages. Hence we must proxy these life-cycle variables by some function of the current (yearly) variables that are actually observable.[24] 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.[25] 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

[24]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.

[25]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.[26]

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.[27] An alternative would have been to take the average of the parental variable (earnings or consumption) for the parents' entire lifetime (till 65 years of age). This would confound a number of effects, in particular, the effect of parental outcomes when children are at home with realisations of parental outcomes after children left home. The latter contemporaneous pass-through may be important for consumption smoothing across generations, but conceptually it is a different mechanism. A further issue with using the average over the entire lifetime is that this would impose that siblings born at different life-stages of the parent face the same parental inputs. Obviously, the age of the parents of different children born in a particular cohort will not be the same when the children reach the age range between 15 and 17. Therefore, we also control for the age of the parental household head.

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

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

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 $\epsilon_{fht}$ reflects factors like luck in labour and marriage markets, intergenerational transmission of genetic traits and other environmental factors (see Peters, 1992). We allow the coefficient $\beta$ to vary by year to capture the time variation in intergenerational persistence. It should be noted that the choice of the normalization age for $a^k_{fht}$ affects the point estimate of $\beta_t$ 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

[26]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.

[27]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 percent, and on the other hand if there were perfect persistence in intergenerational well-being then all the diagonal cells would read 100 percent 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

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

where $Q_{c,i}$ 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 percent are also in the lowest quartile. There is much more mobility in the middle of the distributions.

**Mobility Matrix of Head Earnings**

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

**Mobility Matrix of Total Consumption**

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

**Mobility Matrix of Food Consumption**

| Child \ Parent | $Q_{p,1}$ | $Q_{p,2}$ | $Q_{p,3}$ | $Q_{p,4}$ |
|---|---|---|---|---|
| $Q_{c,1}$ | **40.00** | 26.24 | 21.53 | 10.17 |
| $Q_{c,2}$ | 27.03 | **30.19** | 20.26 | 20.75 |
| $Q_{c,3}$ | 21.11 | 24.00 | **32.07** | 23.30 |
| $Q_{c,4}$ | 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:

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

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

## A.2 Derivation of the Consumption Process

In this appendix we derive the analytical approximation of the optimal consumption processes. Assuming a quadratic utility function and $\beta(1 + r) = 1$, we solve the maximization problem (5) and derive consumption at time $t$ as the annuity value of lifetime resources, as follows:

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

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 $x$, $ln(x) \simeq ln(1) + \frac{x-1}{1} = x - 1 \implies x \simeq 1 + ln(x)$.[28] 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,

$$\begin{aligned} 1 + c_{f,t} \quad &\simeq \quad (1+\bar{e}_f) + (1+\bar{n}_f) + \\ \tfrac{r}{(1+r)-(1+r)^{-(T-t)}} \quad & \left\{(1+a_{f,t}) + \left[\sum_{j=0}^{T-t}\left(\frac{1}{1+r}\right)^{j}\mathbb{E}_t\left(\zeta_{f,t+j}\right) + \sum_{j=0}^{T-t}\left(\frac{1}{1+r}\right)^{j}\mathbb{E}_t\left(u_{f,t+j}\right)\right]\right\} \\ \implies c_{f,t} \quad &\simeq \quad 1 + \frac{r}{(1+r)-(1+r)^{-(T-t)}}\left[(1+a_{f,t}) + (\zeta_{f,t} + u_{f,t})\right] + \bar{e}_f + \bar{n}_f \end{aligned}$$

Let $q_{f,t} \equiv 1 + \alpha_t\left(r\right)\left(1 + a_{f,t}\right)$, with $\alpha_t\left(r\right) = \frac{r}{(1+r)-(1+r)^{-(T-t)}}$. Then we can write the approximate log-consumption processes for an individual as:

$$c_{f,t} = q_{f,t} + \bar{e}_f + \bar{n}_f + \alpha_t\left(r\right)\left(\zeta_{f,t} + u_{f,t}\right)$$

For a large enough $T$ relative to $t$, $\alpha_t(r)$ can be approximated by $\alpha(r) = \frac{r}{1+r}$. Thus, for individuals who are sufficiently away from their demise, we can approximate their log-consumption as:

$$c_{f,t} = q_{f,t} + \bar{e}_f + \bar{n}_f + \alpha\left(r\right)\left(\zeta_{f,t} + u_{f,t}\right) \tag{A.2}$$

**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 $C_{f,t}^{-\tau} = \beta\left(1+r\right)\mathbb{E}_t\left(C_{f,t+1}^{-\tau}\right)$, where $\tau > 0$ is the parameter capturing the degree of risk aversion as also the intertemporal elasticity of substitution. Maintaining the assumption $\beta\left(1+r\right) = 1$, we get from the Euler equation

[28] 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 ($\ln x$), this approximation is valid.

$\mathbb{E}_t\left[\left(\frac{C_{f,t+1}}{C_{f,t}}\right)^{-\tau}\right] = 1$. We define the function $h(g_c) = (1+g_c)^{-\tau}$, where $g_c = \frac{C_{f,t+1}}{C_{f,t}} - 1$ such that $\mathbb{E}_t[h(g_c)] = 1$. A first order Taylor series expansion of $h(g_c)$ around $g_c^* = 0$ yields $h(g_c) \approx 1 - \tau g_c$. Taking expectations on both sides of this approximate equation, we get $\mathbb{E}_t(g_c) = 0$, implying $C_{f,t} = \mathbb{E}_t(C_{f,t+1})$. This is exactly the same as the Euler equation that one obtains from quadratic utility function without any approximation. Now, since we did not derive explicitly the consumption expression from this Euler equation in the paper, we provide the derivation here. Iterating forward the per-period budget constraint $A_{f,t+1} = (1+r)(A_{f,t} + Y_{f,t} - C_{f,t})$ (where $Y_{f,t} = E_{f,t} + N_{f,t}$) by one period and combining it with the Euler equation $C_{f,t} = \mathbb{E}_t(C_{f,t+1})$, we get,

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

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

# B Appendix to Section 3

This appendix complements Section 3 in the main paper by providing further details of the baseline model specification (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 Baseline Model Specification: Additional Moments

The moments used for the identification of the variance-covariance parameters idiosyncratic to the children's generation come from the covariances between earnings, other income and consumption for children:

$$\begin{aligned}
\text{Cov}\left(e_f^k, n_f^k\right) &= \left(\rho\gamma + \theta\lambda\right)\sigma_{\bar{e}^p,\bar{n}^p} + \gamma\lambda\sigma_{\bar{e}^p}^2 + \rho\theta\sigma_{\bar{n}^p}^2 + \sigma_{\delta^k,\varepsilon^k} && \text{(B.1)}\\
\text{Cov}\left(e_f^k, c_f^k\right) &= \gamma\left(\gamma + \lambda\right)\sigma_{\bar{e}^p}^2 + \theta\left(\theta + \rho\right)\sigma_{\bar{n}^p}^2 + \phi\gamma\sigma_{\bar{q}^p,\bar{e}^p} + \phi\theta\sigma_{\bar{q}^p,\bar{n}^p} \\
&+ \left[\gamma\left(\rho + \theta\right) + \theta\left(\gamma + \lambda\right)\right]\sigma_{\bar{e}^p,\bar{n}^p} + \sigma_{\delta^k}^2 + \sigma_{\psi^k,\delta^k} + \sigma_{\delta^k,\varepsilon^k} && \text{(B.2)}\\
\text{Cov}\left(n_f^k, c_f^k\right) &= \lambda\left(\gamma + \lambda\right)\sigma_{\bar{e}^p}^2 + \rho\left(\theta + \rho\right)\sigma_{\bar{n}^p}^2 + \phi\lambda\sigma_{\bar{q}^p,\bar{e}^p} + \phi\rho\sigma_{\bar{q}^p,\bar{n}^p} \\
&+ \left[\lambda\left(\rho + \theta\right) + \rho\left(\gamma + \lambda\right)\right]\sigma_{\bar{e}^p,\bar{n}^p} + \sigma_{\varepsilon^k}^2 + \sigma_{\delta^k,\varepsilon^k} + \sigma_{\psi^k,\varepsilon^k} && \text{(B.3)}
\end{aligned}$$

Some additional cross-generational moments can be used as over-identifying restrictions for the parameter estimates:

$$\begin{aligned}
\text{Cov}\left(e_f^p, c_f^k\right) &= \left(\gamma + \lambda\right)\sigma_{\bar{e}^p}^2 + \phi\sigma_{\bar{q}^p,\bar{e}^p} + \left(\rho + \theta\right)\sigma_{\bar{e}^p,\bar{n}^p} && \text{(B.4)}\\
\text{Cov}\left(n_f^p, c_f^k\right) &= \left(\rho + \theta\right)\sigma_{\bar{n}^p}^2 + \phi\sigma_{\bar{q}^p,\bar{n}^p} + \left(\gamma + \lambda\right)\sigma_{\bar{e}^p,\bar{n}^p} && \text{(B.5)}\\
\text{Cov}\left(c_f^p, e_f^k\right) &= \gamma\left(\sigma_{\bar{e}^p}^2 + \sigma_{\bar{q}^p,\bar{e}^p} + \sigma_{\bar{e}^p,\bar{n}^p}\right) + \theta\left(\sigma_{\bar{n}^p}^2 + \sigma_{\bar{q}^p,\bar{n}^p} + \sigma_{\bar{e}^p,\bar{n}^p}\right) && \text{(B.6)}\\
\text{Cov}\left(c_f^p, n_f^k\right) &= \lambda\left(\sigma_{\bar{e}^p}^2 + \sigma_{\bar{q}^p,\bar{e}^p} + \sigma_{\bar{e}^p,\bar{n}^p}\right) + \rho\left(\sigma_{\bar{n}^p}^2 + \sigma_{\bar{q}^p,\bar{n}^p} + \sigma_{\bar{e}^p,\bar{n}^p}\right) && \text{(B.7)}
\end{aligned}$$

## 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, Li, Samancioglu, and Schoeni (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, Schoeni, Danziger, and Charles (2010) show that the average expenditure since 1999 in PSID and CEX have been fairly close to each other. Moreover, the consumption expenditures in the two datasets vary in a similar way with observable household characteristics like age of household head, household size, educational attainment, marital status, race and home ownership. This average consistency between PSID and CEX data, as well as the fact that total consumption seems to be close to the aggregate consumption estimates in the NIPA (National Income and Product Accounts) data, suggests that PSID expenditure data can be used to draw information about households consumption behaviour.

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

$$ln\left(\tilde{C}_{ft}\right) = Z'_{ft}\omega + p'_t\pi + g(F_{ft};\lambda) + u_{ft}, \tag{B.8}$$

where $N$ is consumption net of food expenditure, $Z$ 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, $p$ are the relative prices (the overall CPI and the CPIs for food at home, food away from home, and rent), $F$ 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 $u$ 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.

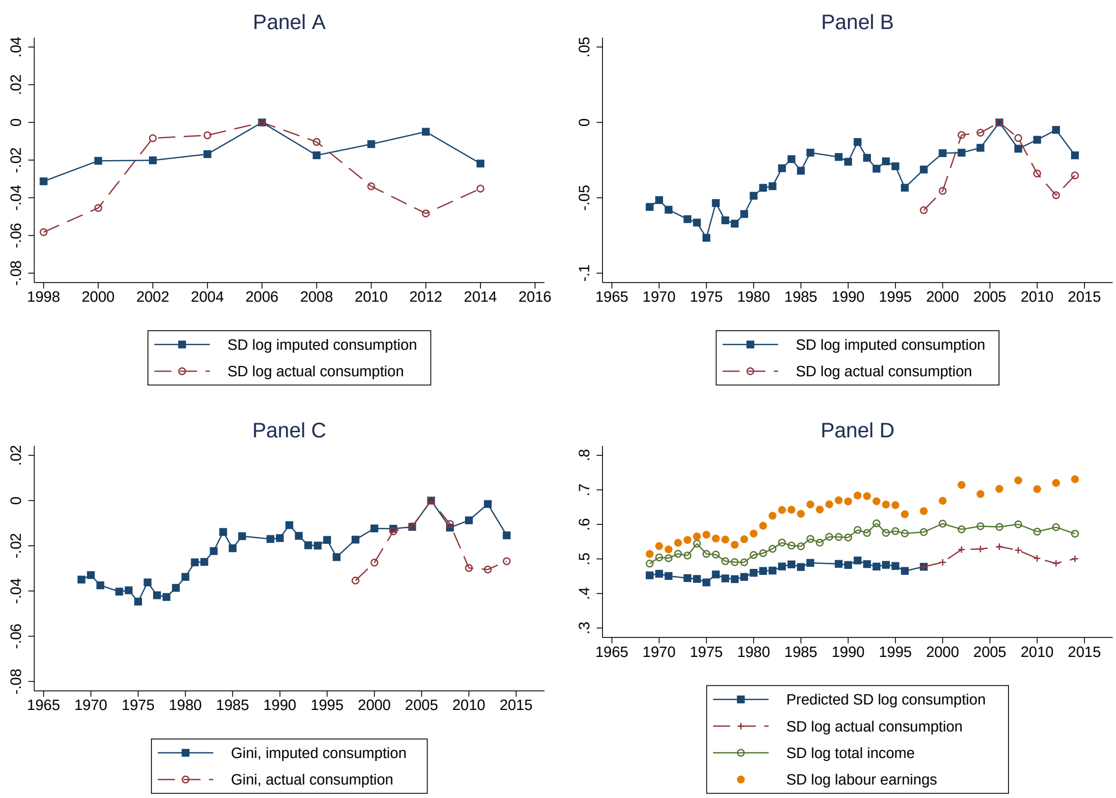


Figure 3: Quality Assessment of Consumption Imputation

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

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

$$\hat{C}_{ft} = F_{ft} + exp\left\{Z'_{ft}\hat{\omega} + p'_t\hat{\pi} + g\left(F_{ft}; \hat{\lambda}\right)\right\}. \tag{B.9}$$

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.

A key question is how well the imputed consumption values match with the observed values during the period when both data series are available. A natural choice for a measure of the goodness of fit is the $R^2$ of the regression (B.8), which is found to be 0.47. However, what we are really interested in is matching the standard deviations of the observed and imputed series because we would be using only the second order moments of income and consumption for estimating our model in Section 2. Like AP, we find that our imputed consumption series can match the observed series quite closely in terms of standard deviation, and similarly well for a more general non-linear measure like the Gini coefficient. Figure 3 presents the Gini coefficients (normalized to their initial values in 2006) of the logs of imputed and actual consumption (in Panel C), and also compares the standard deviations of actual and imputed consumption with those of real income and labour earnings (in Panels A, B, and D). The top-coded values for total family income and the household heads' labour earnings in the PSID are replaced with the estimates obtained from fitting a Pareto distribution to the upper tail of the corresponding distribution.

# C Appendix to Section 4

This appendix is comprised of four main sections. Section C.1 shows the values of the empirical moments that are used to estimate the parameters of the baseline specification. It also shows the internal fit of the baseline model. Section C.2 presents details for computing the importance of parental heterogeneity in explaining cross-sectional dispersion in the children's generation. Section C.3 reports additional estimates from the decomposition of the *other income* measure into wife earnings and transfers, that is considered in Section 4.2.2 of the main paper. In Section C.4, we break down the total cross-sectional variation in the outcome variables into a component explained by observable characteristics and a residual component representing unobserved heterogeneity.

## C.1 Empirical Moments and Baseline Fit

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.

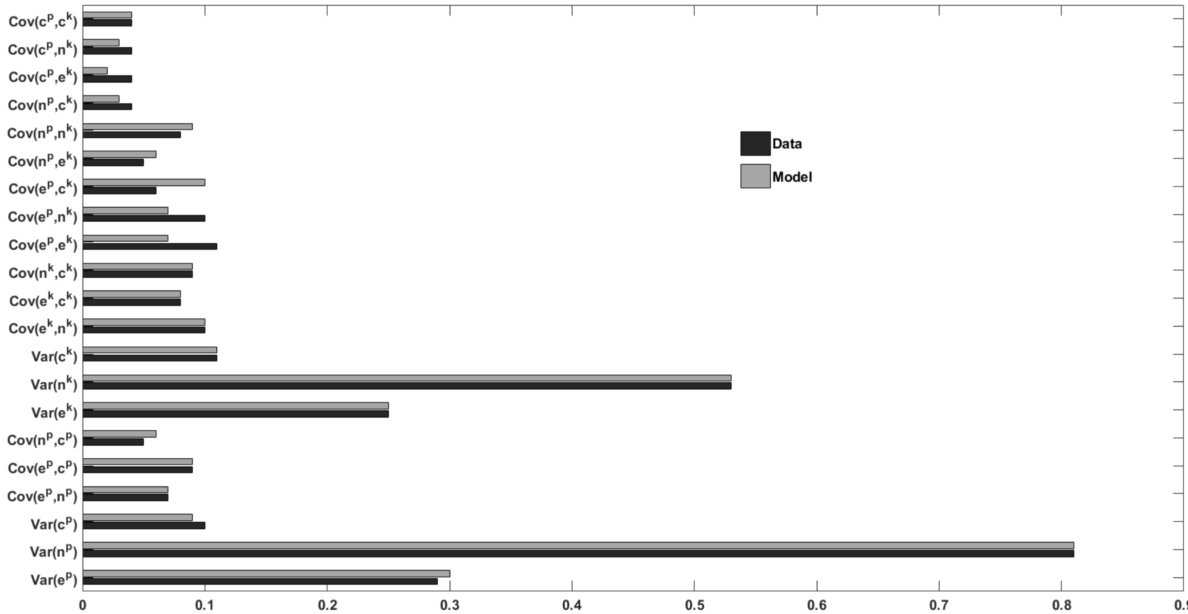


Figure 4: Internal Fit of Baseline Model

**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.

## C.2 The Impact of Parental Factors on Inequality

**Variance Accounting Calculations.** As reported in Section 4.2, the relative contribution of parental factors in the cross-sectional variance of earnings among their kids' generation can be computed as the ratio

$$\frac{Var\left[e^k(p)\right]}{Var\left[e^k\right]} = \frac{\gamma^2\sigma^2_{\bar{e}^p} + \theta^2\sigma^2_{\bar{n}^p} + 2\gamma\theta\sigma_{\bar{e}^p,\bar{n}^p}}{\sigma^2_{\delta^k} + \gamma^2\sigma^2_{\bar{e}^p} + \theta^2\sigma^2_{\bar{n}^p} + 2\gamma\theta\sigma_{\bar{e}^p,\bar{n}^p}}. \tag{C.1}$$

Then, substituting the parameter estimates from Tables 18 and 20 in equation (C.1), one can obtain the estimates in the first row of Table 19. That is, we can write:

$$\begin{aligned} & \frac{\gamma^2\sigma^2_{\bar{e}^p} + \theta^2\sigma^2_{\bar{n}^p} + 2\gamma\theta\sigma_{\bar{e}^p,\bar{n}^p}}{\sigma^2_{\delta^k} + \gamma^2\sigma^2_{\bar{e}^p} + \theta^2\sigma^2_{\bar{n}^p} + 2\gamma\theta\sigma_{\bar{e}^p,\bar{n}^p}} \\ = & \frac{(0.230^2)(0.295) + (0.055^2)(0.806) + 2(0.230)(0.055)(0.070)}{0.228 + (0.230^2)(0.295) + (0.055^2)(0.806) + 2(0.230)(0.055)(0.070)} = 8.0\%. \end{aligned}$$

Similarly, the contribution of parental factors to the cross-sectional variances of other income and consumption in the children's generation is given by the ratios,

$$\frac{Var\left[n^k(p)\right]}{Var\left[n^k\right]} \tag{C.2}$$

and

$$\frac{Var\left[c^k(p)\right]}{Var\left[c^k\right]} \tag{C.3}$$

where

$$\begin{aligned}
Var\left[n^k(p)\right] &= \rho^2\sigma^2_{\bar{n}^p} + \lambda^2\sigma^2_{\bar{e}^p} + 2\rho\lambda\sigma_{\bar{e}^p,\bar{n}^p} && \text{(C.4)}\\
Var\left[n^k\right] &= Var\left[n^k(p)\right] + \sigma^2_{\varepsilon^k} && \text{(C.5)}\\
Var\left[c^k(p)\right] &= \phi^2\sigma^2_{\bar{q}^p} + (\gamma+\lambda)^2\sigma^2_{\bar{e}^p} + (\rho+\theta)^2\sigma^2_{\bar{n}^p}\\
&+ 2\left[(\gamma+\lambda)\phi\sigma_{\bar{e}^p,\bar{q}^p} + (\rho+\theta)\phi\sigma_{\bar{n}^p,\bar{q}^p} + (\rho+\theta)(\gamma+\lambda)\sigma_{\bar{e}^p,\bar{n}^p}\right] && \text{(C.6)}\\
Var\left[c^k\right] &= Var\left[c^k(p)\right] + \sigma^2_{\varepsilon^k} + \sigma^2_{\psi^k} + \sigma^2_{\delta^k} + 2\left(\sigma_{\psi^k,\varepsilon^k} + \sigma_{\psi^k,\delta^k} + \sigma_{\delta^k,\varepsilon^k}\right). && \text{(C.7)}
\end{aligned}$$

**Counterfactual Distributions.** 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[29]:

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

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, $\left(\varepsilon^k_f + \psi^k_f + \delta^k_f\right)$, follows a Normal distribution with zero mean and variance equal to $\sigma^2_{\varepsilon^k} + \sigma^2_{\psi^k} + \sigma^2_{\delta^k} + 2\left(\sigma_{\psi^k,\varepsilon^k} + \sigma_{\psi^k,\delta^k} + \sigma_{\delta^k,\varepsilon^k}\right)$. Such child idiosyncratic components are, by definition, independent of any parental influence, and hence can be used to

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

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 2 in Section 4.3 of the main paper reports the difference in the probability density functions with and without parental influence.

## C.3 Estimates under Alternative Definitions of 'Other Income'

Table 14: Estimated Variances of Components of *Other Income*

| **Variable** | **Generation** | **Just Transfers** (1) | **Spouse Earnings** (2) | **Other Income** (3) |
|---|---|---|---|---|
| **Earnings** | Parent | 0.287 | 0.295 | 0.295 |
| | Child | 0.229 | 0.229 | 0.229 |
| **Other Income Component** | Parent | 1.297 | 0.294 | 0.459 |
| | Child | 1.068 | 0.322 | 0.457 |
| **Consumption** | Parent | 0.098 | 0.094 | 0.096 |
| | Child | 0.113 | 0.113 | 0.113 |

**Note:** This table uses parameter estimates from Tables 5 and 15.

Table 15: Decomposition of Other Income: Variance-Covariance of Idiosyncratic Components

| | Parameters | Just Transfers | Spouse Earnings | Other Income |
|---|---|---|---|---|
| | | (1) | (2) | (3) |
| **Parental Outcomes: Variances** | | | | |
| Permanent Earnings | $\sigma^2_{\bar{e}^p}$ | 0.287 | 0.295 | 0.295 |
| | | (0.027) | (0.027) | (0.027) |
| Permanent Other Income | $\sigma^2_{\bar{n}^p}$ | 1.297 | 0.294 | 0.459 |
| | | (0.128) | (0.021) | (0.041) |
| Permanent Consumption Shifters | $\sigma^2_{\bar{q}^p}$ | 1.504 | 0.502 | 0.650 |
| | | (0.132) | (0.042) | (0.055) |
| **Child Idiosyncratic Heterogeneity: Variances** | | | | |
| Permanent Earnings | $\sigma^2_{\delta^k}$ | 0.213 | 0.196 | 0.205 |
| | | (0.015) | (0.011) | (0.012) |
| Permanent Other Income | $\sigma^2_{\varepsilon^k}$ | 1.063 | 0.296 | 0.441 |
| | | (0.085) | (0.018) | (0.038) |
| Permanent Consumption Shifters | $\sigma^2_{\psi^k}$ | 1.292 | 0.460 | 0.589 |
| | | (0.096) | (0.029) | (0.042) |
| **Parental Outcomes: Covariances** | | | | |
| Consumption Shifters & Earnings | $\sigma_{\bar{q}^p,\bar{e}^p}$ | -0.225 | -0.259 | -0.247 |
| | | (0.042) | (0.029) | (0.026) |
| Consumption Shifters & Other Income | $\sigma_{\bar{q}^p,\bar{n}^p}$ | -1.314 | -0.302 | -0.458 |
| | | (0.125) | (0.027) | (0.045) |
| Earnings and Other Income | $\sigma_{\bar{e}^p,\bar{n}^p}$ | 0.044 | 0.063 | 0.051 |
| | | (0.035) | (0.015) | (0.017) |
| **Child Idiosyncratic Heterogeneity: Covariances** | | | | |
| Consumption Shifters & Earnings | $\sigma_{\psi^k,\delta^k}$ | -0.222 | -0.199 | -0.204 |
| | | (0.033) | (0.017) | (0.021) |
| Consumption Shifters & Other Income | $\sigma_{\psi^k,\varepsilon^k}$ | -1.081 | -0.289 | -0.421 |
| | | (0.103) | ( 0.02) | (0.035) |
| Earnings & Other Income | $\sigma_{\delta^k,\varepsilon^k}$ | 0.059 | 0.056 | 0.050 |
| | | (0.028) | (0.014) | (0.017) |
| *No. of Parent-Child Pairs* | $N$ | 459 | 459 | 459 |

**Note:** Bootstrap standard errors with 100 repetitions are reported in parentheses. This table uses the same sample and model specification as Table 5.

## C.4 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 16: Persistence of Observable Characteristics

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

Table 16 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. Below we address this question.

Denoting the data matrix of the log of individual earnings, other income and consumption as $y_{ft}$, we proceed as follows:

1. We regress the log of each outcome variable, $y_{ft}$, on a full set of year and cohort dummies, and denote estimated residuals as $\hat{y}^{(1)}_{ft}$. These are our baseline outcome measures.

2. Next, we regress our baseline outcomes $\hat{y}^{(1)}_{ft}$ on a set of observables $x_{ft}$. That is, we estimate least square projections:[30]

$$\hat{y}^{(1)}_{ft} = \beta x_{ft} + \varepsilon_{ft}. \tag{C.8}$$

3. From the previous step we recover predicted values, as well as residuals. Specifically, we define:

$$\hat{y}^{(2)}_{ft} \equiv \hat{\beta} x_{ft} \tag{C.9}$$

[30] The matrix of controls $x_{ft}$ includes dummies for family size, number of children, state of residence, employment status, race and education.

and

$$\hat{y}^{(3)}_{ft} \equiv \hat{\varepsilon}_{ft} \tag{C.10}$$

For each of the measures $\hat{y}^{(i)}_{ft}$ we compute a set of variances and covariances. Each set of second moments can then be used to separately estimate structural model parameters.

4. We estimate the GMM model separately for each set of variance-covariance moments of $\hat{y}^{(i)}_{ft}$ $(i \in 1, 2, 3)$. This delivers different sets of parameter estimates. Comparing these estimates is helpful to establish whether the transmission of inequality is due to observable or unobservable components.

Table 17: Variances for Parents and Children

| **Variable** | **Generation** | **Baseline** (1) | **Observable** (2) | **Unobservable** (3) |
|---|---|---|---|---|
| **Earnings** | Parent | 0.291 | 0.093 | 0.182 |
| | Child | 0.248 | 0.057 | 0.177 |
| **Other Income** | Parent | 0.808 | 0.084 | 0.696 |
| | Child | 0.534 | 0.081 | 0.441 |
| **Consumption** | Parent | 0.097 | 0.024 | 0.066 |
| | Child | 0.114 | 0.024 | 0.087 |

Table 17 reports the cross-sectional variances of earnings, other income and consumption for parents and for children. Columns 1-3 correspond to equations (C.8), (C.9) and (C.10): column 1 reports the variance controlling only for time and cohort effects, as in equation (C.8); column 2 reports the fitted variance, defined as the variance explained by observables, as in equation (C.9); and column 3 reports the variance of the residual, equation (C.10).

Next, we use these variances and other covariances amongst the economic outcomes to estimate the parameters for intergenerational elasticity (reported in Table 18) and for the variance-covariance structure of the idiosyncratic shocks specific to a particular generation (reported in Table 20). From Table 18 is clear that all pass-through parameters in the baseline estimation are primarily driven by persistence in observables, while only earnings has some part that is explained by unobservable factors that are linked across generations.

Table 18: Baseline Estimates: Intergenerational Elasticity

| **Variables** | **Parameters** | **Baseline** (1) | **Observable** (2) | **Unobservable** (3) |
|---|---|---|---|---|
| Earnings | $\gamma$ | 0.230 | 0.339 | 0.109 |
| | | (0.027) | (0.022) | (0.027) |
| Other Income | $\rho$ | 0.100 | 0.248 | 0.021 |
| | | (0.023) | (0.039) | (0.029) |
| $\bar{e}^p_f$ on $\bar{n}^k_f$ | $\lambda$ | 0.206 | 0.255 | 0.060 |
| | | (0.032) | (0.028) | (0.038) |
| $\bar{n}^p_f$ on $\bar{e}^k_f$ | $\theta$ | 0.055 | 0.111 | 0.003 |
| | | (0.019) | (0.028) | (0.017) |
| Consumption Shifters | $\phi$ | 0.154 | 0.450 | 0.010 |
| | | (0.032) | (0.042) | (0.034) |
| *No. of Parent-Child Pairs* | $N$ | 760 | 760 | 760 |

**Note:** Bootstrap standard errors (100 repetitions) in parentheses. *Baseline* refers to data that is purged of year and birth cohort effects (viz., $\hat{y}^{(1)}_{ft}$ in equation C.8). These data are then regressed on various controls (namely, dummies for family size, state of residence, number of children, employment status, race and education). *Observable* refers to the fitted values from this regression (viz., $\hat{y}^{(2)}_{ft}$ in equation C.9), while *Unobservable* refers to its residual (viz., $\hat{y}^{(3)}_{ft}$ in equation C.10). The average age for parents in the sample is 47 years; that of children is 37 years.

Table 19: Share (%) of Child Inequality Explained by Parental Heterogeneity

| **Variables** | **Baseline** (1) | **Observable** (2) | **Unobservable** (3) |
|---|---|---|---|
| Earnings | 8.0 | 28.7 | 1.2 |
| Other Income | 4.4 | 23.4 | 0.2 |
| Consumption | 29.9 | 32.8 | 5.6 |

**Note:** Values represent the percentage share of cross-sectional variances for younger generation that is explained by parental factors. Numbers obtained using parameter estimates from Tables 18 and 20.

Table 20: Baseline Estimates: Variances and Covariances of Idiosyncratic Components

| | Parameters | Baseline (1) | Observable (2) | Unobservable (3) |
|---|---|---|---|---|
| **Parental Outcomes: Variances** | | | | |
| Permanent Earnings | $\sigma^2_{\bar{e}^p}$ | 0.295 | 0.095 | 0.182 |
| | | (0.021) | (0.006) | (0.011) |
| Permanent Other Income | $\sigma^2_{\bar{n}^p}$ | 0.806 | 0.084 | 0.696 |
| | | ( 0.06) | ( 0.01) | (0.059) |
| Permanent Consumption Shifters | $\sigma^2_{\bar{q}^p}$ | 1.031 | 0.196 | 0.789 |
| | | (0.065) | (0.022) | (0.064) |
| **Child Idiosyncratic Heterogeneity: Variances** | | | | |
| Permanent Earnings | $\sigma^2_{\delta^k}$ | 0.228 | 0.041 | 0.175 |
| | | (0.011) | (0.002) | ( 0.01) |
| Permanent Other Income | $\sigma^2_{\varepsilon^k}$ | 0.511 | 0.062 | 0.440 |
| | | (0.043) | (0.004) | (0.031) |
| Permanent Consumption Shifters | $\sigma^2_{\psi^k}$ | 0.730 | 0.104 | 0.584 |
| | | (0.056) | (0.008) | (0.039) |
| **Parental Outcomes: Covariances** | | | | |
| Consumption Shifters & Earnings | $\sigma_{\bar{q}^p,\bar{e}^p}$ | -0.271 | -0.120 | -0.120 |
| | | (0.024) | ( 0.01) | (0.016) |
| Consumption Shifters & Other Income | $\sigma_{\bar{q}^p,\bar{n}^p}$ | -0.818 | -0.116 | -0.669 |
| | | (0.061) | (0.015) | (0.062) |
| Earnings and Other Income | $\sigma_{\bar{e}^p,\bar{n}^p}$ | 0.070 | 0.059 | -0.012 |
| | | (0.013) | (0.007) | (0.012) |
| **Child Idiosyncratic Heterogeneity: Covariances** | | | | |
| Consumption Shifters & Earnings | $\sigma_{\psi^k,\delta^k}$ | -0.247 | -0.058 | -0.165 |
| | | (0.018) | (0.004) | (0.016) |
| Consumption Shifters & Other Income | $\sigma_{\psi^k,\varepsilon^k}$ | -0.522 | -0.068 | -0.430 |
| | | (0.048) | (0.005) | (0.034) |
| Earnings & Other Income | $\sigma_{\delta^k,\varepsilon^k}$ | 0.075 | 0.031 | 0.036 |
| | | (0.013) | (0.002) | (0.013) |
| *No. of Parent-Child Pairs* | $N$ | 760 | 760 | 760 |

**Note:** Bootstrap standard errors (100 repetitions) in parentheses. *Baseline* refers to data that is purged of year and birth cohort effects (viz., $\hat{y}^{(1)}_{ft}$ in equation C.8). These data are then regressed on various controls (namely, dummies for family size, state of residence, number of children, employment status, race, and education). *Observable* refers to the fitted value from this regression (viz., $\hat{y}^{(2)}_{ft}$ in equation C.9), while *Unobservable* refers to its residual (viz., $\hat{y}^{(3)}_{ft}$ in equation C.10).

### C.4.1 Role of Education

Table 21: Baseline Estimates: Intergenerational Elasticity for Fitted Variables

| | **Parameters** | **Observable** (2) | **Education** (3) | **Other** (4) |
|---|---|---|---|---|
| Earnings | $\gamma$ | 0.339 | 0.258 | 0.304 |
| | | (0.022) | (0.035) | (0.023) |
| Other Income | $\rho$ | 0.248 | 0.188 | 0.207 |
| | | (0.039) | (0.027) | ( 0.05) |
| $\bar{e}^p_f$ on $\bar{n}^k_f$ | $\lambda$ | 0.255 | 0.183 | 0.271 |
| | | (0.028) | (0.018) | (0.041) |
| $\bar{n}^p_f$ on $\bar{e}^k_f$ | $\theta$ | 0.111 | 0.189 | 0.054 |
| | | (0.028) | (0.033) | (0.028) |
| Consumption Shifters | $\phi$ | 0.450 | 0.410 | 0.354 |
| | | (0.042) | (0.029) | (0.062) |
| *No. of Parent-Child Pairs* | $N$ | 760 | 760 | 760 |

**Note:** Bootstrap standard errors with 100 repetitions are reported in parentheses. *Observable* 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* refers to the fitted value of the regression of the data on education only, while *Other* 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.

Table 22: Mobility Matrix for Education

| **Parent** / **Child** | <12 years | High School | College Dropout | College & above |
|---|---|---|---|---|
| <12 years | **21.83** | 4.93 | 0 | 0 |
| High School | 40.47 | **39.95** | 19.27 | 7.80 |
| College Dropout | 20.93 | 25.58 | **42.52** | 14.99 |
| College & above | 16.77 | 29.54 | 38.21 | **77.20** |

# D Appendix to Section 5

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 $\lambda = \theta = 0$. With these parameter restrictions, earnings evolve through generations of the same family according to:

$$\begin{aligned} e^{k_1} &= \gamma \bar{e}^p + \delta^{k_1} \\ e^{k_2} &= \gamma^2 \bar{e}^p + \gamma \delta^{k_1} + \delta^{k_2} \\ &\vdots \\ e^{k_t} &= \gamma^t \bar{e}^p + \sum_{j=1}^{t} \gamma^{t-j} \delta^{k_t} \end{aligned}$$

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

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

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

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

$$\text{Var}(c^*) = \frac{\sigma^2_{\psi^k}}{1-\phi^2} + \frac{\sigma^2_{\delta^k}}{1-\gamma^2} + \frac{\sigma^2_{\varepsilon^k}}{1-\rho^2} + \frac{2\sigma_{\delta^k,\varepsilon^k}}{1-\gamma\rho} + \frac{2\sigma_{\psi^k,\varepsilon^k}}{1-\phi\rho} + \frac{2\sigma_{\psi^k,\delta^k}}{1-\phi\gamma}. \tag{D.3}$$

Plugging in estimated values for the parameters in equations (D.1) through (D.3),[31] 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 $\gamma$ above which the variance of earnings would grow from the value estimated in the parents' generation: this is the value of $\gamma$ such that $\text{Var}(e^*) \geq \text{Var}(e^p)$. This threshold value of $\gamma$ is given by $\gamma^p \equiv \sqrt{1 - \frac{\sigma^2_{\delta^k}}{\text{Var}(e^p)}}$. Any $\gamma$ larger than $\gamma^p$ implies growing earnings variance. Based on the parameter estimates in Tables 23 and 24,

[31] Since we restrict the parameters $\lambda = \theta = 0$, 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 23 and 24.

Table 23: Intergenerational Elasticities

| | Parameters | Estimates |
|---|---|---|
| | | (1) |
| Earnings | $\gamma$ | 0.279 |
| | | (0.048) |
| Other Income | $\rho$ | 0.020 |
| | | (0.041) |
| Consumption Shifters | $\phi$ | 0.006 |
| | | (0.047) |
| *No. of Parent-Child Pairs* | $N$ | 403 |

**Note:** Bootstrap standard errors (100 repetitions) in parentheses. Parental and child ages vary between 30 and 40. Parameters $\lambda$ and $\theta$ 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.

$\sigma^2_{\delta^k} = 0.246 > \text{Var}\left(e^p\right) = 0.183$, making $\gamma^p$ an imaginary number. This essentially implies that any non-negative value of $\gamma$ would result in increasing earnings inequality from the level in the parents' generation. Since our estimate of the current value of $\gamma$ $(= 0.279)$ is positive, the model implies that the earnings variance should become larger in the next generation $k_1$. In fact, earnings variance in the child generation, $\text{Var}\left(e^{k_1}\right) = 0.261$ 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 $\gamma$ above which the earnings variance after the child generation would be growing; that is,

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

This is plotted as the dashed vertical line in Figure 5. Any value of $\gamma$ to the right of that vertical line implies growing earnings variance. Since our estimate of $\gamma$ $(= 0.279)$ lies to the right of the new threshold $\gamma^{k_1}$, the threshold corresponding to the generation of grandchildren $k_2$ (denoted by the dotted vertical line in Figure 5) will lie further to the right of $\gamma^{k_1}$; one can repeat these calculations over and over again.[32] Eventually, the economy settles down at the stationary distribution of earnings where the threshold is defined as

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

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

Table 24: Idiosyncratic Variances & Covariances

| | Parameters | Estimates |
|---|---|---|
| | | (1) |
| **Parental Outcomes: Variances** | | . |
| Permanent Earnings | $\sigma^2_{\bar{e}^p}$ | 0.183 |
| | | (0.012) |
| Permanent Other Income | $\sigma^2_{\bar{n}^p}$ | 0.877 |
| | | (0.128) |
| Permanent Consumption Shifters | $\sigma^2_{\bar{q}^p}$ | 0.956 |
| | | (0.134) |
| | | . |
| **Child Idiosyncratic Heterogeneity: Variances** | | . |
| Permanent Earnings | $\sigma^2_{\delta^k}$ | 0.246 |
| | | (0.013) |
| Permanent Other Income | $\sigma^2_{\varepsilon^k}$ | 0.630 |
| | | (0.038) |
| Permanent Consumption Shifters | $\sigma^2_{\psi^k}$ | 0.848 |
| | | (0.037) |
| | | . |
| **Parental Outcomes: Covariances** | | . |
| Consumption Shifters & Earnings | $\sigma_{\bar{q}^p,\bar{e}^p}$ | -0.122 |
| | | (0.029) |
| Consumption Shifters & Other Income | $\sigma_{\bar{q}^p,\bar{n}^p}$ | -0.841 |
| | | (0.126) |
| Earnings and Other Income | $\sigma_{\bar{e}^p,\bar{n}^p}$ | -0.000 |
| | | (0.025) |
| | | . |
| **Child Idiosyncratic Heterogeneity: Covariances** | | . |
| Consumption Shifters & Earnings | $\sigma_{\psi^k,\delta^k}$ | -0.247 |
| | | (0.020) |
| Consumption Shifters & Other Income | $\sigma_{\psi^k,\varepsilon^k}$ | -0.620 |
| | | (0.032) |
| Earnings & Other Income | $\sigma_{\delta^k,\varepsilon^k}$ | 0.056 |
| | | (0.017) |
| *No. of Parent-Child Pairs* | $N$ | 403 |

**Note:** Bootstrap standard errors (100 repetitions) in parentheses. This table uses the same sample and model specification as Table 23.

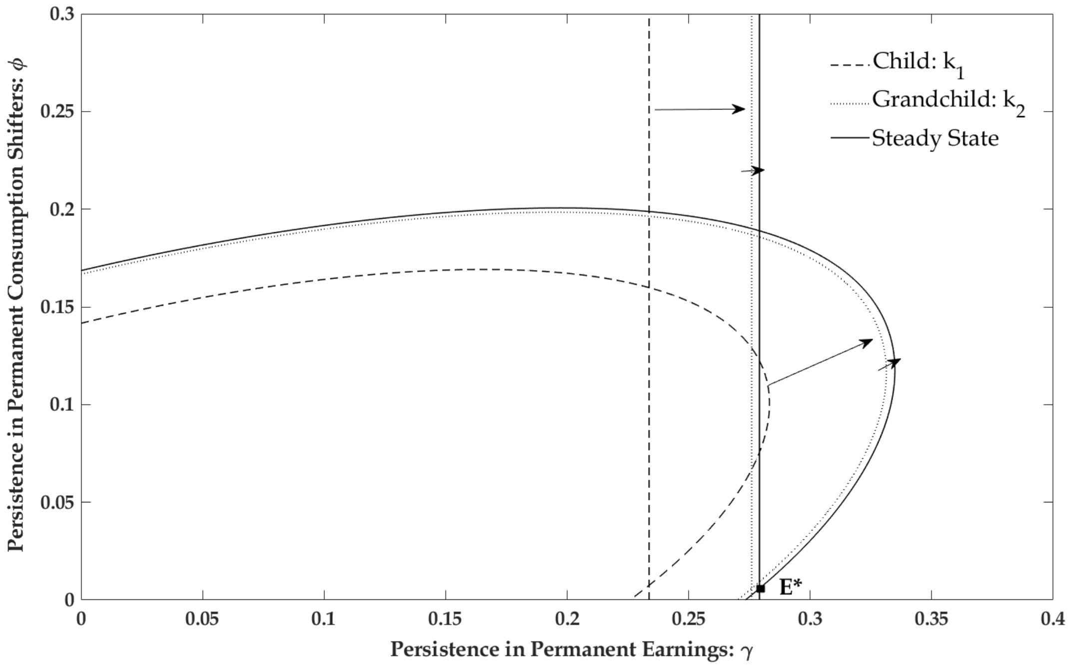


Figure 5: Implication of $\gamma$ and $\phi$ for Long Run Earnings & Consumption Inequality

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

$$\mathrm{Var}(c^g) = \frac{\sigma^2_{\psi^k}}{1-\phi^2} + \frac{\sigma^2_{\delta^k}}{1-\gamma^2} + \frac{\sigma^2_{\varepsilon^k}}{1-\rho^2} + \frac{2\sigma_{\delta^k,\varepsilon^k}}{1-\gamma\rho} + \frac{2\sigma_{\psi^k,\varepsilon^k}}{1-\phi\rho} + \frac{2\sigma_{\psi^k,\delta^k}}{1-\phi\gamma},$$

for each generation $g = \{p, k_1, k_2, ...\}$ as a function of $\gamma$ and $\phi$, holding all other parameters constant. However, there is no combination of $\gamma$ and $\phi$ in the economically meaningful range $[0,1]$ that satisfies the threshold value equation for $\mathrm{Var}(c^p)$. Therefore, any point in the $(\gamma, \phi) \in [0,1]^2$ space will imply rising consumption inequality from the parents' generation. This finding is corroborated by the fact that $\mathrm{Var}\left(c^{k_1}\right) = 0.117 > \mathrm{Var}\left(c^p\right) = 0.09$.

Next, we plot the threshold starting from the children's generation, denoted by the dashed ellipse in Figure 5. Since the estimated point, labelled $E^*$, with values $(\gamma, \phi) = (0.28, 0.01)$, lies outside this ellipse, the grandchildren's generation should have a larger consumption variance than the children's generation. Indeed, plotting the corresponding threshold for the grandchild generation (denoted by the dotted ellipse in Figure 5), we find that it lies outside that for the children with $\text{Var}(c^{k_2}) = 0.124 > \text{Var}(c^{k_1}) = 0.117$. These dynamics are replicated across generations until the economy settles at the stationary distribution of consumption which gives rise to the solid elliptical threshold of $\gamma$ and $\phi$ in Figure 5.[33]

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 11 and 27 which does not restrict the age to be between 30 and 40 years, but keeps the $\lambda = \theta = 0$ restriction. Relaxing our age restriction implies $\text{Var}(e^p) > \text{Var}(e^k)$, so that the thresholds of $\gamma$ approach the long run threshold from the right, rather than from the left as in Figure 5, suggesting decreasing earnings variance across generations. Similarly, the dynamics of consumption and other income inequality in the long run are also dictated by the empirically observed moments.

**Relaxing Age Restriction.** We replicate the above analysis of inequality evolution using a parametrization of the model based on a sample without age restrictions. This means that the relevant parameter estimates are obtained from column 2 of Tables 11 and 27.

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

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

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

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

which is less than $\gamma^p$. Once again the estimated value of $\gamma = 0.340$ lies to the left of this new threshold $\gamma^{k1}$, and so the threshold corresponding to the generation of grandchildren $k_2$ will lie further to the left of $\gamma^{k_1}$, and so on. Eventually, the economy settles down at the stationary

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

distribution of earnings where the threshold is defined as $\gamma^* \equiv \sqrt{1 - \frac{\sigma^2_{\delta^k}}{\mathrm{Var}(e^*)}} = 0.340$, which is the estimated level of $\gamma$.

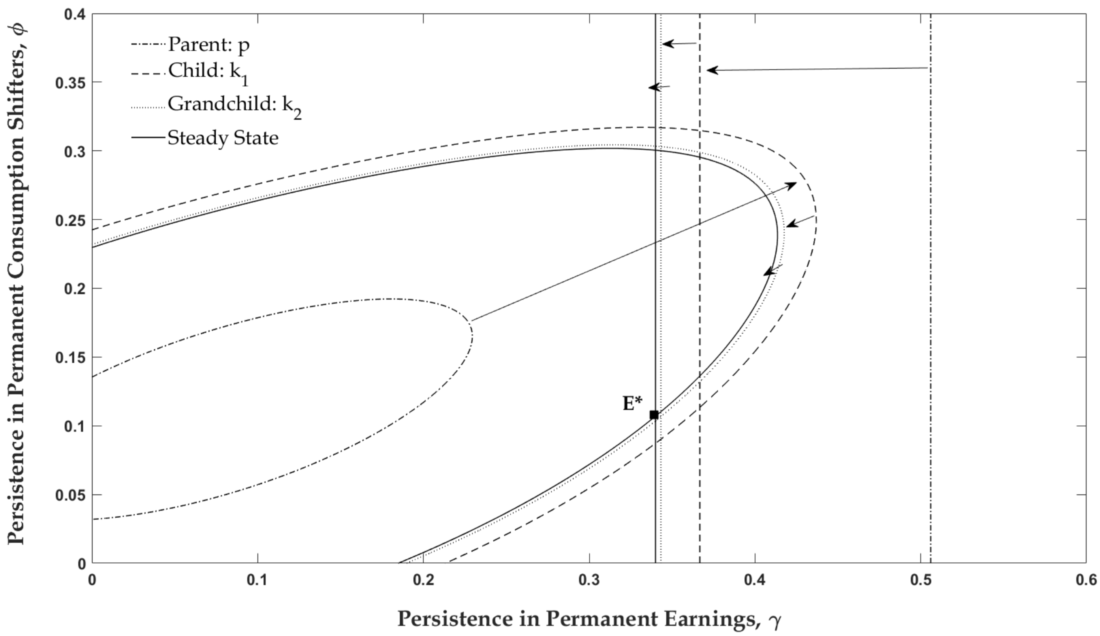


Figure 6: Implication of $\gamma$ and $\phi$ for Long Run Earnings & Consumption Inequality

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: $\gamma$, $\rho$ and $\phi$. We hold $\rho$ constant at its estimated value and study the thresholds of $\gamma$ and $\phi$ that imply increasing or decreasing consumption variance. First we ask what combinations of $\gamma$ and $\phi$ imply that the variance of consumption is increasing across generations. For that we plot the threshold value

$$\mathrm{Var}(c^p) = \frac{\sigma^2_{\psi^k}}{1-\phi^2} + \frac{\sigma^2_{\delta^k}}{1-\gamma^2} + \frac{\sigma^2_{\varepsilon^k}}{1-\rho^2} + \frac{2\sigma_{\delta^k,\varepsilon^k}}{1-\gamma\rho} + \frac{2\sigma_{\psi^k,\varepsilon^k}}{1-\phi\rho} + \frac{2\sigma_{\psi^k,\delta^k}}{1-\phi\gamma},$$

as a function of $\gamma$ and $\phi$. 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 $(\gamma, \phi) = (0.340, 0.107)$, 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 $\mathrm{Var}(c^{k_1}) = 0.114 > \mathrm{Var}(c^p) = 0.096$. However, our estimate values of $(\gamma, \phi) = (0.340, 0.107)$ lie inside the ellipse for the child generation. This means that the generation of grandchildren $k_2$ should exhibit lower consumption variance than the child generation $k_1$, and therefore should have a threshold ellipse which lies inside that for the child generation. These dynamics are replicated across generations until the economy settles at the stationary distribution of consumption which gives rise to the solid black elliptical threshold of $\gamma$ and $\phi$ in Figure 6.

# E Appendix to Section 6

In sections E.1 and E.2 of this appendix, we present additional estimates for the model and data specifications considered in Section 6 — section E.1 reports additional results for the child birth-cohort analysis in Section 6.1, while section E.2 presents the estimates of the variances and co-variances of the fixed effects in earnings, other income and consumption-shifters under various specifications considered in Sections 6.2 through 6.5 of the main paper. Section E.3 presents details of the model estimation that uses panel variation in the data. Section E.4 presents an alternative model that assumes a random walk process for the permanent component of income instead of a fixed effect in the baseline specification.

## E.1 Estimates by Child Birth-Cohort

Table 25: Parental Importance by Child-Cohort (Age: 30-40)

| **Variables** | **All Cohorts** (1) | **1960s Cohort** (2) | **1970s Cohort** (3) |
|---|---|---|---|
| Earnings | 4.0 | 4.4 | 5.3 |
| Other Income | 1.6 | 1.3 | 2.9 |
| Consumption | 24.4 | 37.7 | 15.9 |

**Note:** All numbers are percentages (%) and are based on parameter estimates in Tables 10 and 26.

Table 26: Estimates by Child Cohort: Idiosyncratic Components (Age: 30-40)

| | **Parameters** | **All Cohorts** (1) | **1960s Cohort** (2) | **1970s Cohort** (3) |
|---|---|---|---|---|
| **Parental Outcomes: Variances** | | | | |
| Permanent Earnings | $\sigma^2_{\bar{e}^p}$ | 0.199 | 0.172 | 0.225 |
| | | (0.019) | (0.021) | (0.026) |
| Permanent Other Income | $\sigma^2_{\bar{n}^p}$ | 0.845 | 0.945 | 0.752 |
| | | (0.105) | ( 0.16) | (0.157) |
| Permanent Consumption Shifters | $\sigma^2_{\bar{q}^p}$ | 0.911 | 0.977 | 0.840 |
| | | (0.115) | (0.157) | (0.153) |
| **Child Idiosyncratic Heterogeneity: Variances** | | | | |
| Permanent Earnings | $\sigma^2_{\delta^k}$ | 0.241 | 0.232 | 0.245 |
| | | (0.017) | (0.021) | (0.025) |
| Permanent Other Income | $\sigma^2_{\varepsilon^k}$ | 0.658 | 0.561 | 0.747 |
| | | (0.067) | ( 0.1) | (0.162) |
| Permanent Consumption Shifters | $\sigma^2_{\psi^k}$ | 0.869 | 0.816 | 0.900 |
| | | (0.075) | (0.129) | (0.196) |
| **Parental Outcomes: Covariances** | | | | |
| Consumption Shifters & Earnings | $\sigma_{\bar{q}^p,\bar{e}^p}$ | -0.126 | -0.060 | -0.187 |
| | | (0.037) | (0.031) | (0.041) |
| Consumption Shifters & Other Income | $\sigma_{\bar{q}^p,\bar{n}^p}$ | -0.798 | -0.887 | -0.711 |
| | | (0.106) | (0.152) | (0.149) |
| Earnings and Other Income | $\sigma_{\bar{e}^p,\bar{n}^p}$ | -0.006 | -0.044 | 0.029 |
| | | (0.029) | (0.029) | (0.029) |
| **Child Idiosyncratic Heterogeneity: Covariances** | | | | |
| Consumption Shifters & Earnings | $\sigma_{\psi^k,\delta^k}$ | -0.232 | -0.269 | -0.189 |
| | | (0.028) | (0.036) | (0.039) |
| Consumption Shifters & Other Income | $\sigma_{\psi^k,\varepsilon^k}$ | -0.654 | -0.583 | -0.714 |
| | | (0.069) | (0.114) | (0.181) |
| Earnings & Other Income | $\sigma_{\delta^k,\varepsilon^k}$ | 0.047 | 0.078 | 0.013 |
| | | (0.025) | (0.026) | (0.044) |
| *No. of Parent-Child Pairs* | $N$ | 336 | 166 | 170 |

**Note:** Bootstrap standard errors with 100 repetitions are reported in parentheses. This table uses the same sample and model specification as Table 10.

## E.2 Additional Estimates for Robustness Checks

Table 27: Robustness: Idiosyncratic Components

| **Parameters** | **Baseline** (1) | $\boldsymbol{\lambda = \theta = 0}$ (2) | **Random Match** (3) | **Imputation** (4) | **Panel Data** (5) |
|---|---|---|---|---|---|
| **Parental Outcomes: Variances** | | | | | |
| Permanent Earnings: $\sigma^2_{\bar{e}^p}$ | 0.295 | 0.289 | 0.291 | 0.291 | 0.289 |
| | (0.018) | (0.025) | (0.022) | ( 0.02) | (0.015) |
| Permanent Other Income: $\sigma^2_{\bar{n}^p}$ | 0.806 | 0.806 | 0.808 | 0.807 | 0.478 |
| | (0.076) | (0.074) | (0.071) | (0.072) | (0.037) |
| Permanent Consumption Shifters: $\sigma^2_{\bar{q}^p}$ | 1.031 | 1.053 | 1.032 | 0.861 | 0.689 |
| | (0.081) | ( 0.08) | (0.073) | ( 0.07) | (0.044) |
| **Child Idiosyncratic Heterogeneity: Variances** | | | | | |
| Permanent Earnings: $\sigma^2_{\delta^k}$ | 0.228 | 0.214 | 0.247 | 0.224 | 0.208 |
| | (0.013) | (0.014) | (0.015) | (0.011) | (0.013) |
| Permanent Other Income $\sigma^2_{\varepsilon^k}$ | 0.511 | 0.522 | 0.533 | 0.507 | 0.415 |
| | (0.038) | (0.046) | (0.048) | (0.036) | (0.026) |
| Permanent Consumption Shifters: $\sigma^2_{\psi^k}$ | 0.730 | 0.741 | 0.752 | 0.573 | 0.584 |
| | ( 0.05) | (0.063) | (0.069) | ( 0.04) | (0.037) |
| **Parental Outcomes: Covariances** | | | | | |
| Consumption Shifters & Earnings: $\sigma_{\bar{q}^p,\bar{e}^p}$ | -0.271 | -0.279 | -0.263 | -0.223 | -0.258 |
| | (0.021) | (0.029) | (0.028) | (0.019) | (0.022) |
| Consumption Shifters & Other Income: $\sigma_{\bar{q}^p,\bar{n}^p}$ | -0.818 | -0.833 | -0.821 | -0.769 | -0.480 |
| | (0.077) | (0.076) | (0.069) | ( 0.07) | (0.037) |
| Earnings and Other Income: $\sigma_{\bar{e}^p,\bar{n}^p}$ | 0.070 | 0.086 | 0.067 | 0.068 | 0.058 |
| | (0.015) | (0.018) | (0.017) | (0.013) | (0.012) |
| **Child Idiosyncratic Heterogeneity: Covariances** | | | | | |
| Consumption Shifters & Earnings: $\sigma_{\psi^k,\delta^k}$ | -0.247 | -0.253 | -0.263 | -0.214 | -0.212 |
| | ( 0.02) | (0.024) | (0.025) | (0.016) | ( 0.018) |
| Consumption Shifters & Other Income: $\sigma_{\psi^k,\varepsilon^k}$ | -0.522 | -0.532 | -0.542 | -0.480 | -0.398 |
| | (0.041) | ( 0.05) | (0.055) | (0.036) | (0.029) |
| Earnings & Other Income: $\sigma_{\delta^k,\varepsilon^k}$ | 0.075 | 0.092 | 0.095 | 0.072 | 0.052 |
| | (0.013) | (0.017) | (0.019) | (0.012) | (0.013) |
| *No. of Parent-Child Pairs: N* | 760 | 760 | 760 | 760 | 760 |

**Note:** Bootstrap standard errors (100 repetitions) in parentheses. This table uses the same sample and model specification as Table 11.

## E.3 Model using Panel Data

In this section we present the full set of moment conditions for the model using panel data variation, and the identification argument for all the parameters.

**Parent Variance**

$$
\begin{aligned}
Var\left(e_{f,t}^{p}\right) &= \sigma_{\bar{e}^p}^2 + \sigma_{\zeta^p}^2 && \text{(E.1)}\\
Var\left(n_{f,t}^{p}\right) &= \sigma_{\bar{n}^p}^2 + \sigma_{u^p}^2 && \text{(E.2)}\\
Var\left(c_{f,t}^{p}\right) &= \sigma_{\bar{q}^p}^2 + \sigma_{\bar{e}^p}^2 + \sigma_{\bar{n}^p}^2 + \sigma_{v^p}^2 \\
&+ 2\left(\sigma_{\bar{q}^p,\bar{e}^p} + \sigma_{\bar{q}^p,\bar{n}^p} + \sigma_{\bar{e}^p,\bar{n}^p}\right) + \left[f\left(r\right)\right]^2\left(\sigma_{u^p}^2 + \sigma_{\zeta^p}^2 + 2\sigma_{\zeta^p,u^p}\right) && \text{(E.3)}
\end{aligned}
$$

**Child Variance**

$$
\begin{aligned}
Var\left(e_{f,t}^{k}\right) &= \gamma^2\sigma_{\bar{e}^p}^2 + \theta^2\sigma_{\bar{n}^p}^2 + \sigma_{\delta^k}^2 + \sigma_{\zeta^k}^2 + 2\gamma\theta\sigma_{\bar{e}^p,\bar{n}^p} && \text{(E.4)}\\
Var\left(n_{f,t}^{k}\right) &= \rho^2\sigma_{\bar{n}^p}^2 + \lambda^2\sigma_{\bar{e}^p}^2 + \sigma_{\varepsilon^k}^2 + \sigma_{u^k}^2 + 2\rho\lambda\sigma_{\bar{e}^p,\bar{n}^p} && \text{(E.5)}\\
Var\left(c_{f,t}^{k}\right) &= \phi^2\sigma_{\bar{q}^p}^2 + \left(\gamma+\lambda\right)^2\sigma_{\bar{e}^p}^2 + \left(\rho+\theta\right)^2\sigma_{\bar{n}^p}^2 + \sigma_{\varepsilon^k}^2 + \sigma_{\psi^k}^2 + \sigma_{\delta^k}^2 \\
&+ 2\left[\left(\gamma+\lambda\right)\phi\sigma_{\bar{q}^p,\bar{e}^p} + \left(\rho+\theta\right)\phi\sigma_{\bar{q}^p,\bar{n}^p} + \left(\rho+\theta\right)\left(\gamma+\lambda\right)\sigma_{\bar{e}^p,\bar{n}^p}\right] \\
&+ 2\left[\sigma_{\psi^k,\varepsilon^k} + \sigma_{\psi^k,\delta^k} + \sigma_{\delta^k,\varepsilon^k}\right] \\
&+ \sigma_{v^k}^2 + \left[f\left(r\right)\right]^2\left(\sigma_{u^k}^2 + \sigma_{\zeta^k}^2 + 2\sigma_{\zeta^k,u^k}\right) && \text{(E.6)}
\end{aligned}
$$

**Contemporaneous Parent Covariance**

$$
\begin{aligned}
Cov\left(e_{f,t}^{p}, n_{f,t}^{p}\right) &= \sigma_{\bar{e}^p,\bar{n}^p} + \sigma_{\zeta^p,u^p} && \text{(E.7)}\\
Cov\left(e_{ft}^{p}, c_{ft}^{p}\right) &= \sigma_{\bar{e}^p}^2 + \sigma_{\bar{q}^p,\bar{e}^p} + \sigma_{\bar{e}^p,\bar{n}^p} + f\left(r\right)\left(\sigma_{\zeta^p}^2 + \sigma_{\zeta^p,u^p}\right) && \text{(E.8)}\\
Cov\left(n_{f,t}^{p}, c_{f,t}^{p}\right) &= \sigma_{\bar{n}^p}^2 + \sigma_{\bar{q}^p,\bar{n}^p} + \sigma_{\bar{e}^p,\bar{n}^p} + f\left(r\right)\left(\sigma_{u^p}^2 + \sigma_{\zeta^p,u^p}\right) && \text{(E.9)}
\end{aligned}
$$

**Contemporaneous Child Covariance**

$$
\begin{aligned}
Cov\left(e_{f,t}^{k}, n_{f,t}^{k}\right) &= \left(\rho\gamma + \theta\lambda\right)\sigma_{\bar{e}^p,\bar{n}^p} + \gamma\lambda\sigma_{\bar{e}^p}^2 + \rho\theta\sigma_{\bar{n}^p}^2 + \sigma_{\delta^k,\varepsilon^k} + \sigma_{\zeta^k,u^k} && \text{(E.10)}\\
Cov\left(e_{f,t}^{k}, c_{f,t}^{k}\right) &= \gamma\left(\gamma+\lambda\right)\sigma_{\bar{e}^p}^2 + \theta\left(\theta+\rho\right)\sigma_{\bar{n}^p}^2 + \phi\gamma\sigma_{\bar{q}^p,\bar{e}^p} + \phi\theta\sigma_{\bar{q}^p,\bar{n}^p} \\
&+ \left[\gamma\left(\rho+\theta\right) + \theta\left(\gamma+\lambda\right)\right]\sigma_{\bar{e}^p,\bar{n}^p} \\
&+ \sigma_{\delta^k}^2 + \sigma_{\psi^k,\delta^k} + \sigma_{\delta^k,\varepsilon^k} + f\left(r\right)\left(\sigma_{\zeta^k}^2 + \sigma_{\zeta^k,u^k}\right) && \text{(E.11)}
\end{aligned}
$$

$$
\begin{aligned}
Cov\left(n_{f,t}^{k}, c_{f,t}^{k}\right) &= \lambda\left(\gamma+\lambda\right)\sigma_{\bar{e}^{p}}^{2}+\rho\left(\theta+\rho\right)\sigma_{\bar{n}^{p}}^{2}+\phi\lambda\sigma_{\bar{q}^{p},\bar{e}^{p}}+\phi\rho\sigma_{\bar{q}^{p},\bar{n}^{p}} \\
&+ \left[\lambda\left(\rho+\theta\right)+\rho\left(\gamma+\lambda\right)\right]\sigma_{\bar{e}^{p},\bar{n}^{p}} \\
&+ \sigma_{\varepsilon^{k}}^{2}+\sigma_{\psi^{k},\delta^{k}}+\sigma_{\psi^{k},\varepsilon^{k}}+f\left(r\right)\left(\sigma_{u^{k}}^{2}+\sigma_{\zeta^{k},u^{k}}\right) \qquad \text{(E.12)}
\end{aligned}
$$

**Contemporaneous Cross-Generation Covariance**

$$
\begin{aligned}
Cov\left(e_{f,t}^{p}, e_{f,t}^{k}\right) &= \gamma\sigma_{\bar{e}^{p}}^{2}+\theta\sigma_{\bar{e}^{p},\bar{n}^{p}} \qquad \text{(E.13)} \\
Cov\left(n_{f,t}^{p}, n_{f,t}^{k}\right) &= \rho\sigma_{\bar{n}^{p}}^{2}+\lambda\sigma_{\bar{e}^{p},\bar{n}^{p}} \qquad \text{(E.14)} \\
Cov\left(c_{f,t}^{p}, c_{f,t}^{k}\right) &= \phi\left(\sigma_{\bar{q}^{p}}^{2}+\sigma_{\bar{q}^{p},\bar{e}^{p}}+\sigma_{\bar{q}^{p},\bar{n}^{p}}\right)+\left(\gamma+\lambda\right)\left(\sigma_{\bar{e}^{p}}^{2}+\sigma_{\bar{q}^{p},\bar{e}^{p}}+\sigma_{\bar{e}^{p},\bar{n}^{p}}\right) \\
&+ \left(\rho+\theta\right)\left(\sigma_{\bar{n}^{p}}^{2}+\sigma_{\bar{q}^{p},\bar{n}^{p}}+\sigma_{\bar{e}^{p},\bar{n}^{p}}\right) \qquad \text{(E.15)} \\
Cov\left(e_{f,t}^{p}, n_{f,t}^{k}\right) &= \rho\sigma_{\bar{e}^{p},\bar{n}^{p}}+\lambda\sigma_{\bar{e}^{p}}^{2} \qquad \text{(E.16)} \\
Cov\left(e_{f,t}^{p}, c_{f,t}^{k}\right) &= \left(\gamma+\lambda\right)\sigma_{\bar{e}^{p}}^{2}+\phi\sigma_{\bar{q}^{p},\bar{e}^{p}}+\left(\rho+\theta\right)\sigma_{\bar{e}^{p},\bar{n}^{p}} \qquad \text{(E.17)} \\
Cov\left(n_{f,t}^{p}, e_{f,t}^{k}\right) &= \gamma\sigma_{\bar{e}^{p},\bar{n}^{p}}+\theta\sigma_{\bar{n}^{p}}^{2} \qquad \text{(E.18)} \\
Cov\left(n_{f,t}^{p}, c_{f,t}^{k}\right) &= \left(\rho+\theta\right)\sigma_{\bar{n}^{p}}^{2}+\phi\sigma_{\bar{q}^{p},\bar{n}^{p}}+\left(\gamma+\lambda\right)\sigma_{\bar{e}^{p},\bar{n}^{p}} \qquad \text{(E.19)} \\
Cov\left(c_{f,t}^{p}, e_{f,t}^{k}\right) &= \gamma\left(\sigma_{\bar{e}^{p}}^{2}+\sigma_{\bar{q}^{p},\bar{e}^{p}}+\sigma_{\bar{e}^{p},\bar{n}^{p}}\right)+\theta\left(\sigma_{\bar{n}^{p}}^{2}+\sigma_{\bar{q}^{p},\bar{n}^{p}}+\sigma_{\bar{e}^{p},\bar{n}^{p}}\right) \qquad \text{(E.20)} \\
Cov\left(c_{f,t}^{p}, n_{f,t}^{k}\right) &= \lambda\left(\sigma_{\bar{e}^{p}}^{2}+\sigma_{\bar{q}^{p},\bar{e}^{p}}+\sigma_{\bar{e}^{p},\bar{n}^{p}}\right)+\rho\left(\sigma_{\bar{n}^{p}}^{2}+\sigma_{\bar{q}^{p},\bar{n}^{p}}+\sigma_{\bar{e}^{p},\bar{n}^{p}}\right) \qquad \text{(E.21)}
\end{aligned}
$$

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

$$
\begin{aligned}
Cov\left(e_{f,t}^{p}, e_{f,t+1}^{p}\right) &= \sigma_{\bar{e}^{p}}^{2} \qquad \text{(E.22)} \\
Cov\left(n_{f,t}^{p}, n_{f,t+1}^{p}\right) &= \sigma_{\bar{n}^{p}}^{2} \qquad \text{(E.23)} \\
Cov\left(c_{f,t}^{p}, c_{f,t+1}^{p}\right) &= \sigma_{\bar{q}^{p}}^{2}+\sigma_{\bar{e}^{p}}^{2}+\sigma_{\bar{n}^{p}}^{2}+2\left(\sigma_{\bar{q}^{p},\bar{e}^{p}}+\sigma_{\bar{q}^{p},\bar{n}^{p}}+\sigma_{\bar{e}^{p},\bar{n}^{p}}\right) \qquad \text{(E.24)} \\
Cov\left(e_{f,t}^{p}, n_{f,t+1}^{p}\right) &= \sigma_{\bar{e}^{p},\bar{n}^{p}} \qquad \text{(E.25)} \\
Cov\left(e_{f,t}^{p}, c_{f,t+1}^{p}\right) &= \sigma_{\bar{e}^{p}}^{2}+\sigma_{\bar{q}^{p},\bar{e}^{p}}+\sigma_{\bar{e}^{p},\bar{n}^{p}} \qquad \text{(E.26)} \\
Cov\left(n_{f,t}^{p}, e_{f,t+1}^{p}\right) &= \sigma_{\bar{e}^{p},\bar{n}^{p}} \qquad \text{(E.27)} \\
Cov\left(n_{f,t}^{p}, c_{f,t+1}^{p}\right) &= \sigma_{\bar{n}^{p}}^{2}+\sigma_{\bar{q}^{p},\bar{n}^{p}}+\sigma_{\bar{e}^{p},\bar{n}^{p}} \qquad \text{(E.28)} \\
Cov\left(c_{f,t}^{p}, e_{f,t+1}^{p}\right) &= \sigma_{\bar{e}^{p}}^{2}+\sigma_{\bar{q}^{p},\bar{e}^{p}}+\sigma_{\bar{e}^{p},\bar{n}^{p}} \qquad \text{(E.29)} \\
Cov\left(c_{f,t}^{p}, n_{f,t+1}^{p}\right) &= \sigma_{\bar{n}^{p}}^{2}+\sigma_{\bar{q}^{p},\bar{n}^{p}}+\sigma_{\bar{e}^{p},\bar{n}^{p}} \qquad \text{(E.30)}
\end{aligned}
$$

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

$$
\begin{aligned}
Cov\left(e_{f,t}^{k}, e_{f,t+1}^{k}\right) &= \gamma^2\sigma_{\bar{e}^p}^2 + \theta^2\sigma_{\bar{n}^p}^2 + 2\gamma\theta\sigma_{\bar{e}^p,\bar{n}^p} + \sigma_{\delta^k}^2 &\text{(E.31)}\\
Cov\left(n_{f,t}^{k}, n_{f,t+1}^{k}\right) &= \rho^2\sigma_{\bar{n}^p}^2 + \lambda^2\sigma_{\bar{e}^p}^2 + 2\rho\lambda\sigma_{\bar{e}^p,\bar{n}^p} + \sigma_{\varepsilon^k}^2 &\text{(E.32)}\\
Cov\left(c_{f,t}^{k}, c_{f,t+1}^{k}\right) &= \phi^2\sigma_{\bar{q}^p}^2 + (\gamma+\lambda)^2\sigma_{\bar{e}^p}^2 + (\rho+\theta)^2\sigma_{\bar{n}^p}^2 + \sigma_{\varepsilon^k}^2 + \sigma_{\psi^k}^2 + \sigma_{\delta^k}^2 \\
&+ 2\left[(\gamma+\lambda)\phi\sigma_{\bar{q}^p,\bar{e}^p} + (\rho+\theta)\phi\sigma_{\bar{q}^p,\bar{n}^p} + (\rho+\theta)(\gamma+\lambda)\sigma_{\bar{e}^p,\bar{n}^p}\right] \\
&+ 2\left(\sigma_{\psi^k,\varepsilon^k} + \sigma_{\psi^k,\delta^k} + \sigma_{\delta^k,\varepsilon^k}\right) &\text{(E.33)}\\
Cov\left(e_{f,t}^{k}, n_{f,t+1}^{k}\right) &= (\rho\gamma+\theta\lambda)\sigma_{\bar{e}^p,\bar{n}^p} + \gamma\lambda\sigma_{\bar{e}^p}^2 + \theta\rho\sigma_{\bar{n}^p}^2 + \sigma_{\delta^k,\varepsilon^k} &\text{(E.34)}\\
Cov\left(e_{f,t}^{k}, c_{f,t+1}^{k}\right) &= \gamma\left[(\gamma+\lambda)\sigma_{\bar{e}^p}^2 + (\theta+\rho)\sigma_{\bar{e}^p,\bar{n}^p} + \phi\sigma_{\bar{q}^p,\bar{e}^p}\right] + \sigma_{\delta^k}^2 + \sigma_{\delta^k,\varepsilon^k} + \sigma_{\psi^k,\delta^k} \\
&+ \theta\left[(\theta+\rho)\sigma_{\bar{n}^p}^2 + (\gamma+\lambda)\sigma_{\bar{e}^p,\bar{n}^p} + \phi\sigma_{\bar{q}^p,\bar{n}^p}\right] &\text{(E.35)}\\
Cov\left(n_{f,t}^{k}, e_{f,t+1}^{k}\right) &= (\rho\gamma+\theta\lambda)\sigma_{\bar{e}^p,\bar{n}^p} + \gamma\lambda\sigma_{\bar{e}^p}^2 + \theta\rho\sigma_{\bar{n}^p}^2 + \sigma_{\delta^k,\varepsilon^k} &\text{(E.36)}\\
Cov\left(n_{f,t}^{k}, c_{f,t+1}^{k}\right) &= \rho\left[(\gamma+\lambda)\sigma_{\bar{n}^p}^2 + \phi\sigma_{\bar{q}^p,\bar{n}^p} + (\gamma+\lambda)\sigma_{\bar{e}^p,\bar{n}^p}\right] + \sigma_{\varepsilon^k}^2 + \sigma_{\psi^k,\varepsilon^k} + \sigma_{\delta^k,\varepsilon^k} \\
&+ \lambda\left[(\gamma+\lambda)\sigma_{\bar{e}^p}^2 + \phi\sigma_{\bar{q}^p,\bar{e}^p} + (\theta+\rho)\sigma_{\bar{e}^p,\bar{n}^p}\right] &\text{(E.37)}\\
Cov\left(c_{f,t}^{k}, e_{f,t+1}^{k}\right) &= \gamma\left[(\gamma+\lambda)\sigma_{\bar{e}^p}^2 + (\theta+\rho)\sigma_{\bar{e}^p,\bar{n}^p} + \phi\sigma_{\bar{q}^p,\bar{e}^p}\right] + \sigma_{\delta^k}^2 + \sigma_{\delta^k,\varepsilon^k} + \sigma_{\psi^k,\delta^k} \\
&+ \theta\left[(\theta+\rho)\sigma_{\bar{n}^p}^2 + (\gamma+\lambda)\sigma_{\bar{e}^p,\bar{n}^p} + \phi\sigma_{\bar{q}^p,\bar{n}^p}\right] &\text{(E.38)}\\
Cov\left(c_{f,t}^{k}, n_{f,t+1}^{k}\right) &= \rho\left[(\gamma+\lambda)\sigma_{\bar{n}^p}^2 + \phi\sigma_{\bar{q}^p,\bar{n}^p} + (\gamma+\lambda)\sigma_{\bar{e}^p,\bar{n}^p}\right] + \sigma_{\varepsilon^k}^2 + \sigma_{\psi^k,\varepsilon^k} + \sigma_{\delta^k,\varepsilon^k} \\
&+ \lambda\left[(\gamma+\lambda)\sigma_{\bar{e}^p}^2 + \phi\sigma_{\bar{q}^p,\bar{e}^p} + (\theta+\rho)\sigma_{\bar{e}^p,\bar{n}^p}\right] &\text{(E.39)}
\end{aligned}
$$

**Cross-Generation Covariances: Parent at $t$ & child at $t+1$**

$$
\begin{aligned}
Cov\left(e_{f,t}^{p}, e_{f,t+1}^{k}\right) &= \gamma\sigma_{\bar{e}^p}^2 + \theta\sigma_{\bar{e}^p,\bar{n}^p} &\text{(E.40)}\\
Cov\left(e_{f,t}^{p}, n_{f,t+1}^{k}\right) &= \rho\sigma_{\bar{e}^p,\bar{n}^p} + \lambda\sigma_{\bar{e}^p}^2 &\text{(E.41)}\\
Cov\left(e_{f,t}^{p}, c_{f,t+1}^{k}\right) &= (\gamma+\lambda)\sigma_{\bar{e}^p}^2 + \phi\sigma_{\bar{q}^p,\bar{e}^p} + (\rho+\theta)\sigma_{\bar{e}^p,\bar{n}^p} &\text{(E.42)}\\
Cov\left(n_{f,t}^{p}, e_{f,t+1}^{k}\right) &= \gamma\sigma_{\bar{e}^p,\bar{n}^p} + \theta\sigma_{\bar{n}^p}^2 &\text{(E.43)}\\
Cov\left(n_{f,t}^{p}, n_{f,t+1}^{k}\right) &= \rho\sigma_{\bar{n}^p}^2 + \lambda\sigma_{\bar{e}^p,\bar{n}^p} &\text{(E.44)}\\
Cov\left(n_{f,t}^{p}, c_{f,t+1}^{k}\right) &= (\rho+\theta)\sigma_{\bar{n}^p}^2 + \phi\sigma_{\bar{q}^p,\bar{n}^p} + (\gamma+\lambda)\sigma_{\bar{e}^p,\bar{n}^p} &\text{(E.45)}\\
Cov\left(c_{f,t}^{p}, e_{f,t+1}^{k}\right) &= \gamma\left(\sigma_{\bar{e}^p}^2 + \sigma_{\bar{q}^p,\bar{e}^p} + \sigma_{\bar{e}^p,\bar{n}^p}\right) + \theta\left(\sigma_{\bar{n}^p}^2 + \sigma_{\bar{q}^p,\bar{n}^p} + \sigma_{\bar{e}^p,\bar{n}^p}\right) &\text{(E.46)}\\
Cov\left(c_{f,t}^{p}, n_{f,t+1}^{k}\right) &= \lambda\left(\sigma_{\bar{e}^p}^2 + \sigma_{\bar{q}^p,\bar{e}^p} + \sigma_{\bar{e}^p,\bar{n}^p}\right) + \rho\left(\sigma_{\bar{n}^p}^2 + \sigma_{\bar{q}^p,\bar{n}^p} + \sigma_{\bar{e}^p,\bar{n}^p}\right) &\text{(E.47)}\\
Cov\left(c_{f,t}^{p}, c_{f,t+1}^{k}\right) &= \phi\left(\sigma_{\bar{q}^p}^2 + \sigma_{\bar{q}^p,\bar{e}^p} + \sigma_{\bar{q}^p,\bar{n}^p}\right) + (\gamma+\lambda)\left(\sigma_{\bar{e}^p}^2 + \sigma_{\bar{q}^p,\bar{e}^p} + \sigma_{\bar{e}^p,\bar{n}^p}\right) \\
&+ (\rho+\theta)\left(\sigma_{\bar{n}^p}^2 + \sigma_{\bar{q}^p,\bar{n}^p} + \sigma_{\bar{e}^p,\bar{n}^p}\right) &\text{(E.48)}
\end{aligned}
$$

**Identification.** There are 25 parameters to be identified from 48 equations. We will proceed with the identification argument in the following three steps:
(i) First, we identify 10 parameters linked to earnings, income and consumption processes for par-

ents. Equations (E.22), (E.23), (E.1), (E.2), (E.25), (E.28), (E.29), (E.24), (E.7) and (E.3) can be considered sequentially to identify $\sigma^2_{\bar{e}^p}$, $\sigma^2_{\bar{n}^p}$, $\sigma^2_{\zeta^p}$, $\sigma^2_{u^p}$, $\sigma_{\bar{e}^p,\bar{n}^p}$, $\sigma_{\bar{q}^p,\bar{n}^p}$, $\sigma_{\bar{q}^p,\bar{e}^p}$, $\sigma^2_{\bar{q}^p}$, $\sigma_{\zeta^p,u^p}$ and $\sigma^2_{v^p}$ respectively.

(ii) Next, we identify 5 parameters which denote intergenerational elasticities. Equations (E.13) and (E.20) can simultaneously identify $\gamma$ and $\theta$, while $\rho$ and $\lambda$ are identified from equations (E.14) and (E.21). Finally, $\phi$ is identified from equation (E.15).

(iii) Lastly, the 10 parameters associated with the child's earnings, income and consumption processes are identified. Equations (E.31), (E.32), (E.4), (E.5), (E.34), (E.37), (E.38), (E.33), (E.10) and (E.6) can be considered sequentially to identify $\sigma^2_{\delta^k}$, $\sigma^2_{\varepsilon^k}$, $\sigma^2_{\zeta^k}$, $\sigma^2_{u^k}$, $\sigma_{\delta^k,\varepsilon^k}$, $\sigma_{\psi^k,\varepsilon^k}$, $\sigma_{\psi^k,\delta^k}$, $\sigma^2_{\psi^k}$, $\sigma_{\zeta^k,u^k}$ and $\sigma^2_{v^k}$ respectively.

Table 28: Transitory Shocks Estimates

| | **Parameters** | **Estimates** (1) |
|---|---|---|
| **Parental Transitory Shocks** | | . |
| Earnings | $\sigma^2_{\zeta^p}$ | 0.095 |
| | | (0.006) |
| Other Income | $\sigma^2_{u^p}$ | 0.393 |
| | | (0.025) |
| Consumption | $\sigma^2_{v^p}$ | 0.069 |
| | | (0.004) |
| Earnings on Other Income | $\sigma_{u^p,\zeta^p}$ | -0.022 |
| | | (0.004) |
| | | . |
| **Child Transitory Shocks** | | . |
| Earnings | $\sigma^2_{\zeta^k}$ | 0.097 |
| | | (0.006) |
| Other Income | $\sigma^2_{u^k}$ | 0.366 |
| | | (0.029) |
| Consumption | $\sigma^2_{v^k}$ | 0.086 |
| | | (0.006) |
| Earnings on Other Income | $\sigma_{u^k,\zeta^k}$ | 0.004 |
| | | (0.007) |

**Note:** Bootstrap standard errors (100 repetitions) in parentheses. This table uses the same sample and model specification as column 5 of Tables 11 and 27.

## E.4 Random Walk Model

In this appendix, we consider an alternative to our baseline model of intergenerational persistence in individual fixed effects of income and consumption levels. We assume that the permanent component of both head earnings and other income of the family is a random walk process, and explore the extent of intergenerational persistence in the permanent innovations to these random walk components. Identification of intergenerational persistence in permanent life-cycle shocks involves calculating the growth rates of the outcome variables, which in turn implies that one can no longer identify the persistence in fixed effects, which are differenced out in growth rates.

Under this alternative view of intergenerational persistence, the model equations describing earnings and other income are:

$$e^p_{f,t} = \bar{e}^p_f + P^p_{f,t} + u^p_{f,t} \tag{E.49}$$
$$P^p_{f,t} = P^p_{f,t-1} + v^p_{f,t} \tag{E.50}$$

$$n^p_{f,t} = \bar{n}^p_f + Q^p_{f,t} + \zeta^p_{f,t} \tag{E.51}$$
$$Q^p_{f,t} = Q^p_{f,t-1} + \nu^p_{f,t} \tag{E.52}$$

A similar set of equations for earnings and other income holds true for the children. In addition, we assume that intergenerational linkages follow:

$$v^k_{f,t} = \rho v^p_{f,t} + \varepsilon^k_{f,t}$$

and

$$\nu^k_{f,t} = \lambda \nu^p_{f,t} + \theta^k_{f,t}.$$

Time differencing the income equations over successive sample years delivers the following equations:

$$\Delta_2 e^p_{f,t} = \left(v^p_{f,t} + v^p_{f,t-1}\right) + \Delta_2 u^p_{f,t} \tag{E.53}$$
$$\Delta_2 n^p_{f,t} = \left(\nu^p_{f,t} + \nu^p_{f,t-1}\right) + \Delta_2 \zeta^p_{f,t} \tag{E.54}$$
$$\Delta_2 e^k_{f,t} = \rho\left(v^p_{f,t} + v^p_{f,t-1}\right) + \left(\varepsilon^k_{f,t} + \varepsilon^k_{f,t}\right) + \Delta_2 u^k_{f,t} \tag{E.55}$$
$$\Delta_2 n^k_{f,t} = \lambda\left(\nu^p_{f,t} + \nu^p_{f,t-1}\right) + \left(\theta^k_{f,t} + \theta^k_{f,t}\right) + \Delta_2 \zeta^k_{f,t} \tag{E.56}$$

Here, we use the notation $\Delta_2 x_t \equiv x_t - x_{t-2}$ to denote the two-year time difference for any variable $x_t$. Since PSID data are only available every two years after 1998, we consider two-year time differences throughout so as to use data from both pre- and post-1998 interview rounds.

In this setting, the growth rate of consumption depends on the transitory and permanent innovations to earnings and other income, as well as on consumption-specific transitory heterogeneity, just as in the well-known work of Blundell, Pistaferri, and Preston (2008):

$$\Delta c^j_{f,t} = \phi_{e^j} v^j_{f,t} + \psi_{e^j} u^j_{f,t} + \psi_{n^j} \nu^j_{f,t} + \psi_{n^j} \zeta^j_{f,t} + \xi^j_{f,t} \quad \textit{where } j = \{p, k\}.$$

The loading parameters of permanent innovations to earnings and other income in the consumption growth equation are interpreted as inverse measures of consumption insurance. For example, when $\phi_{e^j}$ is close to zero, permanent shocks to earnings have little or no effect on expenditure growth, which suggests the presence of effective consumption smoothing mechanisms. On the other hand, if $\phi_{e^j}$ is close to unity there is little insurance against innovations to permanent earnings. We also allow for the possibility of direct persistence in consumption growth so that $\xi^k_{f,t} = \gamma \xi^p_{f,t} + \chi^k_{f,t}$. This alternative model results in equations:

$$\begin{aligned}
\Delta_2 c^p_{f,t} &= \phi_{e^p}\left(v^p_{f,t} + v^p_{f,t-1}\right) + \phi_{n^p}\left(\nu^p_{f,t} + \nu^p_{f,t-1}\right) \\
&+ \psi_{e^p}\left(u^p_{f,t} + u^p_{f,t-1}\right) + \psi_{n^p}\left(\zeta^p_{f,t} + \zeta^p_{f,t-1}\right) + \left(\xi^p_{f,t} + \xi^p_{f,t-1}\right)
\end{aligned} \tag{E.57}$$

$$\begin{aligned}
\Delta_2 c^k_{f,t} &= \phi_{e^k}\left[\rho\left(v^p_{f,t} + v^p_{f,t-1}\right) + \left(\varepsilon^k_{f,t} + \varepsilon^k_{f,t-1}\right)\right] + \psi_{e^k}\left(u^k_{f,t} + u^k_{f,t-1}\right) \\
&+ \phi_{n^k}\left[\lambda\left(\nu^p_{f,t} + \nu^p_{f,t-1}\right) + \left(\theta^k_{f,t} + \theta^k_{f,t-1}\right)\right] + \psi_{n^k}\left(\zeta^k_{f,t} + \zeta^k_{f,t-1}\right) \\
&+ \gamma\left(\xi^p_{f,t} + \xi^p_{f,t-1}\right) + \left(\chi^k_{f,t} + \chi^k_{f,t-1}\right)
\end{aligned} \tag{E.58}$$

#### E.4.1 Moment Conditions

**Parent Variance**

$$Var\left(\Delta_2 e^p_{f,t}\right) = 2\left(\sigma^2_{v^p} + \sigma^2_{u^p}\right) \tag{E.59}$$

$$Var\left(\Delta_2 n^p_{f,t}\right) = 2\left(\sigma^2_{\nu^p} + \sigma^2_{\zeta^p}\right) \tag{E.60}$$

$$Var\left(\Delta_2 c^p_{f,t}\right) = 2\left(\phi^2_{e^p}\sigma^2_{v^p} + \phi^2_{n^p}\sigma^2_{\nu^p} + \psi^2_{e^p}\sigma^2_{u^p} + \psi^2_{n^p}\sigma^2_{\zeta^p} + \sigma^2_{\xi^p}\right) \tag{E.61}$$

**Child Variance**

$$
\begin{aligned}
Var\left(\Delta_2 e^k_{f,t}\right) &= 2\left(\rho^2\sigma^2_{\upsilon^p}+\sigma^2_{u^k}+\sigma^2_{\varepsilon^k}\right) && \text{(E.62)}\\
Var\left(\Delta_2 n^k_{f,t}\right) &= 2\left(\lambda^2\sigma^2_{\nu^p}+\sigma^2_{\zeta^k}+\sigma^2_{\theta^k}\right) && \text{(E.63)}\\
Var\left(\Delta_2 c^k_{f,t}\right) &= 2\left(\rho^2\phi^2_{e^k}\sigma^2_{\upsilon^p}+\phi^2_{e^k}\sigma^2_{\varepsilon^k}+\psi^2_{e^k}\sigma^2_{u^k}\right)\\
&+ 2\left(\lambda^2\phi^2_{n^k}\sigma^2_{\nu^p}+\phi^2_{n^k}\sigma^2_{\theta^k}+\psi^2_{n^k}\sigma^2_{\zeta^k}+\gamma^2\sigma^2_{\xi^p}+\sigma^2_{\chi^k}\right) && \text{(E.64)}
\end{aligned}
$$

**Contemporaneous Parent Covariance**

$$
\begin{aligned}
Cov\left(\Delta_2 e^p_{f,t},\Delta_2 c^p_{f,t}\right) &= 2\phi_{e^p}\sigma^2_{\upsilon^p}+\psi_{e^p}\sigma^2_{u^p} && \text{(E.65)}\\
Cov\left(\Delta_2 n^p_{f,t},\Delta_2 c^p_{f,t}\right) &= 2\phi_{n^p}\sigma^2_{\nu^p}+\psi_{n^p}\sigma^2_{\zeta^p} && \text{(E.66)}
\end{aligned}
$$

**Contemporaneous Child Covariance**

$$
\begin{aligned}
Cov\left(\Delta_2 e^k_{f,t},\Delta_2 c^k_{f,t}\right) &= 2\rho^2\phi_{e^k}\sigma^2_{\upsilon^p}+2\phi_{e^k}\sigma^2_{\varepsilon^k}+\psi_{e^k}\sigma^2_{u^k} && \text{(E.67)}\\
Cov\left(\Delta_2 n^k_{f,t},\Delta_2 c^k_{f,t}\right) &= 2\lambda^2\phi_{n^k}\sigma^2_{\nu^p}+2\phi_{n^k}\sigma^2_{\theta^k}+\psi_{n^k}\sigma^2_{\zeta^k} && \text{(E.68)}
\end{aligned}
$$

**Contemporaneous Cross-Generation Covariance**

$$
\begin{aligned}
Cov\left(\Delta_2 e^p_{f,t},\Delta_2 e^k_{f,t}\right) &= 2\rho\sigma^2_{\upsilon^p} && \text{(E.69)}\\
Cov\left(\Delta_2 n^p_{f,t},\Delta_2 n^k_{f,t}\right) &= 2\lambda\sigma^2_{\nu^p} && \text{(E.70)}\\
Cov\left(\Delta_2 c^p_{f,t},\Delta_2 c^k_{f,t}\right) &= 2\left(\rho\phi_{e^p}\phi_{e^k}\sigma^2_{\upsilon^p}+\lambda\phi_{n^p}\phi_{n^k}\sigma^2_{\nu^p}+\gamma\sigma^2_{\xi^p}\right) && \text{(E.71)}\\
Cov\left(\Delta_2 e^p_{f,t},\Delta_2 c^k_{f,t}\right) &= 2\rho\phi_{e^k}\sigma^2_{\upsilon^p} && \text{(E.72)}\\
Cov\left(\Delta_2 n^p_{f,t},\Delta_2 c^k_{f,t}\right) &= 2\lambda\phi_{n^k}\sigma^2_{\nu^p} && \text{(E.73)}\\
Cov\left(\Delta_2 c^p_{f,t},\Delta_2 e^k_{f,t}\right) &= 2\rho\phi_{e^p}\sigma^2_{\upsilon^p} && \text{(E.74)}\\
Cov\left(\Delta_2 c^p_{f,t},\Delta_2 n^k_{f,t}\right) &= 2\lambda\phi_{n^p}\sigma^2_{\nu^p} && \text{(E.75)}
\end{aligned}
$$

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

$$
\begin{aligned}
Cov\left(\Delta_2 e^p_{f,t},\Delta_2 e^p_{f,t+2}\right) &= -\sigma^2_{u^p} && \text{(E.76)}\\
Cov\left(\Delta_2 n^p_{f,t},\Delta_2 n^p_{f,t+2}\right) &= -\sigma^2_{\zeta^p} && \text{(E.77)}\\
Cov\left(\Delta_2 c^p_{f,t},\Delta_2 e^p_{f,t+2}\right) &= -\psi_{e^p}\sigma^2_{u^p} && \text{(E.78)}\\
Cov\left(\Delta_2 c^p_{f,t},\Delta_2 n^p_{f,t+2}\right) &= -\psi_{n^p}\sigma^2_{\zeta^p} && \text{(E.79)}
\end{aligned}
$$

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

$$Cov\left(\Delta_2 e^k_{f,t}, \Delta_2 e^k_{f,t+2}\right) = -\sigma^2_{u^k} \tag{E.80}$$
$$Cov\left(\Delta_2 n^k_{f,t}, \Delta_2 n^k_{f,t+2}\right) = -\sigma^2_{\zeta^k} \tag{E.81}$$
$$Cov\left(\Delta_2 c^k_{f,t}, \Delta_2 e^k_{f,t+2}\right) = -\psi_{e^k}\sigma^2_{u^k} \tag{E.82}$$
$$Cov\left(\Delta_2 c^k_{f,t}, \Delta_2 n^k_{f,t+2}\right) = -\psi_{n^k}\sigma^2_{\zeta^k} \tag{E.83}$$

### E.4.2 Identification

There are 21 parameters to be identified from 25 moment conditions. It is straightforward to see the identification of $\sigma^2_{u^p}$, $\sigma^2_{\zeta^p}$, $\psi_{e^p}$, $\psi_{n^p}$, $\sigma^2_{u^k}$, $\sigma^2_{\zeta^k}$, $\psi_{e^k}$ and $\psi_{n^k}$ from equations (E.76) through (E.83). Subsequently, $\sigma^2_{\upsilon^p}$ and $\sigma^2_{\nu^p}$ can be identified from equations (E.59) and (E.60). This allows identification of $\rho$ and $\lambda$ from equations (E.69) and (E.70); and consequently $\phi_{e^k}$, $\phi_{n^k}$, $\phi_{e^p}$ and $\phi_{n^p}$ from equations (E.72) through (E.75) respectively. Now, equations (E.61), (E.62) and (E.63) can identify $\sigma^2_{\xi^p}$, $\sigma^2_{\varepsilon^k}$ and $\sigma^2_{\theta^k}$ respectively. Finally, $\gamma$ is identified from equation (E.71), which leaves $\sigma^2_{\chi^k}$ to be identified from (E.64).

### E.4.3 Results and Empirical Moments

Table 29: Intergenerational Growth Elasticities

| | Parameters | Imputed (1) | Food (2) |
|---|---|---|---|
| Earnings Growth | $\rho$ | 0.241 | 0.256 |
| | | (0.161) | (0.193) |
| Other Income Growth | $\lambda$ | 0.094 | 0.095 |
| | | (0.071) | (0.059) |
| Consumption Growth Shifter | $\gamma$ | 0.009 | 0.047 |
| | | (0.048) | (0.056) |
| *No. of Parent-Child Pairs* | $N$ | 760 | 760 |

**Note:** Bootstrap standard errors (100 repetitions) in parentheses. Year and cohort effects have been removed.

Estimates of the intragenerational insurance parameters, and of the variances of both permanent and transitory life-cycle heterogeneity, are shown in Tables 30 and 31 of the Appendix. In Table

29, we present two sets of estimates for this random walk model. 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.[34] Table 29 shows that innovations to earnings, other income and consumption 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.

Table 30: Partial Insurance Parameters

| | **Parameters** | **Imputed** (1) | **Food** (2) |
|---|---|---|---|
| **Parents** | | | |
| Permanent Earnings | $\phi_e^p$ | 0.230 | 0.104 |
| | | (0.037) | (0.085) |
| Permanent Other Income | $\phi_n^p$ | 0.069 | 0.033 |
| | | (0.017) | (0.025) |
| Transitory Earnings | $\psi_e^p$ | 0.147 | 0.057 |
| | | (0.034) | (0.094) |
| Transitory Other Income | $\psi_n^p$ | 0.033 | -0.047 |
| | | (0.042) | (0.066) |
| **Children** | | | |
| Permanent Earnings | $\phi_e^k$ | 0.237 | 0.034 |
| | | (0.053) | (0.102) |
| Permanent Other Income | $\phi_n^k$ | 0.127 | 0.076 |
| | | (0.021) | (0.022) |
| Transitory Earnings | $\psi_e^k$ | 0.201 | 0.023 |
| | | (0.036) | (0.067) |
| Transitory Other Income | $\psi_n^k$ | 0.046 | -0.042 |
| | | (0.025) | (0.065) |
| *No. of Parent-Child Pairs* | *N* | 760 | 760 |

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

[34] 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 30 shows that we estimate higher value of consumption insurance when using food expenditures rather than imputed consumption data.

Table 31: Variances of Shocks

| | Parameters | Imputed (1) | Food (2) |
|---|---|---|---|
| **Parental Shocks** | | | |
| Transitory Earnings | $\sigma^2_{u^p}$ | 0.048 | 0.048 |
| | | (0.005) | (0.004) |
| Transitory Other Income | $\sigma^2_{\zeta^p}$ | 0.068 | 0.068 |
| | | (0.015) | (0.016) |
| Permanent Earnings | $\sigma^2_{\upsilon^p}$ | 0.033 | 0.033 |
| | | (0.004) | (0.004) |
| Permanent Other Income | $\sigma^2_{\nu^p}$ | 0.108 | 0.107 |
| | | (0.012) | (0.013) |
| Consumption Growth | $\sigma^2_{\xi^p}$ | 0.017 | 0.070 |
| | | (0.001) | (0.004) |
| **Child Shocks** | | | |
| Transitory Earnings | $\sigma^2_{u^k}$ | 0.048 | 0.049 |
| | | (0.005) | (0.006) |
| Transitory Other Income | $\sigma^2_{\zeta^k}$ | 0.087 | 0.087 |
| | | (0.013) | (0.013) |
| Permanent Earnings | $\sigma^2_{\varepsilon^k}$ | 0.024 | 0.023 |
| | | (0.004) | (0.005) |
| Permanent Other Income | $\sigma^2_{\theta^k}$ | 0.095 | 0.095 |
| | | (0.014) | (0.015) |
| Consumption Growth | $\sigma^2_{\chi^k}$ | 0.016 | 0.088 |
| | | (0.001) | (0.006) |
| *No. of Parent-Child Pairs* | $N$ | 760 | 760 |

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

Table 32: Growth Model Moments

| Moments | Imputed (1) | Food (2) |
|---|---|---|
| $Var\left(\Delta_2 e^p_{f,t}\right)$ | 0.161 | 0.161 |
| | (0.009) | (0.007) |
| $Var\left(\Delta_2 n^p_{f,t}\right)$ | 0.351 | 0.351 |
| | (0.036) | (0.036) |
| $Var\left(\Delta_2 c^p_{f,t}\right)$ | 0.041 | 0.142 |
| | (0.002) | (0.007) |
| $Var\left(\Delta_2 e^k_{f,t}\right)$ | 0.148 | 0.148 |
| | ( 0.01) | (0.009) |
| $Var\left(\Delta_2 n^k_{f,t}\right)$ | 0.366 | 0.366 |
| | (0.033) | (0.034) |
| $Var\left(\Delta_2 c^k_{f,t}\right)$ | 0.042 | 0.177 |
| | (0.001) | (0.011) |
| $\text{Cov}\left(\Delta_2 e^p_{f,t}\Delta_2 e^k_{f,t}\right)$ | 0.017 | 0.017 |
| | (0.011) | (0.012) |
| $\text{Cov}\left(\Delta_2 n^p_{f,t}\Delta_2 n^k_{f,t}\right)$ | 0.020 | 0.020 |
| | (0.014) | (0.013) |
| $\text{Cov}\left(\Delta_2 c^p_{f,t}\Delta_2 c^k_{f,t}\right)$ | 0.001 | 0.007 |
| | (0.002) | (0.008) |
| $\text{Cov}\left(\Delta_2 e^p_{f,t}\Delta_2 e^p_{f,t+2}\right)$ | -0.048 | -0.048 |
| | (0.005) | (0.004) |
| $\text{Cov}\left(\Delta_2 n^p_{f,t}\Delta_2 n^p_{f,t+2}\right)$ | -0.068 | -0.068 |
| | (0.015) | (0.016) |
| $\text{Cov}\left(\Delta_2 e^k_{f,t}\Delta_2 e^k_{f,t+2}\right)$ | -0.049 | -0.049 |
| | (0.005) | (0.006) |
| $\text{Cov}\left(\Delta_2 n^k_{f,t}\Delta_2 n^k_{f,t+2}\right)$ | -0.087 | -0.087 |
| | (0.013) | (0.013) |
| $\text{Cov}\left(\Delta_2 e^p_{f,t}\Delta_2 c^p_{f,t}\right)$ | 0.023 | 0.011 |
| | (0.002) | (0.003) |
| $\text{Cov}\left(\Delta_2 e^p_{f,t+2}\Delta_2 c^p_{f,t}\right)$ | -0.006 | -0.002 |
| | (0.002) | (0.004) |
| $\text{Cov}\left(\Delta_2 n^p_{f,t}\Delta_2 c^p_{f,t}\right)$ | 0.017 | 0.004 |
| | (0.003) | (0.003) |
| $\text{Cov}\left(\Delta_2 n^p_{f,t+2}\Delta_2 c^p_{f,t}\right)$ | -0.002 | 0.003 |
| | (0.002) | (0.005) |
| $\text{Cov}\left(\Delta_2 e^k_{f,t}\Delta_2 c^k_{f,t}\right)$ | 0.023 | 0.004 |
| | (0.002) | (0.003) |
| $\text{Cov}\left(\Delta_2 e^k_{f,t+2}\Delta_2 c^k_{f,t}\right)$ | -0.008 | 0.000 |
| | (0.002) | (0.003) |
| $\text{Cov}\left(\Delta_2 n^k_{f,t}\Delta_2 c^k_{f,t}\right)$ | 0.028 | 0.010 |
| | (0.003) | (0.004) |
| $\text{Cov}\left(\Delta_2 n^k_{f,t+2}\Delta_2 c^k_{f,t}\right)$ | -0.004 | 0.003 |
| | (0.002) | (0.005) |
| $\text{Cov}\left(\Delta_2 e^p_{f,t}\Delta_2 c^k_{f,t}\right)$ | -0.001 | -0.003 |
| | (0.004) | (0.009) |
| $\text{Cov}\left(\Delta_2 n^p_{f,t}\Delta_2 c^k_{f,t}\right)$ | 0.005 | 0.006 |
| | (0.003) | (0.006) |
| $\text{Cov}\left(\Delta_2 c^p_{f,t}\Delta_2 e^k_{f,t}\right)$ | 0.001 | -0.003 |
| | (0.003) | (0.006) |
| $\text{Cov}\left(\Delta_2 c^p_{f,t}\Delta_2 n^k_{f,t}\right)$ | -0.003 | -0.002 |
| | (0.008) | (0.011) |

**Note:** These empirical moments are used to generate the parameter estimates in Tables 29, 30 and 31 through GMM. Bootstrap standard errors are reported in parentheses.