

The Importance of Inter Vivos Transfers: Insuring and Investing in Children

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Abstract

We argue that inter vivos transfers from parents to children are much more important than previously thought for the cross-sectional dispersion of income and wealth as well as the inter-generational persistence of those quantities. We document two common features of transfers, front-loading and insurance, that account for their power. We also show how the size and type of transfers made to children vary across the wealth distribution and develop micro-level estimates of the effects of different types of transfers on children's choices. We establish the importance of these features for macroeconomic outcomes by embedding them in a quantitative overlapping generations (OLG) model with incomplete markets, education choice, and human capital accumulation.

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1 Introduction

It's a popular and well-documented fact that parents play a large role in shaping their children's economic outcomes. We observe a great deal of similarity between parents and children in their decisions regarding consumption, saving, education, labor-supply, portfolio composition, and other economically-relevant variables,¹ a similarity that exists in spite of the massive cross-sectional dispersion apparent in such quantities. It is so suggestive of parental influence, which was already an intuitive and salient factor in the minds of both researchers and the general public, that a very large and very old literature formed to understand the ways in which parents affect their children's economic lives.

Among the many channels that have been studied, transfers receive less attention as a source of persistence in outcomes and, within that category, inter vivos transfers (IVTs) receive even less. There are reasonable explanations for why they have been somewhat neglected. For one, compared to bequests, they are smaller in magnitude. Average annual bequest payments stand at \$476bn while parents disbursed \$160bn in inter vivos transfers, excluding educational transfers.² For another, there is a substantial body of work³ establishing the considerable power of early-childhood investments and parenting decisions to determine children's long-run outcomes, leading to a reduced focus on parental investments in adult children.

While bequests and the circumstances of one's upbringing are rightfully at the center of discussions on the variation in and persistence of consumption, income, and wealth, we wish to argue that inter vivos transfers in adulthood belong there as well.

Though smaller than bequests, they are still quite sizable in the aggregate: if they were to become a separate budget function, inter vivos transfers would represent one of the ten largest paid for by the US Federal Government.⁴ Moreover, empirical work by [Fagereng et al. \(2021\)](#) using quasi-random variation in assignment of adoptees in Norway already documents a significant role for inter vivos transfers in the persistence of wealth levels across generations.

¹Foremost is [Charles and Hurst \(2003\)](#). A selection of other papers documenting inter-generational persistence: [Couch and Dunn \(1997\)](#), [Belzil and Hansen \(2003\)](#), [Restuccia and Urrutia \(2004\)](#), [Waldfkirch et al. \(2004\)](#), [Charles et al. \(2014\)](#), [Cronqvist and Siegel \(2015\)](#), [Boserup et al. \(2016\)](#), [Fagereng et al. \(2020\)](#), [Coda Moscarola et al. \(2025\)](#).

²According to our calculations using Health and Retirement Survey data from 1996 to 2019, in which we observe the transfers made by parents over the age of 50. These numbers are somewhat larger than those documented in [Feiveson and Sabelhaus \(2018\)](#) using Survey of Consumer Finances (SCF) data.

³Surveyed in [Heckman and Mosso \(2014\)](#) and [Doepke et al. \(2019\)](#).

⁴It would rank eighth, slightly higher than transportation, which stands at \$145bn in spending per year ([PGPF 2026](#)) and, among the income security programs, it would be significantly larger than unemployment insurance (UI) and slightly larger than Food and Nutrition Services ([CBO 2024](#)).

We build on this body of work first by documenting features of inter vivos transfers across the wealth distribution. We argue that they have several characteristics that generate large indirect effects, which help them punch above their already substantial weight. We document that they are *front-loaded*, occurring at the beginning of children’s careers and *provide insurance*, paying out primarily in response to unexpected increases in expenses or decreases in incomes. Second, we provide micro-level estimates of the effects of transfers on children’s decisions. Third, we embed these channels in a structural overlapping generations (OLG) model to understand their impact on aggregate variables and inter-generational dynamics.

Front-loading of transfers. Front-loading transfers increases their value to the children who receive them. The simplest reason is that, in present-value terms, a transfer received earlier is worth more than a transfer of the same nominal value received later. Beyond that, transfers that occur earlier also occur in periods where their marginal value is highest, which magnifies their impact on saving and investment decisions. Both have effects that are felt for years in the future, so earlier investments have benefits that accrue over longer periods of time, which is another feature that accounts for the power of front-loading.

We assess the degree of front-loading by computing the paths of cumulative transfers received by children over their adulthood. Certainly, educational transfers come sooner than any others, but we show that, even excluding educational transfers, a majority of the transfers children receive come before their parents reach retirement age. Moreover, the vast majority of all transfers are given within the first ten years of children’s adult lives, when their effects on children are the largest.

We also illustrate how earlier receipts of inter vivos transfers magnify their importance relative to bequests by computing present values of transfers and bequests for different wealth groups, from the perspective of an eighteen year-old. In all cases with a discount rate of 2%, inter vivos transfers are comparable in value to bequests and represent the majority of transfer wealth⁵ for children of parents in the bottom 75% of the wealth distribution. When increasing the discount rate to 5%, as the literature argues that rates of return are higher for the wealthy,⁶ inter vivos transfers represent the majority of transfer wealth for all wealth groups. Further increases in the discount rate only make the comparison more extreme, with early transfers and early income accounting for even larger shares of

⁵Transfer wealth being the sum of present values of bequests and inter vivos transfers.

⁶See [Fagereng et al. \(2020\)](#) for evidence from Norway and [Bach et al. \(2020\)](#) for evidence from Sweden. [Kuhn et al. \(2020\)](#) also demonstrate the importance of high returns obtained wealthy individuals for explaining trends in wealth inequality in the US. See also [Saez and Zucman \(2016\)](#), [Smith et al. \(2023\)](#), [Bricker et al. \(2025\)](#), and [Bhandari et al. \(2026\)](#).

total wealth.

Insurance via transfers. The insurance function of inter-generational transfers also provides a boost to the effectiveness of inter vivos transfers. From the child's perspective, these transfers are valued more highly than their nominal amount would suggest because they receive them in states of the world where their marginal value of wealth is high. Then, because they're concentrated in states where children are constrained or very-nearly constrained, insurance transfers induce greater behavioral modifications than transfers in higher income states.

Yet, even if parents never actually make any insurance transfers, the whole risk/return calculus of children's human capital investment is changed by virtue of the fact that they would have been paid out if needed. Eliminating some negative states makes the same risky investment more attractive for children *ex ante*. Additionally, because parents' insurance substitutes for children's self-insurance, it also changes the balance between saving and investing. Partially freed up from the need to accumulate buffer stock savings early in their careers, children can target steeper income paths, ones that start with lower incomes but are ultimately more lucrative.

To study the degree of insurance provided by parents to children via transfers, we look at the transfers given in response to adverse changes in children's incomes and expenditures. In particular, we want to know when the changes are large enough to trigger payments and how much of the adverse change is absorbed by the corresponding transfers. We also want to know how to value these transfers from the perspective of the child.

We find that the changes in net income required to prompt a transfer are fairly large, at least on the order of going from full-time to part-time work, though small enough that they're not uncommonly observed in the data. Though, on the other hand, the states in which parents step in to help children vary across the wealth distribution, with wealthier parents providing assistance sooner than poorer parents, consistent with the fact that they have the resources with which to do so.

Then, when transfers are ultimately made in response to these events, we find that the replacement rate is significant. For parents in the top quartile of the wealth distribution, the average insurance transfers made to children ages 18-30 after these events ranged from \$2,265 to \$4,652. Of course, these estimates obscure a large degree of heterogeneity in parents' generosity within wealth groups. Among parents responsive to children's income changes, the number is even larger.⁷

⁷Compared to the estimates in [Andersen et al. \(2020\)](#), which are based on highly detailed transaction-level data from Denmark, ours are much larger. However, given that Denmark's social safety net is much

The next part of our analysis is aimed at understanding the effects of parental insurance on the decisions made by children. In particular, we focus on how the amount of risk children take on is impacted by the provision of parental insurance, which takes the form of saving on behalf of children, named *dynastic precautionary saving* in Boar (2021).

Because dynastic precautionary saving responds to children's risk levels even as it affects them, we instrument for it using parents' wealth levels before their children reach adulthood. Following this approach, we find that parental insurance leads to higher levels of equity ownership, business ownership, and permanent income risk. That is, parents' decisions to insure their children incentivize their children to take on a larger degree of productive risk. Consistent also with the hypothesis of parental insurance partially substituting for children's self-insurance, we find that children's saving rates are decreasing in the amount of savings held by their parents.

Propagation of transfer heterogeneity. The amplification of the effects of transfer payments that comes from front-loading and insurance also, therefore, amplifies heterogeneity in parents' transfer policies. This is especially striking because we already observe considerable differences in transfers both within and across wealth groups, differences that would be non-negligible even without amplification.

While parents generally prefer, regardless of their own individual characteristics, to make transfers in their children's early adulthood, the amount of transfers they make increase strongly with parents financial resources. We also find that, while the overall mix of transfers is very similar across wealth groups, insurance transfers account for a larger share of transfers made by parents in the highest wealth group.

Our approach to understanding the importance of these channels for cross-sectional variation and inter-generational persistence of income, wealth, and consumption is structural. We start by specifying a life-cycle model with human capital accumulation, endogenous college attendance decisions, incomplete markets, and idiosyncratic income risk. We add to this a Markov process for the parameters of the human capital accumulation function, including the starting level of human capital, in order to capture the factors of inter-generational persistence that come from investments in children that are made before they enter adulthood, as well as any hereditary factors.

The model's defining feature, which makes it suitable for our purposes, is that we allow for variations in transfer functions for each agent in the model: cross-sectional differences in the size and type of transfers each person can expect to give and receive over their

more generous than its US equivalent, it makes sense that informal insurance would play a larger role in the US.

life spans. We allow for the distribution of transfer functions to depend on the parameters of a child's human capital process, so that the model, if it is necessary to fit the data, can generate a degree of persistence in transfers across generations. We also allow the distributions of transfers received to depend on the children's college attendance to capture the possibility that parents may try to incentivize their children to attend college by committing to more generous transfer functions, given attendance.

We choose the parameters of the Markov processes in order to match the average income and transfers received by the children of each wealth bucket over their lives. We also fit the share of total transfers accounted for by each type. Then having a model that can match the relevant conditional moments, we're able to assess the importance of transfers in explaining the persistence of wealth and income ranks.

In effect, we can decompose the persistence and variability into portions determined by other factors, like early-life investments, and portions determined by transfers. We may also change the distribution of transfers over time, ask how reductions in front-loading or reductions in insurance would change the effectiveness of transfers for shaping children's behavior. More concretely, we can understand how policies that incentivize a particular distribution of transfers over children's lifetimes, such as stepped-up basis, also shape children's outcomes.

The results of our exercises suggest that transfers are highly consequential and that, indeed, the timing of transfers is essential for their power. We find that income levels would be uniformly lower without inter vivos transfers by around \$20,000 in present-value terms without general equilibrium price responses and \$15,000 with them. Moreover, eliminating transfers would increase wealth mobility among for all but the bottom quartile, for whom self-financing of human capital accumulation is more difficult. Consistent with this, we also find that further front-loading would increase persistence, but primarily at the top of the wealth distribution.

Related literature. Our paper fits broadly into two strands of literature. The first strand studies risk-sharing within the family and is primarily empirical in nature, which is also true of our approach. The empirical component of our paper corresponding to documenting facts about transfers builds on the work of McGarry (2016) and Andersen et al. (2020), who document that parents give transfers in response to adverse life events, including job losses, unexpected expenditures, and changes in family composition. We complement them by measuring how transfer size and composition vary across the wealth distribution.

Our analysis of the effects of parental insurance on children's decisions is also heavily indebted to Boar (2021), which demonstrates that parents save to insure their children

against permanent income risk. We expand on this work by considering the other side, children's responses rather than parents, in more detail. Our methods for doing so also attempt to capture the possibility that the transfers and insurance provided by parents may be jointly determined with children's choices.

The second strand studies the factors that contribute to the inter-generational persistence of income and wealth as well as the inequalities observed in them. This literature is primarily structural, using calibrated life-cycle models to account for the facts. This includes the foundational work of [Huggett et al. \(2011\)](#), which identifies initial variation in human capital as the crucial factor in explaining the dispersion of life outcomes. It also includes more recent papers, such as [Abbott et al. \(2019\)](#), [Lee and Seshadri \(2019\)](#), [Boar and Lashkari \(2021\)](#), [Gallipoli et al. \(2026\)](#), and [Alon et al. \(2026\)](#), which attempt, via comprehensive structural models, to obtain a deeper understanding of the sources of persistence and inequality, as well as the relationship between the two. Our paper is part of the same family, though it is unique for its detailed modeling of inter vivos transfers over the life cycle.

There are also a number of papers that study this issue using empirical methods which are complementary to the structural approach that we and others take. [Charles and Hurst \(2003\)](#) document the high degree of persistence in wealth levels, decomposing the persistence into a component explained by the persistence of permanent income and a component explained by the persistence of portfolio choices. [Fagereng et al. \(2021\)](#), mentioned earlier, use highly detailed Norwegian administrative data to study wealth persistence and its mediators. Focusing instead on permanent income, [Lefgren et al. \(2012\)](#) perform a decomposition of inter-generational persistence with restrictions based on [Becker and Tomes \(1979\)](#).

Layout. The paper is structured as follows. Section [2](#) establishes the aggregate facts regarding inter vivos transfers. Section [3](#) provides the micro-level evidence of the relationship between the amount of insurance provided by parents and the amount of risk taken on by children. Section [4](#) outlines the structural model we'll use to understand the macro-level effects of inter vivos transfers. Section [5](#) details the calibration procedure, the moments we aim to match, and the results of our counterfactuals. Section [6](#) concludes.

2 Facts about inter vivos transfers

In this section we describe the household survey data used throughout the paper and document several facts about inter vivos transfers from parent to child: (i) aggregate inter vivos transfers are economically large; (ii) transfers have a fat right tail and are disproportionately given by wealthy parents; (iii) the probability and size of transfers increase with job losses and other life events of the recipient, especially for wealthy parents; and (iv) transfers come disproportionately early in the recipients' life, and the type of transfers vary across the lifecycle.

2.1 Survey data

Health and Retirement Study. Our primary data on inter vivos transfers come from the Health and Retirement Study (HRS), a biennial panel survey detailing the health, wealth, income, and demographic characteristics of a representative sample of the U.S. population aged 50 and older. The original cohort, first surveyed in 1992, comprised individuals born between 1931 and 1941. Starting in 1998, the HRS began regularly adding new cohorts to preserve the survey's cross-sectional representativeness alongside its longitudinal structure. To avoid structural breaks associated with early changes in the survey design, our empirical analysis restricts the sample to the 1998–2022 waves.

In addition to detailed respondent-level data, the HRS collects broad demographic, employment, and income information about respondents' children, including those no longer living in the household. Crucially for our analysis, respondents report whether they made monetary transfers totaling at least \$500 to each child since the previous interview, as well as the precise transfer amounts. We supplement this main sample with data from the 1992 and 1994 waves, which specifically query respondents on the total educational expenses incurred for each child. Finally, when a respondent passes away, the HRS conducts an exit interview with a proxy informant who knew the deceased well (typically a spouse, child, or other close family member). These exit surveys contain detailed questions regarding the allocation and exact values of any bequests, both monetary and real estate, and serve as our primary source for bequest data.

Panel Study of Income Dynamics. For supplementary data on transfers, income, and wealth we use the Panel Study of Income Dynamics (PSID). The PSID provides longitudinal information on a representative sample of U.S. households starting in 1968. The PSID began with an annual survey design, but starting in 1997 changed to conducting surveys

every two years. Each survey provides granular income, wealth, demographic, and consumption information. A key feature of the survey design, is that When children move out of an original sample PSID household they break off as their own sample unit and are thereafter surveyed in subsequent years. This structure allows one to form parent-child linkages, while obtaining detailed information on both. Moreover, the PSID asks recipients (donors) about the amount of transfers they receive (send) each survey. However the information is less detailed than that of the HRS; in particular, respondents are only asked about the total amount of transfers they receive or send from all family members. Nonetheless, as the PSID provides more detailed information about the recipient it serves as a useful supplement to our main empirical analysis in the paper. Due to changes in the survey design, a limited number of parent-child linkages in earlier years, and a desire to remain consistent with the HRS sample we focus on the 1999 to 2021 surveys.

2.2 Quantifying inter vivos transfers

We start by measuring aggregate yearly inter vivos transfers in the HRS. Due to the survey structure, we focus in particular on transfers from parent to child where the parent is at least 50 years old. We also exclude transfers in the form of tuition payments, which are explored further later in this section. Due to these caveats, along with potential under reporting bias, we interpret our estimates as a lower bound for the magnitude of inter vivos transfers.

Transfer Type	Avg. Annual Transfer	Source
Inter vivos (50 and older)	\$161B	HRS
Bequest (50 and older)	\$476B	HRS
Federal UI	\$78B	BEA
Federal Welfare	\$240B	BEA
<i>All</i>	<i>\$955B</i>	

Table 1: Annual Transfers, 1996-2019

Notes: This table reports the average annual transfers between 1996-2019. inter vivos transfers and bequests are calculated using the HRS, while Federal UI and welfare transfers come from the BEA. Direct educational payments are excluded from inter vivos transfers.

Table 1 reports the average yearly inter vivos transfers from 1996-2019⁸ along with other commonly studied forms of transfers: bequests, federal UI payments, and federal

⁸We exclude 2020 and 2021 data to avoid including extreme values associated with the Covid-19 period.

welfare payments. For representativeness, inter vivos transfers and bequests are calculated using survey weighted sums.⁹ Federal UI and welfare data come from the Bureau of Economic Analysis (BEA). The table indicates that inter vivos transfers are smaller than bequests and federal welfare in aggregate, averaging roughly 1/3 and 2/3 the magnitude of each respective transfer type. On the other hand, they are more than double the size of federal unemployment insurance payments. Overall, total inter vivos transfers are economically large, and on a similar order of magnitude to other commonly studied forms of transfers.

Lifetime transfers. An object of interest is the lifetime transfers received (sent) by each recipient (donor). However, due to the limited sample length this object is not directly observable. For instance, a donor that is 50 years old in the 1998 wave and participates in every survey only reports transfers up to the age of 75. With this limitation in mind we calculate total per child inter vivos transfers between 1996 and 2021 at the donor level. Since we are interested in distributional features of these transfers, and thus ideally compare donors at similar ages, we restrict the sample to those that are between the ages of 50 and 55 in their first survey. Furthermore, we only consider households that participate in at least five surveys.¹⁰ Figure 1 plots the distribution of total per child inter vivos transfers between 1996 and 2021. There is a large degree of heterogeneity. Approximately 30% of parents transferred nothing to their children, while 22% transferred at least \$50,000 per child. Furthermore, over 2% of parents sent an astonishing \$200,000+ per child. To capture the degree of upper tail inequality we estimate the Pareto coefficient of the top 10% using the Hill estimator:

$$\hat{\alpha}_{TR} = \left(\frac{1}{n} \sum_{i=1}^n \log \left(\frac{TR_i}{TR_{\min}} \right) \right)^{-1}, \quad (1)$$

where $i \in [1, n]$ are the set of donors with cumulative transfers in the 90th percentile, and $TR_{\min}$ is the lowest transfer amount of this set. The resulting Pareto coefficient is $\hat{\alpha}_{TR} = 2$, indicating that cumulative inter vivos transfers display a similar degree of concentration as labor income (Gallipoli et al., 2026) and slightly less concentration than bequests, which we estimate to be $\hat{\alpha}_{BEQ} = 1.46$.

While not possible at the donor level, average lifetime transfers can be estimated by

⁹To adjust for missing bequest information, we rescale the survey weights to match the U.S. death distribution.

¹⁰In the case that a household misses one or more survey we re-normalize their cumulative transfers based on the number of missed observations.

Moment	Value
Mean	\$33,836
<i>Percentiles</i>	
14.3%	\$0
25%	\$2,951
Median	\$17,639
75%	\$44,092
<i>Share of all transfers</i>	
Top 10%	43.0%
Top 5%	26.5%

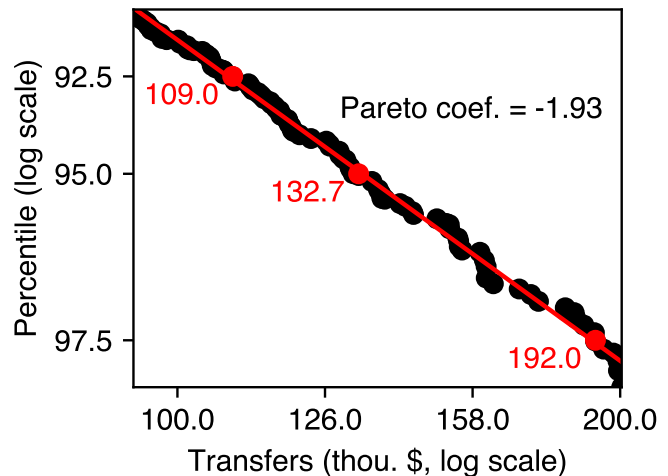


Figure 1: Distribution of cumulative transfers

Notes: This figure plots the donor-level distribution of total per child inter vivos transfers from 1996-2021.

combining the HRS data with mortality statistics. Using the pooled HRS panel from 1996-2021 we calculate the average transfer amount received by children at each age. We then normalize each average using the cumulative mortality rate of the parents for a given cohort using the life tables provided by the U.S. Social Security Administration (SSA) to account for survivor bias in the sample. Overall, this exercise yields estimates of the expected per child transfer amount at each age conditional on the donor being at least 50 years of age.¹¹ Finally, we estimate direct educational transfers that took place before the survey years using the 1992-1994 supplementary data.

Given the evidence provided in figure 1 that lifetime transfers are highly unequal, we repeat the analysis above separately for different parental wealth groups. We choose to focus on a measure of lifetime wealth, rather than contemporaneous wealth, to limit the causal effect of transfers on wealth. Our baseline measure of lifetime wealth is total wealth when the household head is age 65.¹² Finally, we split donors into four wealth groups based on wealth percentile: 0-25th, 25th-75th, 75th-95th, and >95th, representing the poor, middle, upper, and wealthy classes, respectively. Wealth groups are formed within birth cohorts, particularly those born in 1918-1927 (the Greatest Generation), 1928-1945 (the Silent Generation), and 1946-1965 (Baby Boomers).

We further decompose transfers into four broad categories. First, human capital trans-

¹¹We do not account for potential differences in mortality rates between donors with different characteristics. Since wealthier individuals have higher life expectancy, this likely downward biases our results, particularly for top wealth groups.

¹²In cases where the head is not observed at age 65, we choose wealth at the closest age in the range of 55-75, dropping any households not observed in this window.

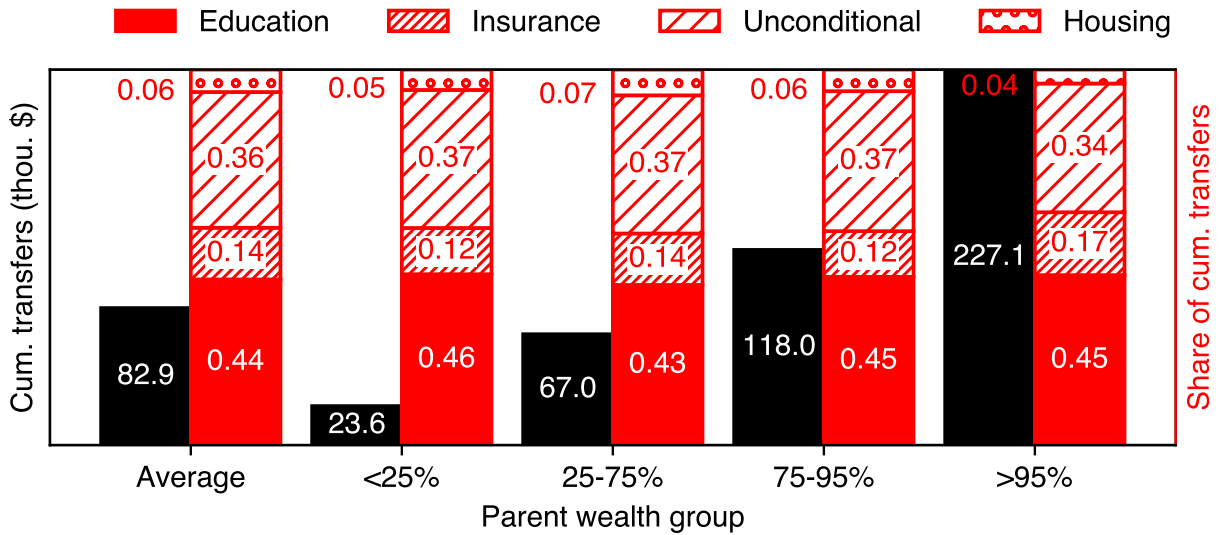


Figure 2: Average cumulative lifetime transfers share of total by type, by parent wealth group

Notes: This figure plots the estimated average lifetime transfers a child receives from their parents for the entire sample as well as broken out by lifetime donor wealth group. Shares of cumulative lifetime transfers are broken into fractions that went towards human capital, insurance of life events, home ownership, or miscellaneous (unconditional).

fers include direct education and school expense payments, as well as any monetary transfers made while the recipient is away at school. Second, insurance payments cover transfers tied to life events that reduce income or increase expenses, specifically: employment reductions (moving from full- to part-time, or becoming unemployed), marriage, divorce, or the birth of a child. Third, housing transfers include the value of directly transferred real estate and monetary support given when the child becomes a first-time homeowner.¹³ Fourth, unconditional transfers comprise all remaining payments that do not fit into the previous three categories.

Figure 2 plots the average transfers received by children, both in aggregate, and for each of the four donor wealth groups. Average lifetime transfers are roughly \$83,000, made up of 44% human capital transfers, 14% insurance transfers, 6% home transfers, and 36% unconditional transfers. The amount of transfers increases monotonically with each wealth group: the poor, middle, upper, and rich classes transfer approximately \$24,000, \$67,000, \$118,000, and \$227,000 to each child, respectively, illustrating that wealthier parents transfer more to their children. The composition of transfers also varies by group. For instance, the insurance category make up 17% of rich class' transfers but

¹³Because we cannot detect when a child moves between owned homes, we exclude transfers occurring during subsequent moves.

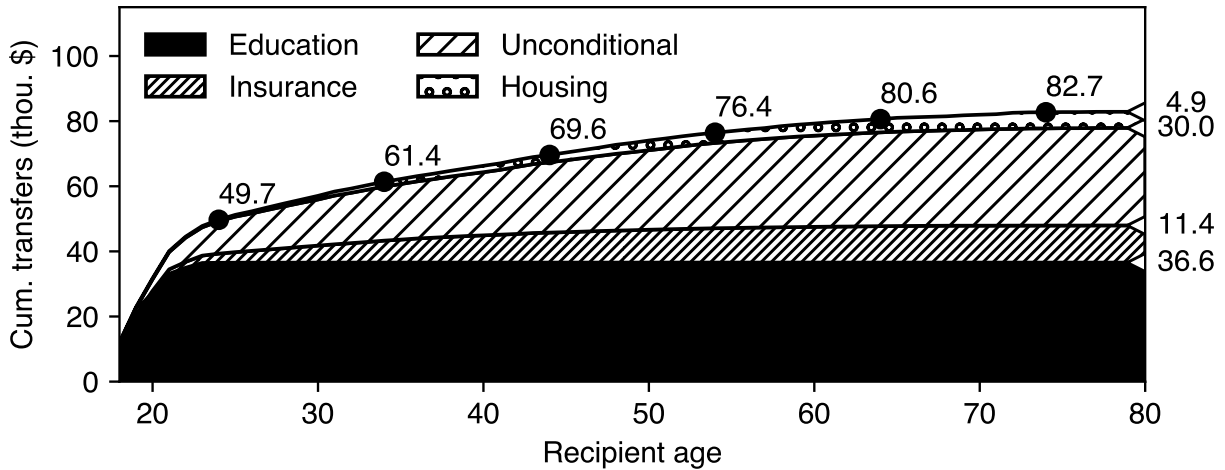


Figure 3: Average cumulative life cycle transfers by type

Notes: This figure plots the cumulative average lifetime transfers by recipient (child) age. Transfers are grouped by those that went towards human capital, insurance of life events, home ownership, or miscellaneous (unconditional).

only 12% of the poor class.¹⁴ On the other hand, the rich class maintains the lowest proportion of transfers for home ownership of 4%. Interestingly, human capital transfers consistently make up between 43-46% of each wealth groups' lifetime transfers, suggesting that education is the dominant type of transfer for parents across the wealth distribution.

2.3 The timing of inter vivos transfers

We now turn our focus to the dynamics of inter vivos transfers. We broadly ask three questions: (i) how do the magnitudes and types of inter vivos transfers evolve over a recipients lifetime; (ii) to what extent do inter vivos transfers condition on recipient outcomes; and (iii) do these dynamics vary by donor wealth group.

Figure 3 plots the cumulative average transfers a child received from age 18 to 80. Strikingly, inter vivos transfers disproportionately come at the beginning of life: 69% of transfers come by the age of 30. Unsurprisingly, these front loaded transfers are dominated by human capital transfers, which tend to take place between the ages of 18 and 25. Conversely, just 11% of total transfers take place after age 50. While mortality rates explain some of this decline, other factors—such as greater financial stability in middle age—likely play a role.

¹⁴It is worth noting that children of the rich experience far fewer insurance events, suggesting that these differences understate the difference in the degree of insurance present. We discuss this issue further in Section 2.3.

Given the skewed timing of the transfers an exercise of interest is to measure the present value of the transfers. Intuitively, earlier transfers are more valued due to household impatience and their potential for real financial returns overtime. We specifically estimate the present value of the expected future lifetime transfers when the recipient is age 18 years old as:

$$PV_{TR}^{AVG} = \sum_{a=18}^{80} \frac{E[TR_a]}{(1+r)^{a-18}},$$

where r is the real interest rate and TR_a is the transfer amount at age a . Table 2 reports the present values of expected inter vivos transfers and bequests for interest rates of 2%, 5%, and 7%. The first four rows report values for each of the wealth groups, while the last row reports values for the entire population. While lifetime aggregate bequests¹⁵ are more than twice the size of aggregate inter vivos transfers, the aggregate present values tell a different story. At the lowest reported interest rate, the present value of bequests is only 24% higher than that of inter vivos transfers. Moreover, at the higher interest rates of 5% and 7%, the present value of inter vivos transfers is *larger* than the present value of bequests. Intuitively, because inter vivos transfers are more frontloaded than bequests, they are subject to a smaller discounting penalty at higher interest rates. The magnitude of inter vivos transfers relative to bequests also varies by wealth group. In particular, for the poor and middle classes, inter vivos transfers have a higher present value even at the lowest reported interest rate. Conversely, for the top 5%, the present value of bequests is approximately twice as large as the present value of inter vivos transfers at the same interest rate. This heterogeneity in relative present values is driven by the even heavier concentration of bequests at the top of the wealth distribution.¹⁶ Nonetheless, for all wealth groups, inter vivos transfers maintain higher present values at interest rates of 5% and 7%. Overall, these results indicate that the economic importance of inter vivos transfers is consistently greater than raw nominal aggregates suggest.

The insurance channel. Beyond the mechanical value derived from their earlier timing, inter vivos transfers may provide additional utility because they can be strategically adjusted to align with the recipient's marginal needs. Figure 2 indicates that a small portion of transfers occurs during life events that likely lower the recipient's disposable income. However, this type of descriptive analysis does not identify whether transfers systematically increase during these periods. Moreover, because these life events are somewhat rare, the unconditional averages of their associated transfers may understate the role of

¹⁵Lifecycle bequests are reported in appendix figure A.1

¹⁶Appendix figure A.2 plots average lifecycle bequests by wealth group.

Bucket	r = 2%		r = 5%		r = 7%	
	PV ^{AVG} _{IVT}	PV ^{AVG} _{BEQ}	PV ^{AVG} _{IVT}	PV ^{AVG} _{BEQ}	PV ^{AVG} _{IVT}	PV ^{AVG} _{BEQ}
Bottom 25%	\$20,006	\$5,039	\$16,832	\$1,823	\$15,464	\$1,014
25 - 75%	\$56,238	\$38,447	\$47,226	\$14,490	\$43,508	\$8,355
75 - 95%	\$97,892	\$139,483	\$81,316	\$53,992	\$74,517	\$31,591
Top 5%	\$187,822	\$373,458	\$153,226	\$149,634	\$138,585	\$89,651
<i>All</i>	<i>\$68,919</i>	<i>\$85,715</i>	<i>\$57,242</i>	<i>\$32,017</i>	<i>\$52,420</i>	<i>\$18,353</i>

Table 2: Present discounted value of transfers by parent wealth group

Notes: This table reports the estimated present value of expected lifetime inter vivos transfers and bequests when the recipient is 18 years old. Values are reported separately by donor (parent) wealth group, and for different interest rates.

transfers in insuring against changes in disposable income. To provide more causal evidence for this channel, we estimate the equation:

$$TR_{i,t}^{(g)} = \alpha + \beta \text{Event}_{i,t} + \sum_{a \in \{Y, M\}} [\gamma_a \text{Age}_{a,i,t} + \lambda_a (\text{Event}_{i,t} \times \text{Age}_{a,i,t})] + \mathbf{X}'_{i,t} \theta + \delta_t + \epsilon_{i,t}, \quad (2)$$

where $TR_{i,t}^{(g)}$ denotes the transfer amount estimated for all recipients and separately across the four parental wealth groups (indexed by g), $\text{Event}_{i,t}$ represents a life event of the type described in section 2.2. The terms $a \in \{Y, M\}$ are indicator variables equal to 1 when the recipient is young (ages 18-30), and middle-aged (ages 31-54), respectively, $\mathbf{X}_{i,t}$ represents a vector of demographic controls including education, sex, marital status, and race, and δ_t captures year fixed effects. We note that this exercise is in a similar spirit to one conducted by McGarry (2016). The two main differences are that we allow for both heterogeneity by parental wealth and the age of the recipient.

Figure 4 reports the estimates over our sample, specifically for the event of a “job loss.” The first column indicates that a recipient’s job loss is associated with higher total transfers since the last interview, especially when the recipient is young, but also when they are middle-aged. Holding demographic factors and year fixed effects constant, the point estimates indicate that young recipients who lost their jobs between interviews received a predicted \$2,809 per year: a 57% increase (\$1,016 more) relative to the conditional baseline without a job loss. However, the magnitude of baseline transfers and the degree of adjustment vary considerably by donor wealth group. For example, a young recipient with parents in the bottom wealth group receives an expected \$141 in yearly transfers when there is no job loss, a figure that does not significantly change upon job loss. Conversely,

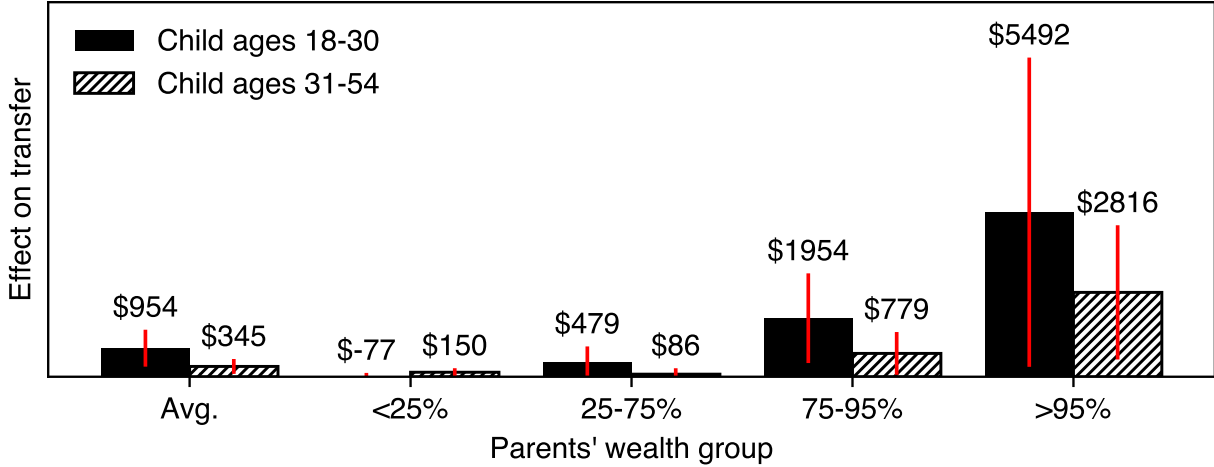


Figure 4: Job loss and transfers by age, by parent wealth group

Notes: This table reports the coefficients and 95% confidence intervals from estimating equation 2. The dependent variable is total transfer amount (2024 USD), and Job Loss is an indicator variable equal to 1 when the recipient changes job status from working to not working between consecutive surveys. The full table of regression coefficients can be found in appendix table B.1.

a young recipient with parents in the top wealth group receives a predicted baseline of \$6,905, which increases by 67% to \$11,557 following a job loss. The two middle wealth groups exhibit baseline magnitudes and job-loss adjustments that fall between these two extremes. Appendix tables B.3 and B.4 show that these patterns generally remain consistent for a larger set of life events in both the HRS and PSID, respectively. We interpret these estimates as lower bounds for the degree of adjustment to life events, since the data require us to average transfers over a two-year period, whereas the actual adjustment may occur over just a few months. Nonetheless, these results indicate that wealthier parents not only provide larger baseline transfers to their children, but they also adjust their transfers by a larger magnitude following a job loss.

3 Evidence for insurance and investment effects

In this section, motivated by the empirical evidence for parental insurance in section 2.3, we analyze how the risk taking behavior of children varies with parental wealth. We hypothesize that children with wealthier parents, and thus a higher level of parental insurance, may be willing to take on more risk (with higher expected returns). Intuitively, and as documented in the large literature on conditional transfer programs (Hubbard et al., 1995; Engen and Gruber, 2001), a cushioning of severe income losses lessens precautionary savings motives. We choose to focus in particular on the asset portfolios of PSID recip-

ients, while providing supplementary evidence on entrepreneurship. Wealth groups are formed in the same fashion as in the main HRS analysis in section 2.2, with the addition of the Gen X (1965-1980), Millennial (1981-1996), and Gen Z (1997-2012) cohorts.¹⁷

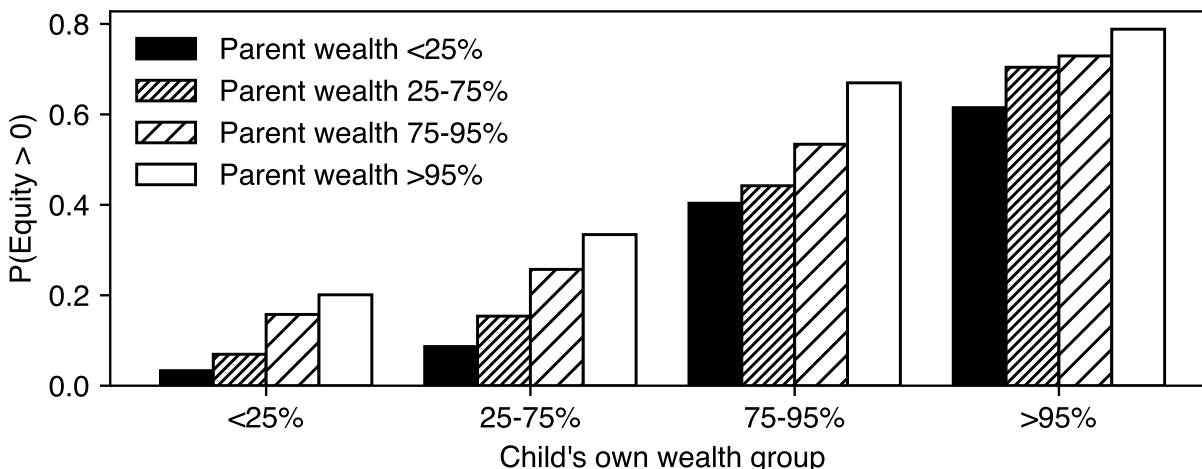


Figure 5: Fraction holding positive equity by parental wealth group, by child's own wealth group

Notes: This figure plots the fraction of recipients that hold positive equity, broken out by their own wealth group as well as their parent wealth group.

Figure 5 plots the fraction of households across the wealth and parental wealth distribution that own *any* equity, where equity is defined as stocks, mutual funds, or business ownership. First, as previously documented, wealthier households are generally more likely to hold equity. For example comparing individuals who have parents with wealth in the 25-75th percentile, the fraction holding positive equity is monotonically increasing with wealth. However, a striking new fact emerges: participation rates in equity markets are increasing in parental wealth *even when holding fixed own wealth*. In fact, across all four wealth groups, the fraction of households that hold equity is monotonically increasing in parental wealth group. For instance, only 2% of households in the bottom wealth group hold equity when their parents are also in the bottom wealth group, while 34% of households in the same wealth group hold equity when their parents are in the top wealth group. Appendix figure B.1 documents that this fact remains broadly true hold on the intensive margin as well.

There are other feasible explanations for this result other than our hypothesized insurance channel. Two salient possibilities are: (i) individuals with wealthier parents have

¹⁷We only consider the parental wealth of the household head. In unreported results we repeat the analysis with only unmarried individuals, and all the main results are largely unchanged.

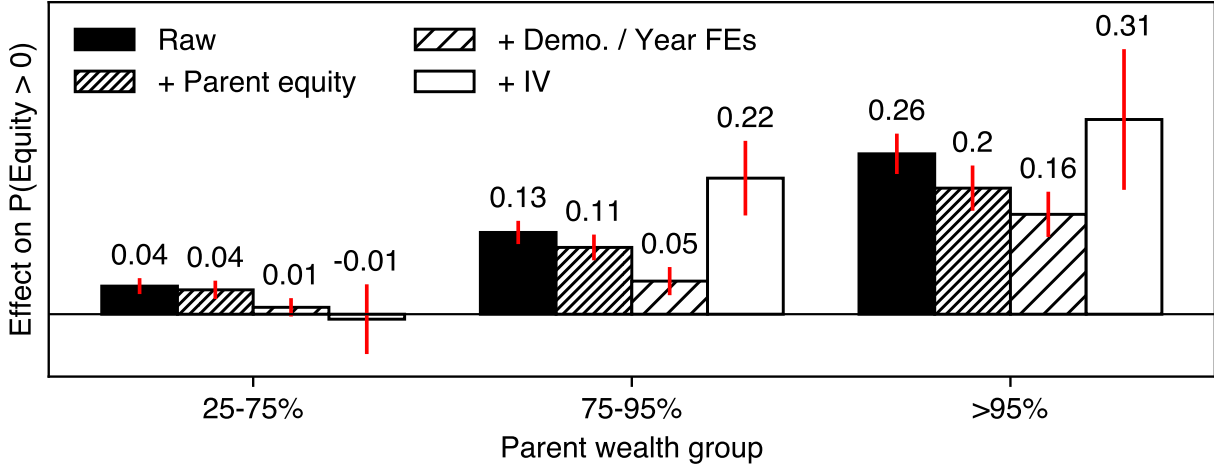


Figure 6: Equity participation and parent wealth

Notes: This figure reports the coefficients and 95% confidence intervals from estimating equation 3. The full table of regression coefficients can be found in appendix table B.2.

higher “financial literacy” (Chiteji and Stafford, 1999) or; (ii) individuals tend to imitate their parents’ investment behaviors. To account for these two interpretations we control for parental investment behavior. In particular, we estimate the equation:

$$\mathbb{I}(\text{Equity}_{i,t} > 0) = \sum_{g=2}^4 \beta_g \mathbb{I}(\text{PWealth}_{i,t} = g) + \gamma \text{ParentEqFrac}_{i,t} + \alpha_{w(i,t)} + \mathbf{X}'_{i,t} \theta + \delta_t + \epsilon_{i,t}, \quad (3)$$

where the dependent variable is an indicator equal to 1 if individual i holds positive equity in year t . The coefficients β_g capture the effect of the parents belonging to wealth group g (relative to the omitted bottom wealth group), and γ measures the marginal effect of the parents’ fraction of assets held in equity. We absorb individual wealth group fixed effects α_w , year fixed effects δ_t , and a vector of demographic fixed effects $\mathbf{X}_{i,t}$. The results are reported in figure 6.

Column 1 controls only for children wealth group, and replicates the findings of figure 5. Column 2 shows that, even after controlling for parent equity, higher parent wealth is associated with a higher probability of investing in equity. We note that the associated increase relative to the bottom parent wealth group is lower in all cases, suggesting that some combination of financial literacy and imitation accounts for the differences in investment behavior, though only a small proportion of it. Finally, column 3 additionally controls for demographic and year fixed effects, and the results broadly hold, albeit with smaller magnitudes. Appendix figure B.2 and table B.5 repeat the analysis from this section, while replacing the positive equity indicator with a business ownership indicator. Overall, these

results paired with the analysis in section 2.3 suggest that parental wealth affects the risk taking behavior of individuals through the insurance channel. In other words, children are more willing to take risks when they have a parental safety net to fall back on. We study this issue in more detail in section 4.

4 Modeling the effects of transfers

The model in which we study the effects of *inter vivos* transfers is very close to the now workhorse model of Huggett et al. (2011) and the richly extended version of it in Alon et al. (2026). Like theirs, it is a discrete-time overlapping generations (OLG) economy with endogenous human capital accumulation, idiosyncratic income risk, incomplete markets, and borrowing constraints. Like Alon et al. (2026), we pursue the added complications of college attendance decisions, but we depart from their approach by abstracting from occupational choice in order to focus on heterogeneity in inter-generational transfers from parents to children.

Each period in the model is a year and life begins when the agent is 18 years old. If the agent immediately begins work, they may receive transfers from their parents for 30 years, until they're 48. If the agent goes to college, which takes four years, they may receive transfers for the 26 years after graduating. Then, for the next 30 years, the agent may give transfers to their own children. Life ends after 60 years, when the agent is 78 years old. All of the agents in the model may work for, at most, 47 years of their life, until they retire at age 65. Following their working lives, they are retired for the remaining 13 years, during which they receive social security payments.

4.1 The college decision

Before they begin working, however, agents must decide whether they will attend college, or not. If they decide not to attend, they proceed immediately to their working life with their endowed attributes and work until retirement.

The cost of college. Each year of college costs, in total, P dollars, which includes all the expenses involved in schooling. For simplicity, we assume no interest accrues while in school,¹⁸ so the total principal outstanding at the time of graduation is PT_c . We also assume that this loan is paid in constant installments over a fixed term T_{sl} and that the

¹⁸This is the case with federal subsidized loans, but other types of loans accrue interest during schooling. If one desires to add it, it could be folded into the cost P or added directly in the formula for the principal.

remaining balance accumulates interest at the rate R_{sl} . Then, the yearly payments are equal to

$$p_{sl} = \left(1 - \frac{1}{R_{sl}}\right) \left(1 + \frac{1}{R_{sl}^{T_c} - 1}\right) P T_c. \quad (4)$$

Life at college. A fraction θ of the cost of college P represents the costs that are associated with agents' consumption while away at school, such as the cost of room and board as well as various amenities offered by the college. Hence, for each of the T_c years at school, agents receive endowments of the single consumption good equal to θP . We make the additional assumptions that this endowment is non-transferable and cannot be stored across periods.

The remaining fraction $1 - \theta$ of college costs consists of the payments, part of tuition and fees, that go toward the costs of human capital accumulation but lack direct consumption value. Then, paying that cost, agents that attend college produce human capital for the next year according to the production function

$$F(h, i, z) = z(hi)^\gamma + (1 - \phi)h, \quad (5)$$

where h is the starting level of human capital, i is the fraction of the agent's time allocated to learning, and z is the agent's learning ability. While in college, we assume that $i = 1$, so that all the time which could be allocated to productive uses during one's college years is allocated to learning. A student that matriculates with human capital h and learning rate z would therefore graduate with human capital equal to $F^{(\circ T_c)}(h, 1, z)$, where $F^{(\circ T_c)}$ denotes T_c applications of the function $F(\cdot, 1, z)$ to the input level of human capital. Similarly, we may also define the growth rate in human capital over while at college as $g(h, z) = F^{(\circ T_c)}(h, 1, z)/h$.¹⁹

Since we regard earlier investments by parents as complementary to college education, increasing its returns as well as those of subsequent investments of agents' time, it's natural for us to think of those investments as primarily impacting the learning rate z rather than the level of human capital h . On the other hand, we might think of the starting level of human capital h as a bundle of skills with some level of marketability if one were to join the labor force immediately, which implies those with more human capital at the end of high school may find college a less attractive option, though this is not always the case.

¹⁹Under the assumption that $F(\cdot)$ takes the form in (5) with $\gamma \in (0, 1)$, it is straightforward to show that $\partial_h g(h, z) < 0$ and $\partial_z g(h, z) > 0$. In other words, the potential returns to college education right out of college are decreasing in the starting level of human capital and increasing in the learning rate.

We have in mind here, for example, students with exceptional programming abilities as well as students that spent time in vocational or trade programs in high school.

Deciding on college. Whether it is worthwhile to go to college depends on the agent's human capital h and learning ability z upon graduating from high school, any college wage premia, and the agent's expectations about what transfers they'll receive from their parents and what transfers they expect to give to their own children. In our analysis, we'll allow for parents to condition the transfers they make and their types on children's college attendance.

After graduating from college, the agent starts work with zero assets, human capital equal to $g(h, z)h$, and idiosyncratic labor productivity ε . The value of being at this particular state is $V_{c,0}(0, g(h, z)h, \varepsilon; z, \omega_c)$, taking as given the agent's learning ability z and transfer type ω_c . The transfer type ω_c is a collection of objects that defines the agent's parents' transfer function, their own expected transfer function once they have children, and any payments they'll be required to make on their student loans after they graduate. It captures the lump sum payments the agent will make and receive, as well as the degree of insurance they'll receive from their parents.

Then, the expected value of the agent going to college is

$$W_c(h, z; \omega_c) = \left(\sum_{t=0}^{T_c-1} \beta^t (\theta P)^{\frac{\eta_c-1}{\eta_c}} + \beta^{T_c} \left(\mathbb{E}_\varepsilon [V_{c,0}(0, g(h, z)h, \varepsilon; z, \omega_c)^{1-\eta_r}]^{\frac{1}{1-\eta_r}} \right)^{\frac{\eta_c-1}{\eta_c}} \right)^{\frac{\eta_c}{\eta_c-1}} \quad (6)$$

and this includes the value of consumption while at college as well as the certainty equivalent of the agent's value once they graduate college. If the child does not go to college, their expected value is

$$W_n(h, z; \omega_n) = \mathbb{E}_\varepsilon [V_{n,0}(0, h, \varepsilon; z, \omega_n)^{1-\eta_r}]^{\frac{1}{1-\eta_r}}, \quad (7)$$

which is the certainty equivalent of the value of starting work immediately, where ω_n is the agent's transfer type if they don't go to college.

The agent chooses whether to go to college by solving the discrete choice problem

$$\max_{j \in \{c, n\}} W_j(h, z; \omega_j) + \varepsilon_j, \quad (8)$$

where ε_j is an i.i.d. Gumbel (GEV1) taste shock with scale parameter σ . Under these assumptions, the probability that an agent goes to college is a function of h , z , ω_c , and ω_n , which takes a standard form, provided in appendix C.3.

4.2 Working lives

After an agent has graduated college or made the decision to forgo it, they begin work. During their work lives, agents take their learning ability and transfer type as given. We index agent types by $j \in \{c, n\}$, where c denotes a college attendee and n indicates the agent did not attend. Further, as we mentioned before, the length of the work life of an agent depends on their type. The number of periods an agent of type j works before retiring is $T_{w,j}$, which is equal to $T_w - T_c$ for college attendees ($j = c$) and T_w for non-attendees ($j = n$).

We assume that an agent is endowed with a single unit of time. The agent chooses a fraction i of their time to spend building new human capital, which is produced according to the production function $F(h, i, \delta^t z)$, defined in (5). Here $\delta^t z$ reflects the change in the agent's learning ability over time, δ is the rate at which the agent's learning ability increases or decreases while in the labor force and t is the number of periods since entry. This captures the potential difficulty of retraining once job or firm-specific human capital has been accumulated.

The remaining fraction of agents' time $1 - i$ is supplied inelastically in the labor market. In this model, the agents do not experience any disutility from working, so the trade-off between working and learning comes only from trading current income for future income.

For each unit of time supplied in the labor market, the agent earns $w \exp(\varepsilon)$ units of income, where w is the wage rate, h is human capital, and ε is an i.i.d. idiosyncratic labor productivity shock. As in [Huggett et al. \(2011\)](#) and other papers, we will assume that $\varepsilon \sim N(\mu_\varepsilon, \sigma_\varepsilon^2)$, so that $\exp(\varepsilon)$ is a log-normal random variable.

Depending on the agent's transfer type ω and productivity realization ε , agents may receive an insurance transfer from their parents $\text{whf}_t(\varepsilon, \omega)$, where $f_t(\varepsilon, \omega)$ is a function that defines the size of the shock-dependent insurance transfer agents receive. Similarly, $\tau_{j,t}(\omega)$ is a type-specific sequence of net unconditional transfers given or received by the agent over their life. The specific forms of these functions and their relationship to the transfer type ω will be discussed in more detail later in the section.

The final type of income received by an agent is capital income. An agent endowed with a units of a risk-free one-period asset receives Ra units of income, where R is the gross risk-free rate. Then, a portion of all the income received by the agent may be used to purchase consumption c or a' units of the risk-free asset. We assume that agents cannot borrow, so we require $a' \geq 0$.

Then for all the periods $t \in \{0, \dots, T_{w,j} - 2\}$, the periods up to and including the

penultimate period before retirement, agents' value functions satisfy

$$\begin{aligned}
V_{j,t}(a, h, \varepsilon; z, \omega) &= \max_{c, a', i, h'} \left(c^{\frac{\eta_c - 1}{\eta_c}} + \beta \left(\mathbb{E}_{\varepsilon'} [V_{j,t+1}(a', h', \varepsilon'; z, \omega)^{1-\eta_r}]^{\frac{1}{1-\eta_r}} \right)^{\frac{\eta_c - 1}{\eta_c}} \right)^{\frac{\eta_c}{\eta_c - 1}} \\
a' + c &\leq Ra + (1 - \mathcal{T}_\ell) \text{wh exp}(\varepsilon)(1 - i) + \text{whf}_t(\varepsilon, \omega) + \tau_{j,t}(\omega) \\
h' &= \delta^t z(hi)^\gamma + (1 - \phi)h \\
a' &\geq 0; i \in [0, 1].
\end{aligned} \tag{9}$$

For $T_{w,j} - 1$, the last period before retirement, we assume that agents work for their full unit of time and they only make a decision about the amount of consumption and saving before retirement, so the value functions in this period instead satisfy

$$\begin{aligned}
V_{j,(T_{w,j}-1)}(a, h, \varepsilon; z, \omega) &= \max_{c, a'} \left(c^{\frac{\eta_c - 1}{\eta_c}} + \beta V_{j,T_{w,j}}(a', h; \omega)^{\frac{\eta_c - 1}{\eta_c}} \right)^{\frac{\eta_c}{\eta_c - 1}} \\
a' + c &\leq Ra + (1 - \mathcal{T}_\ell) \text{wh exp}(\varepsilon) + \text{whf}_{(T_{w,j}-1)}(\varepsilon, \omega) + \tau_{j,(T_{w,j}-1)}(\omega) \\
a' &\geq 0.
\end{aligned} \tag{10}$$

4.3 Retirement

During retirement periods, agents receive a constant stream of income from social security $\mathcal{S}(\text{wh})$. Similar to the approach in [Lee and Seshadri \(2019\)](#), we assume this income is a function of agents' base income before retirement.²⁰ As before retirement, agents also receive net unconditional transfers and capital income. This income is either consumed or saved, with asset choices subject to a borrowing constraint. Then, for periods $t \in \{T_{w,j}, \dots, T_{\ell,j} - 2\}$,²¹ agents' value functions are given by

$$\begin{aligned}
V_{j,t}(a, h; \omega) &= \max_{c, a'} \left(c^{\frac{\eta_c - 1}{\eta_c}} + \beta V_{j,t+1}(a', h; \omega)^{\frac{\eta_c - 1}{\eta_c}} \right)^{\frac{\eta_c}{\eta_c - 1}} \\
a' + c &\leq Ra + \mathcal{S}(\text{wh}) + \tau_{j,t}(\omega) \\
a' &\geq 0,
\end{aligned} \tag{11}$$

²⁰This is necessary to economize on the number of state variables. If we were to use a formula for social security payments closer to that in reality, it would be necessary to include the average lifetime income as a state variable. In practice, however, appropriately chosen functions of wh can approximate the average income reasonably well. Like [Lee and Seshadri \(2019\)](#), we assume that $\mathcal{S}$ is a linear function so $\mathcal{S}(x) = s_0 + s_1 x$.

²¹As with the agent's working life, the life span is measured from entry into the labor force, so $T_{\ell,j} = T_\ell$ for non-attendees ($j = n$) and $T_\ell - T_c$ for college graduates ($j = c$).

while in the final period $t = T_{\ell,j} - 1$, agents' choose $a' = 0$ and set $c = Ra + S(wh) + \tau_{j,t}(\omega) \geq 0$, so

$$V_{j,T_{\ell}-1}(a, h; \omega) = Ra + S(wh) + \tau_{j,t}(\omega). \quad (12)$$

In this model, the term $\tau_{j,t}(\omega)$ includes the bequests made by parents to children, showing up as a negative value on the income side of the budget constraint.

4.4 Transfer types and transfer functions

As we mentioned earlier, the transfer type ω_j , which we have allowed to depend on the agent's education status captures the sequence of net unconditional transfers the agent will give or receive, as well as the sequence of potential state-dependent transfers the agent might receive.

Insurance transfers and insurance policies. On the recipient side, the children's side, the function $f_t(x, \omega)$, which defines the replacement rate in terms of the realization of $\varepsilon = x$, is a function of three parameters, which are indexed by the period t and the transfer type ω . In the function

$$f_t(x, \omega) = \alpha_{0,t}(\omega) \Gamma(\alpha_{1,t}(\omega)x + \alpha_{2,t}(\omega)) (\mathbb{E}_{\varepsilon}[\exp(\varepsilon)] - \exp(x)) \quad (13)$$

$\Gamma(\cdot)$ is a CDF, α_0 is the maximum replacement rate, α_1 captures the how the replacement rate varies with the realization of ε , and α_2 is a shifter that effectively determines the states in which an agent receives an insurance transfer.²² We assume that these may depend on time, though in our exercise we only assume that the replacement rate $\alpha_{1,t}(\omega)$ varies with time. The sequences of parameters that determine the situations in which a child will receive a transfer $\{\alpha_{1,t}(\omega), \alpha_{2,t}(\omega)\}$ are fixed in time.

Having the parent keep track of the child's level of human capital and idiosyncratic productivity increases the size of the parents' state space greatly. Therefore, we assume that, instead paying for all the insurance transfers directly, parents buy an insurance policy with payments included into the fixed type-specific sequence of transfers $\{\tau_{g,t}(\omega)\}_t$ they give to their children. We'll discuss this sequence in more detail later on.

²²In essence, this is a smooth version of an insurance policy that yields a fixed replacement rate if realization for productivity is low enough.

Educational and unconditional transfers received. We assume that parents decide to pay for a fraction $e(\omega_c)$ of their child's educational costs, which are remitted directly to the school. Therefore, the school receives four payments of $e(\omega_c)P$ from the parents and the child makes T_{sl} annual payments of $(1 - e(\omega_c))p_{sl}$ after graduating.

After graduation, we assume that children receive a fixed sequence of payments $\{\tau_{u,t}(\omega_c)\}_{t=0}^{T-T_c-1}$. If the child, instead, goes immediately into the workforce, they receive the sequence $\{\tau_{u,t}(\omega_n)\}_{t=0}^{T-1}$. Notice that this sequence of transfers, like insurance transfers, depends on time. We choose this sequence to be decreasing in time, at a rate which broadly matches the time path of average unconditional transfers given.

Transfers given and the net transfer sequence. The sequence of transfers given by parents $\tau_{g,t}(\omega)$ is, conditional on transfer type ω , a deterministic sequence of transfers made to children. We choose the parameters of these sequences to approximate the average paths of transfers that children receive over their lives.²³

It is important to note that parents do not directly choose the timing of transfers given here. The timing is chosen to reflect the transfer paths realized in the data. Moreover, conditional on ω , parents take the sequence of transfers they give as given. This does not mean, however, it is not the result of a choice that individuals make. We interpret it as reflecting the outcome of a discrete choice problem over the possible transfer paths, with timing of the paths chosen beforehand with children's interests in mind.

These simplifications in parents' transfer functions matter less for our results because our focus is primarily on the children's side, how the timing and mix of transfers we observe in the data affects children's outcomes, than the parents' side, how parents decide the particular timing and mix we observe. Though, we want to emphasize the fact that the model is not silent on parents' motivations, since we are able to back out the way parents value their children's welfare from our modeling assumptions and the data.

Now, having defined the all the sequences of lump-sum transfers given and received, we may define the net transfer function over an agent's entire life $\tau_{j,t}(\omega)$, which is

$$\tau_{j,t}(\omega) = \begin{cases} \tau_{u,t}(\omega); & (t < T) \wedge (j = n) \\ \tau_{u,t}(\omega) - (1 - e(\omega))p_{sl}; & (t < T_{sl} < T - T_c) \wedge (j = c) \\ \tau_{u,t}(\omega); & (T_{sl} \leq t < T - T_c) \wedge (j = c) \\ -\tau_{g,t}(\omega); & ((T \leq t) \wedge (j = n)) \vee ((T - T_c \leq t) \wedge (j = c)) \end{cases} \quad (14)$$

²³Parents save to make the transfers, some of which will be used to insure children, meaning we capture a part of the dynastic precautionary savings motive. However because they are deterministic, not responding directly to children's idiosyncratic states, we don't entirely capture the precautionary savings in Boar (2021) that generate an increasing path of consumption post-retirement.

4.5 Closing the model

Having described the households in this model, we turn to the remaining participants in the economy, the firms and the government, as well as the market-clearing conditions that link them together with the households. We will specify all of components under the assumption of a stationary equilibrium.

Firms. In this model, firms produce output using a production function that exhibits constant returns-to-scale in capital and labor. They take wages w and interest rates r as given. Firms rent capital K from the households, paying the interest rate r plus the depreciation δ_k on each unit. They also rent effective labor hours N from households at wage w . Both capital K and labor N are chosen to maximize flow profits, which are given by

$$\Pi = \Theta K^\alpha N^{1-\alpha} - wN - (r + \delta_k)K. \quad (15)$$

Government. The government issues loans to students whose parents don't pay for all of their schooling and collects the annual payments on those loans. It also makes social security payments to the households in the economy. We assume that the government balances its budget in each period. Consequently, it levies taxes on labor income at rate $\mathcal{T}_\ell$ in order to fulfill that objective. This leads us to the budget constraint

$$\underbrace{\mathcal{T}_\ell wN}_{\text{Income tax receipts}} = \underbrace{\left(\sum_{\omega} P(j = c, \omega)(1 - e(\omega)) \right) (PT_c - p_{sl}T_{sl})}_{\text{Net student loan disbursements}} + \underbrace{(2T - T_w) \left(P(j = c) \int \mathcal{S}(wh)dD_{c, T_w, c}(h) + P(j = n) \int \mathcal{S}(wh)dD_{n, T_w, n}(h) \right)}_{\text{Social security payments}}, \quad (16)$$

where $D_{j, T_{w,j}}(h)$ is the measure over human capital, conditional on education level j upon starting retirement in the $T_{w,j}$ -th year after entering the labor force.²⁴ $P(j)$ is the probability of education status j in the population.

²⁴We multiply by the number of retirement periods because social security payments are constant throughout retirement.

Market-clearing conditions. Finally, we come to the market clearing conditions, which are, for capital and labor, the following:

$$N = \sum_{\omega} \sum_z \sum_{j \in \{n,c\}} P(j, z, \omega) \left(\sum_{t=0}^{T_w - T_c \times \mathbb{I}(j=c) - 1} \int h(1 - i_{j,t}(a, h, \varepsilon; z, \omega)) \exp(\varepsilon) dD_{j,t}(a, h, \varepsilon | z, \omega) \right) \quad (17)$$

$$K = \sum_{\omega} \sum_z \sum_{j \in \{n,c\}} P(j, z, \omega) \left(\sum_{t=0}^{2T - T_c \times \mathbb{I}(j=c) - 1} \int a dD_{j,t}(a, h, \varepsilon | z, \omega) \right). \quad (18)$$

In the above, $i_{j,s}(a, h, \varepsilon; z, \omega)$ is the time allocated by an agent with education level j to learning s periods after entering the labor force, while having idiosyncratic state (a, h, ε) and type (z, ω) . Then $D_{j,s}(a, h, \varepsilon; z, \omega)$ is the measure over idiosyncratic states for such an agent and $P(j, z, \omega)$ is the joint distribution of education levels and types.

We end with the condition for the transfer market, which is that there are zero net transfers in the economy, so that, in each year, the total amount of transfers received by children is equal to the total amount of transfers given by parents. This can be represented by

$$0 = \sum_{\omega} \sum_z \sum_{j \in \{n,c\}} P(j, z, \omega) \left[e(\omega) P T_c + \sum_{t=0}^{T_w - T_c \times \mathbb{I}(j=c) - 1} \left(\tau_{j,t}(\omega) + w \int h f_t(\varepsilon, \omega)(a, h, \varepsilon; z, \omega) \exp(\varepsilon) dD_{j,t}(a, h, \varepsilon | z, \omega) \right) \right]. \quad (19)$$

5 What do transfers do?

In this section we first cover the approach to calibrating the model and the quality of the fit. We then perform several exercises to understand the role of insurance in children's life outcomes and discuss the results. Finally, we consider an experiment in which parents are unable to give inter vivos transfers to their children in order to understand the impact of transfers on the economy as a whole.

5.1 Calibrating the model

Having outlined the model, we turn to cover in more detail the choice of parameters in the model and the estimation of the processes that govern children's initial conditions

$(h, z, \omega_c, \omega_n)$. We also specify how they depend on the parents' values for starting human capital h_p and learning rates z_p .

Externally calibrated parameters. The values for the parameters which aren't calibrated within the model are displayed in table 3. The first block of parameters consists of those which are standard in business cycle models. The parameters that pertain to agents' preferences, the discount rate β , the EIS η_c , and the CRRA η_r , are chosen to be consistent with those typically used in the business cycle literature at annual frequencies. Then, the parameters governing the production sector in the economy, the capital share α and the depreciation rate δ_k , are chosen to match the real interest rate r and pre-tax wage w in the economy, while remaining close to the standard values used in the literature.

The next block concerns the dynamics of human capital and income risk over the life cycle. The parameters of the human capital production function that govern human capital depreciation ϕ and the decline in the ability to replenish it δ are set to match the observed decline in earnings near retirement and the decline in the fraction of time used for human capital accumulation over one's work life.²⁵ We set the scale γ of the human capital production function to capture decreasing returns in human capital accumulation and the variance of idiosyncratic shocks σ_ε^2 to capture income risk over the life-cycle. Both are chosen to remain close to the values used in Huggett et al. (2011) and others. The mean of μ_ε is set to normalize $\mathbb{E}[\exp(\varepsilon)]$ to 1.

The remaining parameters capture the value of variables relevant to the economy as a whole, to student loans, and to the cost of education. The real interest rate is set at a standard level, while the income tax rate is chosen to balance the government's budget. The parameters for student loans reflect observed values for the average rate on student loans and the average time it takes to pay off one's loans. The cost of college P is chosen to match the total annual cost of college at a four-year institution in the US in 2026 from Hanson (2026).²⁶ The consumption fraction θ roughly is chosen to match the average fraction of the cost spent on room and board, plus the assumption that half of tuition costs go toward consumption value for the student (i.e. consumption value of education).

Inter-generational driving processes. Now we focus on the processes we estimate from the data. We assume that, given their parents' state (h_p, z_p) , each child's state is

²⁵The assumption that social security payments are a function of wages in the economy as well as one's level of human capital in the final year before retiring means that, absent learning ability depreciation (i.e. $\delta \geq 1$), agents would spend much more time learning on the job later in life than is observed in the data. Hence, $\delta < 1$ is crucial. We choose it to roughly coincide with the time path in Huggett et al. (2011).

²⁶Uses National Center for Education Statistics (NCES) data.

Model parameters			Prices, loan terms, and tax rates	
Parameter		Value	Quantity	Value
<i>Business cycle</i>			<i>Macro values</i>	
β	Discount rate	0.96	Real interest rate	2.0%
η_c	EIS	0.5	Income tax rate	27.8%
η_r	CRRA	3.0	<i>Student loans</i>	
δ_k	Capital depreciation	11.5%	Interest rate	6.52%
α	Capital share	0.2	Loan term	20 years
<i>Human capital</i>			<i>College</i>	
γ	Human capital scale	0.65	Annual cost	\$40,000
ϕ	Human capital depreciation	0.005	Consumption fraction	75%
δ	Learning ability depreciation	0.95		
μ_ε	Mean of $\log(\varepsilon)$	-0.01		
σ_ε^2	Variance of $\log(\varepsilon)$	0.02		

Table 3: Baseline model parameters and inputs (annual parametrization)

drawn from the distribution $Q_0(h, z \mid h_p, z_p)$. In other words, the state (h, z) follows a first-order Markov process across generations. Then we assume that, given children's state (h, z) , ω_c and ω_n are drawn independently from the distributions $Q_1(\omega_c \mid h, z)$ and $Q_2(\omega_n \mid h, z)$.²⁷

For a given j , $\omega_j = \{\omega_{\text{Ins.},j}, \omega_{\text{Unc.},j}, \omega_{\text{Giving},j}\}$ is a tuple of indices. $\omega_{\text{Ins.},j}$ insurance is the index referring to a specific set of parameters for the parental insurance the child receives over their life, while $\omega_{\text{Unc.},j}$ indexes the sequences of educational and unconditional transfers received and $\omega_{\text{Giving},j}$ indexes the sequence of transfers that the child will give once they become a parent themselves.

At this point, it is important to note that only the probabilities of drawing of the processes are estimated. The values of (h, z) in the chain or the sequences indexed by each ω are not estimated. We choose them so that the set of sequences is wide enough so that we can find combinations that fit the moments we estimate from the data. Additional details on these processes are provided in appendix D.1.

The moments and the fit. In this paper we aim to understand the relationship between transfers, income, and wealth, as well as the inter-generational persistence in those quantities. Therefore, we find it natural to set the parameters of Q_0 , Q_1 , and Q_2 based on conditional moments for income and transfers.

More specifically, we choose the parameters to fit the paths of the five-year moving

²⁷That Q_1 and Q_2 do not depend on the parents' state does not mean that the distributions of ω_c and ω_n in the economy are independent of parents' states, merely that the assumption on the Markovian relationship between draws of (h, z) across generations allows us to write the distributions in these forms.

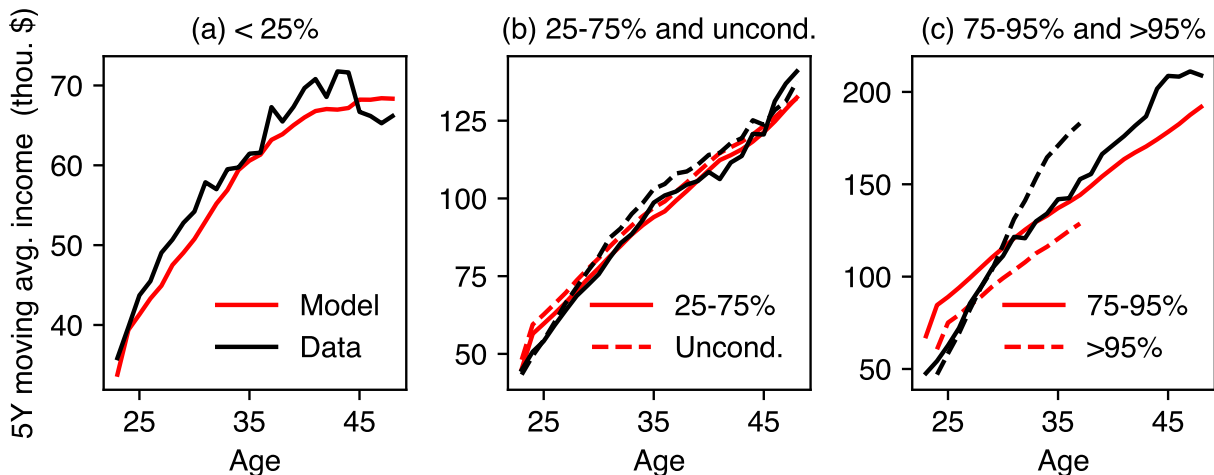


Figure 7: Five-year moving avg. income of children by parents' wealth group (model v. data)

Notes: Computed from PSID data. In all subfigures, red lines are the values in the model, while black lines are the values in the data.

average income over children's lives, both unconditionally and conditional on their parents' wealth group. We do the same for paths of educational transfers, insurance transfers and unconditional transfers. Ultimately, we choose the parameters that minimize the total root mean squared error (RMSE) over all moments, jointly.

We present results showing the quality of the fit for the income moments in figure 7 and the the fit for the average transfers in figure 8. The plots displaying the fit quality for the transfers children receive, conditional on parents' wealth group, are in figure D.1 of appendix D.3, along with a number of untargeted moments produced by the model.

Overall, the quality of the fit is quite good across all moments. The model is able to replicate the dependence of children's incomes on parents' wealth. It is also able to match the time path and mix of transfers received by children. Moreover, it can replicate the dependence of these values on parents' wealth groups. This allows us to be confident in the idea that the exogenous processes we've specified are able to capture the most salient features of the data.

5.2 A world without transfers

In our baseline, we've calibrated the Markov process Q_0 that determines the transmission of the learning rate z and initial human capital h across generations. This process, which we take as given, represents all of the elements of inter-generational transmission not determined by the processes for inter vivos transfers Q_1 and Q_2 .

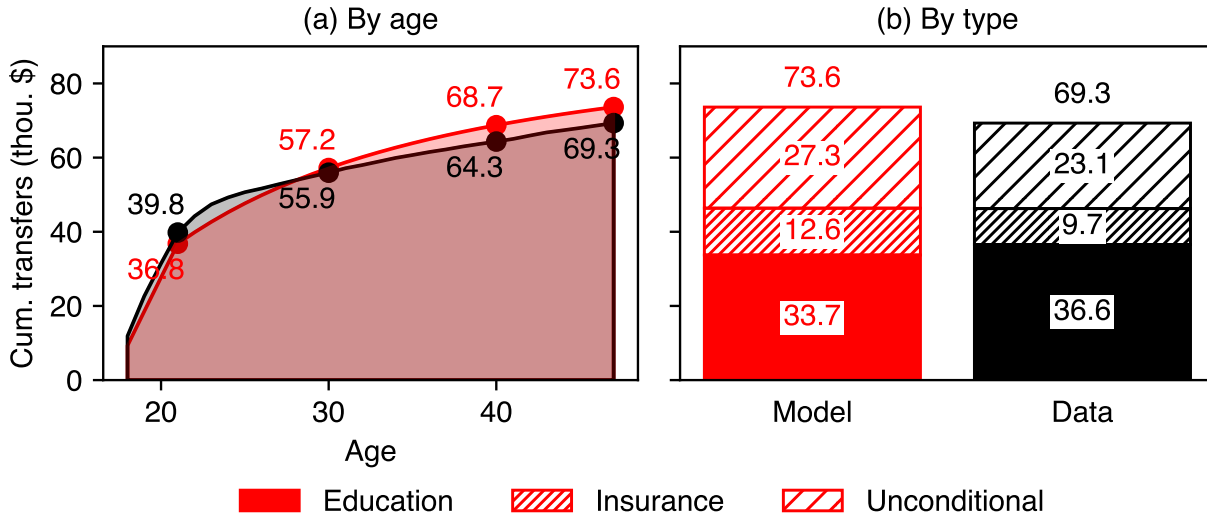


Figure 8: Average cumulative transfers received children, by age and type (model v. data)

Notes: Moments in the data computed from HRS.

Here, we consider a counterfactual world where parents no longer give transfers to their adult children. How are macroeconomic outcomes affected by this fact? How do prices and quantities respond? Moreover, now that Q_0 is the only source of inter-generational linkages, how does the persistence of income and wealth change?

There are two scenarios we consider in this experiment. The first and simplest is the partial equilibrium (PE) scenario, where prices do not adjust. This is the pure decomposition exercise, measuring the contribution of parents' transfers to the determination of individual and economy-wide outcomes. Moreover, we're able to identify, on the basis of this exercise, the types of individuals for whom inter vivos transfers are making the biggest difference under the status quo.

The second scenario is the general equilibrium (GE) counterfactual. In this case, we explore the effectiveness of price changes in mitigating the impacts of eliminating inter vivos transfers. In particular, we allow wages and tax rates to adjust, but we hold the Markov transition matrix Q_0 constant. This exercise isolates the ability of price adjustments to absorb and substitute for the targeted transfers that parents provide.

How much can transfers explain? We begin by studying the importance of transfers for the levels of economic variables under each of the two scenarios. Table 4 displays the moments of the distribution of permanent income and the distribution of wealth at retirement age. For both retirement wealth and permanent income, eliminating transfers

Moment	Baseline		No transfers (PE)		No transfers (GE)	
	Perm. inc.	Ret. wealth	Perm. inc.	Ret. wealth	Perm. inc.	Ret. wealth
Mean	\$2,897k	\$626k	\$2,571k	\$542k	\$2,874k	\$580k
Std. dev.	\$1,665k	\$394k	\$1,516k	\$336k	\$1,199k	\$250k
Gini	0.32	0.35	0.33	0.34	0.23	0.24
<i>Percentiles</i>						
25%	\$1,211k	\$293k	\$1,033k	\$202k	\$1,420k	\$285k
Median	\$2,635k	\$512k	\$2,516k	\$493k	\$3,342k	\$647k
75%	\$3,822k	\$839k	\$3,525k	\$712k	\$3,727k	\$732k
95%	\$5,781k	\$1,367k	\$5,603k	\$1,240k	\$4,803k	\$923k

Table 4: Model-generated moments of post-tax permanent income and retirement wealth (age 65) distribution under baseline and counterfactuals

reduces the mean and the variance of the distribution.

In the partial equilibrium exercise, our results tell us that permanent incomes are roughly \$326,000 lower without transfers. This excludes the average present value of the transfers themselves, which means that the indirect effects associated with giving and receiving inter vivos transfers generate about 11% of the average post-tax permanent income earned by individuals in the status quo. Moreover, the standard deviation of permanent income is reduced by \$149,000. This corresponds to a roughly 17% decline the variance of permanent income, which we can interpret as the fraction of the variance in permanent income explained by inter vivos transfers.

In the same exercise, the average level of wealth at retirement is \$84,000 lower, while the standard deviation of wealth is \$58,000 lower. For wealth, these imply that the indirect effects of inter vivos transfers can account for 13% of the average level of retirement wealth and 26% of its variance. These numbers are striking as they imply that the indirect effects of transfers are even larger than their direct effects. The average effect on permanent incomes is almost five times the size of the average present value of transfers, about \$69,000, shown in table 2.

For both variables, the effects are occur disproportionately at the bottom of the distribution, though transfers do have sizable impacts on the individuals in the upper tail. For this reason, measures of inequality in the model, like the Gini index, are mostly unaffected by the lack of transfers.

How much can prices change things? We turn to the general equilibrium exercise now, contained in the ‘No transfers (GE)’ portion of table 4, considering how price re-

sponses can alter the results of the previous exercise. We find that, because of the large declines in human capital accumulation along the intensive and extensive margins, the post-tax wage rate rises over 30%, erasing almost all of the declines in the permanent income. The overall average permanent income only falls by about \$23,000, a number that would fall even more with a higher discount rate. Yet, because the saving rate is still low, output is significantly depressed in the general equilibrium counterfactual relative to our baseline, by even more than indicated by the average permanent income. We may conclude then that price changes are an imperfect substitute for the transfers parents provide their children, as far as their effects on macroeconomic outcomes.

On top of the other changes that occurring in this counterfactual, the large jump in wages also precipitates a large decline in income and wealth inequality. We would caution against putting too much stock in this result, however. Because we have assumed that all the effective labor hours are paid the same return regardless of whether they're rented from college graduates or not, wage rates rise for everyone, which leads to progressive redistribution. If we were to make the assumption that different types of human capital were, instead, imperfectly substitutable, this would likely change.

The role of transfers in persistence. Now we want to know how the inter-generational persistence of these quantities is affected by transfers. One measure of inter-generational transmission is the inter-generational elasticity (IGE), typically computed for income and wealth, which quantifies the sensitivity of percentage changes in children's values to percentage changes in their parents' values.

In the model, we estimate these quantities for permanent income and retirement wealth with regressions of the form

$$\log(x_c)_i = \alpha + \beta \log(x_p)_i + \varepsilon_i, \quad (20)$$

where $\log(x_c)$ is the log of variable x for child i and $\log(x_p)$ is the same for parent i . The results for this exercise are collected in table 5. In the baseline, the intergenerational elasticity of permanent income is 0.72, meaning that a 1% increase in the parent's permanent income leads to a 0.72% increase in the child's permanent income. For wealth at retirement, the IGE is 0.61.

Compared to the estimate of 0.34 for the IGE of income obtained by Chetty et al. (2014), which Lee and Seshadri (2019) prefer to match, the value in our model is exceptionally high. However, it is very much in line with the estimates of around 0.66 found by Mazumder (2016), whose method for estimating the IGE, using longer weighted averages

	Permanent income	Retirement wealth
Non-transfer effects	0.654 (91.2%)	0.531 (86.7%)
+ Insurance effects	0.031 (4.3%)	0.036 (5.9%)
+ Other transfer effects	0.033 (4.5%)	0.046 (7.4%)
= Baseline	0.717 (100%)	0.613 (100%)

Table 5: Decomposing inter-generational elasticities in the model

Notes: Fraction of total IGE accounted for in parentheses.

of parents' and children's mid-career incomes,²⁸ makes it a more appropriate comparison for the IGE of permanent income in our model. Chetty et al. (2014) measure the elasticity of children's average income from ages 30 to 31 to parents' average income from 44 to 48, which is conceptually more distant from our model's elasticities of permanent income than empirical estimates using long averages centered around middle-age.²⁹

Within table 5, we decompose the IGEs for permanent income and retirement wealth into the pieces not explained by transfers and the components attributable to transfers. Then, we can split the transfer effect into the insurance effect of transfers and the other effects of transfers. We find that transfers account for almost 9% of the IGE of permanent income and 13% of the IGE for wealth at retirement. The insurance effect can account for 49% of the transfer effect for permanent income and 44% for wealth. In both cases transfers account for a considerable fraction of the IGE and about half of that effect comes from their insurance effects.

With the IGE, we assessed the persistence of magnitudes across generations. Now, we consider cross-generational transition matrices, which provide an account of the level of wealth and income mobility in the economy by assessing the dependence of children's ranks on parents' ranks. In tables 6 and 7, under the 'Baseline' heading, we present the matrices generated by the model for retirement wealth and permanent income.

Under the 'No transfers (PE)' heading, we perform an experiment to understand transfers' contributions to children's ability to obtain particular ranks in the distributions. Supposing that the distribution of initial human capital and learning rates (h, z) for parents, given their wealth rank, is the same as in the 'Baseline' scenario, we ask: what is the

²⁸Using a full 15 years of parents' income data, from ages 33 to 47, and a range of averages for children's income, centered around age 40.

²⁹Our main rationale for preferring 0.66 estimate mostly has to do with the comparability of the estimands to the model's moments. However, estimates far above 0.34 are also very plausible due to the sources of downward bias in the IGE discussed in Mazumder (2016) and others surveyed by Mogstad and Torsvik (2023).

		Baseline				No transfers (PE)			
Child grp.		<25%	25-75%	75-95%	>95%	<25%	25-75%	75-95%	>95%
Parent grp.	<25%	0.51	0.49	0.0	0.0	0.59 ↑	0.41 ↓	0.0 ↓	0.0 ↓
	25-75%	0.24	0.48	0.21	0.07	0.32 ↑	0.5 ↑	0.17 ↓	0.01 ↓
	75-95%	0.0	0.5	0.4	0.09	0.0 ↑	0.74 ↑	0.24 ↓	0.02 ↓
	>95%	0.0	0.64	0.33	0.03	0.0 ↑	0.88 ↑	0.12 ↓	0.01 ↓

Table 6: Probability of child retirement wealth group, given retirement wealth group, baseline v. partial eq. counterfactual

Notes: Retirement wealth is the level of assets held at age 65, when agents retire. Bold entries in the transition matrix for the counterfactual represent values that change relative to the baseline. Those in black with “up”-arrows have increased. Those in red with “down”-arrows have decreased.

probability that the child of a parent in a particular wealth group makes it into each wealth group if that child never receives any inter vivos transfers? How do those probabilities depend on parents’ wealth groups?

Across wealth groups, we find that transfers are crucial for inter-generational mobility. However, from table 6, they appear to far more central to the maintenance of rank at the tops of the distributions. For children whose parents are in the top 5% of the wealth distribution, the fact that they don’t receive any transfers reduces the change of staying in the top quartile of wealth by over 20 percentage points. The same is true for the children of parents in the 75-95th percentiles.

When we perform the same exercise for permanent income, categorizing parents on the basis of their permanent income group, the results are qualitatively the same, though the magnitudes of the effects are even larger. This is unsurprising when we consider that, by retirement, wealthier parents happen also to have given a substantial amount of resources to their children, as well as receiving them from their own parents. We would, therefore, expect permanent labor income ranks in the model, which are only indirectly affected by transfers, to have a stronger correlation than we observe for wealth ranks.

Across all of these exercises, the results are remarkably consistent: inter vivos transfers have strong effects on the wealth and permanent income of their recipients, effects that are about four to five times the size of the transfers themselves. They also have appreciable effects on the persistence of magnitudes and ranks of income and wealth across generations, especially at the top of the distribution.

		Baseline				No transfers (PE)			
<i>Child grp.</i>		<25%	25-75%	75-95%	>95%	<25%	25-75%	75-95%	>95%
<i>Parent grp.</i>	<25%	0.53	0.47	0.0	0.0	0.61 ↑	0.39 ↓	0.0 ↓	0.0 ↓
	25-75%	0.22	0.48	0.22	0.07	0.3 ↑	0.52 ↑	0.17 ↓	0.01 ↓
	75-95%	0.0	0.5	0.41	0.09	0.0 ↑	0.77 ↑	0.21 ↓	0.02 ↓
	>95%	0.0	0.66	0.31	0.03	0.0 ↑	0.93 ↑	0.07 ↓	0.01 ↓

Table 7: Probability of child permanent income group, given parent’s permanent income group, baseline v. partial eq. counterfactual

Notes: Bold entries in the transition matrix for the counterfactual represent values that change relative to the baseline. Those in black with “up”-arrows have increased. Those in red with “down”-arrows have decreased.

5.3 Transfers and their value

We’ve covered transfers’ ability to explain features in the data, but we want to know how children value transfers. How valuable are they, relative to other sources of variation? Which transfers are particularly valuable?

The value of having wealthy parents. The value function we obtain in solving the model is in terms of a consumption equivalent $W_j(h, z, \omega)$. So, the value of having parents in a particular wealth bracket q_p is determined by these values and the distribution³⁰

$$P(h, z, \omega, j \mid q_p) = P(\omega, j \mid h, z) P(h, z \mid q_p). \quad (21)$$

That is, having wealthy parents influences the distribution of human capital h and the learning rate z , which also, in turn, influences the distribution over transfer types ω and education levels j .

With all of these channels for influence, there is a natural point of comparison. We imagine a child drawing their endowment of (h, z) from the unconditional distribution $P(h, z)$ in a world where they won’t receive inter vivos transfers from their parents. For each q_p , how much would their value be changed by drawing their endowment from $P(h, z \mid q_p)$ in a world with transfers?

Figure 9 shows the results from this experiment in the red dots in subplot (a). Regardless of with wealth group you select into, transfers mean you’re still better off. More concretely, drawing from $P(h, z \mid q_p)$ is worse than drawing from $P(h, z)$ for all but the two highest wealth groups $q_p = \{75-95\%, >95\%\}$, but the potential to receive transfers can make up for the difference.

³⁰The decomposition follows from Bayes’ rule and the fact that $P(\omega, j \mid h, z, q_p) = P(\omega, j \mid h, z)$

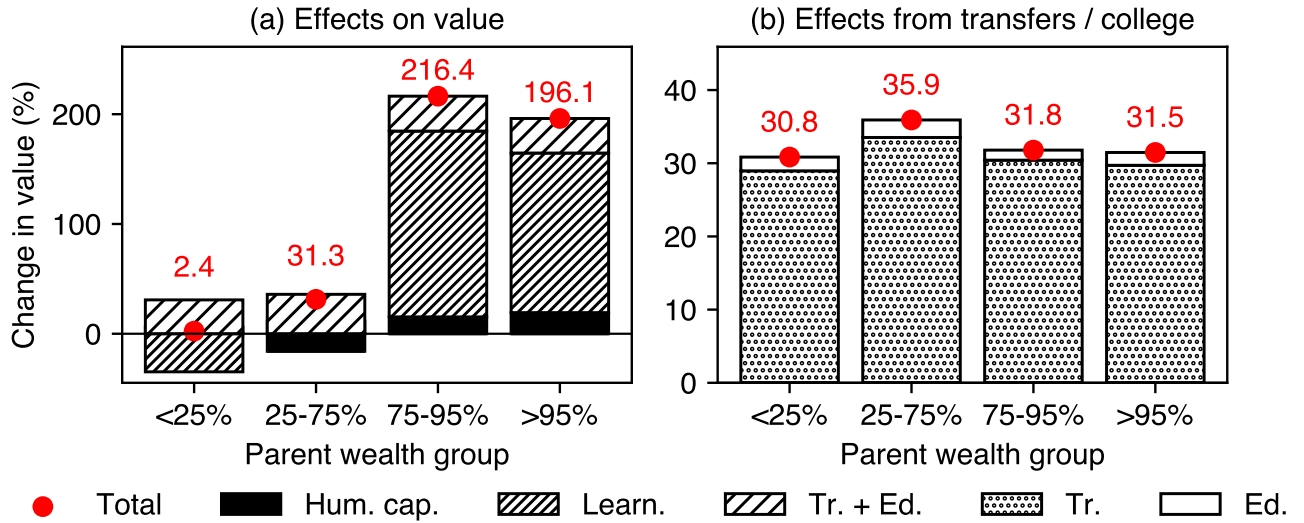


Figure 9: Decomposing the value of having wealthy parents

Notes: Subplot (a) combines transfer effects (Tr.) and education effects (Ed.) into one. Subplot (b) shows the split between transfers and education effects. Scale is relative to unconditional baseline without transfers.

Figure 9 also displays the effects decomposed³¹ into the parts that can be accounted for by differences in the distribution of initial human capital h by parent group, in the distribution of learning rates z , transfers, and college attendance rates.

What we observe is that variation in the distribution of learning rates, which increase the returns to college and the growth rates of income while in the work force, are the main driver behind the value of having parents in a higher wealth group. Following behind that is the value from transfers, which make up a smaller, but still respectable, portion of the increase in value. Variation in the distribution of initial human capital and changes in the probability of college attendance account for even smaller portions of the change in value.

Interestingly, the increase in value from receiving transfers is relatively uniform across parents' wealth groups, even though children of parents in higher wealth groups receive much more in transfers than children of parents in lower wealth groups. The much higher marginal value of transfers for the children of poorer parents almost exactly balances out the lower level of transfers received, so that inter vivos transfers generate large increases in value across the wealth distribution.

The value of insurance transfers. In this paper, we've emphasized the importance of parental insurance. Who do insurance transfers benefit the most? We evaluate this in

³¹We follow Shorrocks et al. (2013), Lundberg and Lee (2017), and Bhandari et al. (2026) in using Shapley values to compute our decompositions.

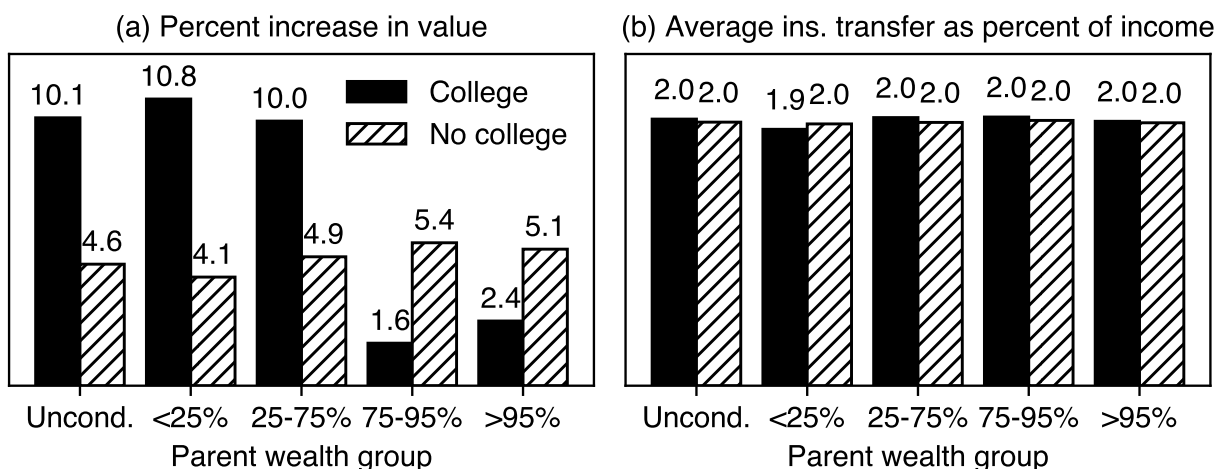


Figure 10: The value of generous parental insurance

Notes: Subplot (a) shows how the value increases, relative to a life without any transfers. Subplot (b) shows the average insurance transfer as a percent of labor income in each period.

terms of the average increase in value generated by having the most comprehensive insurance transfer type relative to a life without transfers, shown in figure 10(a). It's very intuitive that the effects are highest among college attendees whose student loan payments make up a large fraction of their income. For these individuals, who very often find themselves constrained, negative shocks are especially painful, but generous parental insurance can go a long way in softening the blows.

It is for this reason that insurance transfers are especially valuable for most groups. For all but college attendees whose parents are in the 75-95% group, insurance transfers generate increases far in excess of their size relative to labor income, which is uniformly around 2%. Of course, their value is lower for those whose lifetime incomes are expected to be especially high and who can insure themselves to a reasonable degree, but they remain a powerful source of insurance for the vast majority of individuals.

6 Conclusion

In this paper, we argue that inter vivos transfers (IVTs) from parents to children play a substantially larger role in driving the cross-sectional dispersion and intergenerational persistence of income and wealth than their raw magnitudes imply. Using survey data, we document that the disproportionate impact of IVTs stems from two distinct features. First, they are heavily front-loaded toward the beginning of the recipient's adult life, generating a mechanical present-value advantage relative to other types of transfers. Furthermore, a

large proportion of these early transfers go toward human capital accumulation, amplifying their effects through increases to lifetime income. Second, IVTs serve as an informal form of insurance. Wealthy parents, in particular, increase transfers when their children experience adverse labor market events or other financial shocks. We provide empirical evidence that the presence of this parental safety net fundamentally alters children's risk-taking behavior, incentivizing them to allocate a larger share of their portfolios to equities.

To quantify these mechanisms, we embed them in a structural overlapping generations model with incomplete markets and endogenous human capital accumulation. The model matches both the unconditional and conditional income and transfer paths observed in the data well. Counterfactual exercises reveal that eliminating IVTs yields declines in lifetime income across the population, driven by reductions in college attendance and intensive human capital investments. The ability of parents to front-load transfers and insure against downside risk is critical in shielding children from binding liquidity constraints during peak investment years. Furthermore, we find that the implications for intergenerational wealth mobility are highly heterogeneous. While shutting down IVTs generally increases wealth mobility for the middle and upper classes by severing a primary mechanism of wealth transmission, it decreases mobility for the poor. Without parental transfers, children from the poorest households face severe difficulties in self-financing educational investments, effectively trapping them at the bottom of the distribution.

Ultimately, our findings suggest that the timing and state-contingency of intergenerational transfers are just as vital as their overall size. Recognizing IVTs as both a funding source for early-life investments and a substitute for self-insurance offers a clearer lens through which to evaluate the persistence of inequality. This framework highlights the need to carefully consider policies that alter the timing of wealth transmission—such as the taxation of gifts versus estates or the treatment of stepped-up basis—as these policies potentially have downstream effects on human capital formation, aggregate productivity, and intergenerational mobility.

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A Appendix to section 2

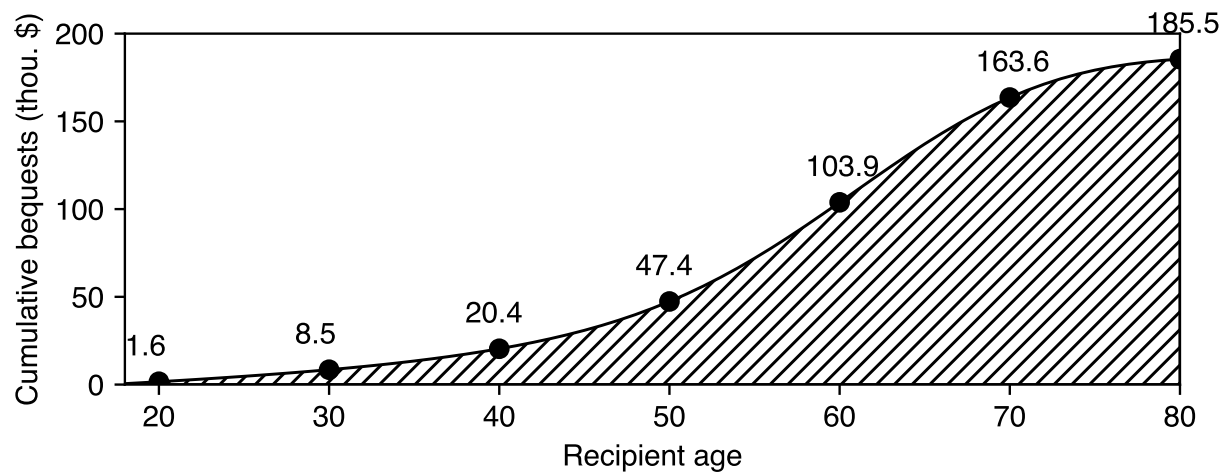


Figure A.1: Average life cycle bequests

Notes: This figure plots the cumulative average lifetime bequests by recipient (child) age.

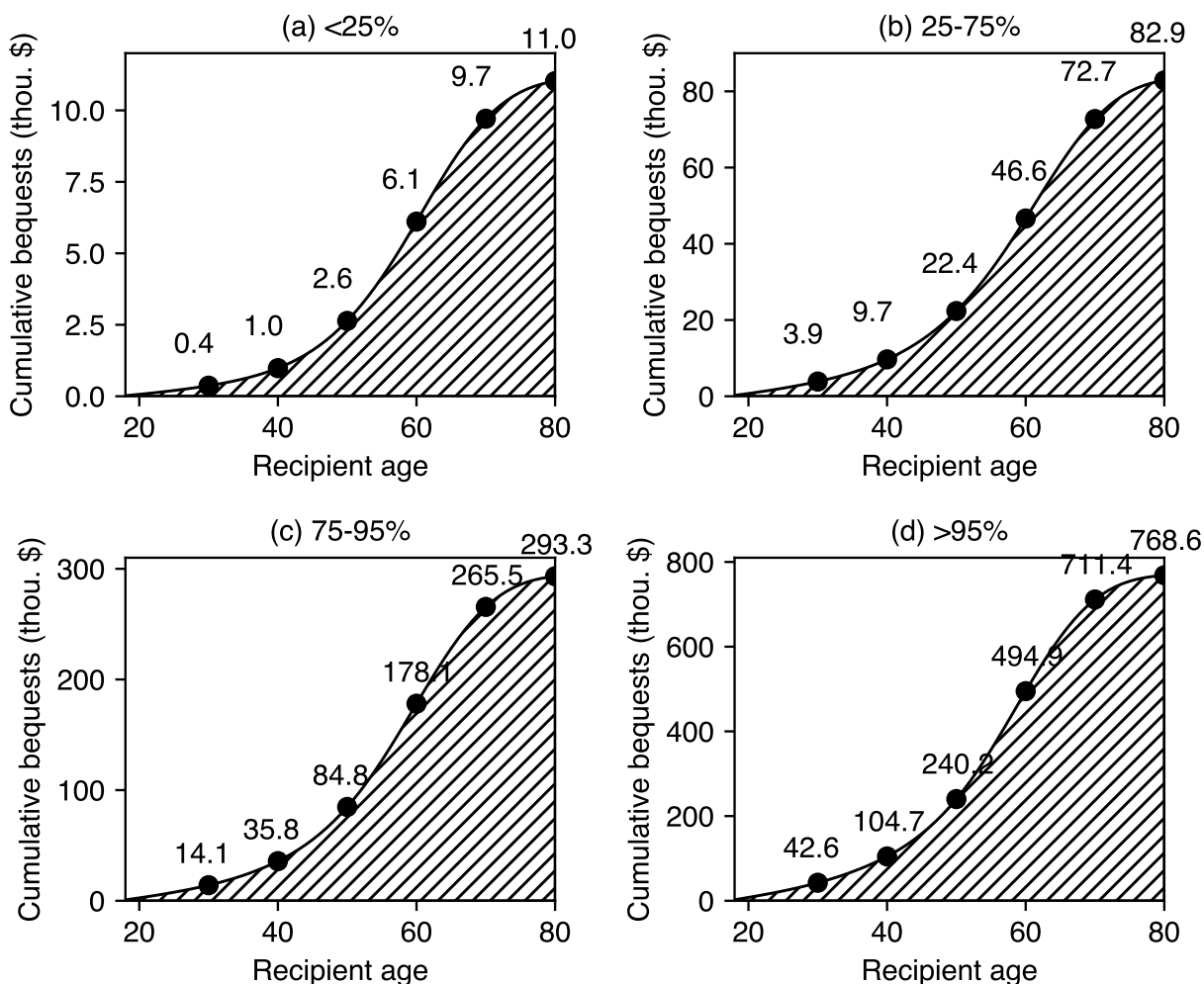


Figure A.2: Average life cycle bequests by parent wealth group

Notes: This figure plots the cumulative average lifetime bequests by recipient (child) age and donor (parent) wealth group.

B Appendix to section 3

	(1) Avg	(2) 0-25th	(3) 25-75th	(4) 75-95th	(5) >95th
Job Loss	51.333 (60.886)	-18.805 (21.263)	79.091 (55.092)	165.978 (213.406)	-897.119** (411.165)
Age 18-30	1,287.212*** (75.850)	399.507*** (48.845)	853.780*** (54.585)	1,628.739*** (133.794)	5,126.556*** (849.683)
Age 31-54	402.934*** (45.423)	77.073*** (18.940)	235.389*** (25.359)	470.769*** (70.605)	2,746.002*** (661.810)
Age 18-30 X Job Loss	964.519*** (283.704)	-97.288 (78.252)	461.138* (253.148)	2,098.992*** (759.418)	5,549.055** (2,487.342)
Age 31-54 X Job Loss	330.014*** (97.914)	156.605*** (42.171)	77.880 (69.822)	733.690** (333.424)	2,797.830** (1,146.635)
Constant	506.008*** (23.025)	63.828*** (16.179)	281.070*** (19.223)	1,071.463*** (55.785)	1,778.676*** (225.736)
Observations	227,530	49,503	119,875	46,874	11,278
R-squared	0.011	0.013	0.015	0.014	0.012
Demographic FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Table B.1: Job Loss and Transfers by Parent Wealth Group

Notes: This table reports the coefficients and standard errors from estimating equation 2. The dependent variable is total transfer amount (2024 USD), and Job Loss is an indicator variable equal to 1 when the recipient changes job status from working to not working between consecutive surveys.

	(1) Equity > 0	(2) Equity > 0	(3) Equity > 0
Parent Wealth 25-75th	0.051*** (0.006)	0.037*** (0.006)	0.008 (0.006)
Parent Wealth 75-95th	0.155*** (0.011)	0.129*** (0.012)	0.063*** (0.012)
Parent Wealth >95th	0.256*** (0.014)	0.212*** (0.016)	0.147*** (0.016)
Parent Equity Frac		0.117*** (0.021)	0.092*** (0.021)
Constant	0.118*** (0.004)	0.126*** (0.005)	0.160*** (0.006)
Observations	24,800	21,273	21,217
R-squared	0.239	0.235	0.277
Wealth FE	Yes	Yes	Yes
Parent Equity	No	Yes	Yes
Demographic FE	No	No	Yes
Year FE	No	No	Yes

Table B.2: Equity Participation and Parent Wealth

Notes: This table reports the coefficients and standard errors from estimating equation 3.

	(1) Avg	(2) 0-25th	(3) 25-75th	(4) 75-95th	(5) >95th
Job Loss	65.656 (63.838)	-25.080 (22.604)	79.562 (57.260)	201.362 (222.189)	-852.775* (437.017)
Work Down	104.767 (80.520)	-40.634* (24.250)	48.486 (97.795)	-12.271 (184.799)	-83.536 (600.347)
New Child	424.124*** (100.447)	85.421* (49.814)	404.584*** (98.534)	51.743 (264.276)	3,268.321** (1,594.894)
Divorce	-157.645* (95.554)	-25.132 (52.956)	-167.443** (80.713)	-419.514 (267.889)	550.073 (931.380)
Marriage	36.302 (71.793)	10.289 (25.519)	49.348 (66.901)	-80.564 (211.608)	-658.446 (639.420)
Age 18-30	1,284.089*** (82.219)	367.035*** (45.341)	854.669*** (73.747)	1,664.015*** (167.145)	4,388.585*** (832.017)
Age 31-54	364.038*** (56.750)	58.915** (23.575)	214.825*** (29.537)	347.409*** (76.835)	2,764.158*** (872.383)
Age 18-30 X Job Loss	1,194.754*** (301.042)	-24.037 (85.388)	573.429** (270.811)	2,217.685*** (779.513)	6,960.479*** (2,513.244)
Age 31-54 X Job Loss	328.557*** (105.225)	180.642*** (45.873)	92.734 (73.622)	682.968* (353.261)	2,654.371** (1,233.551)
Age 18-30 X Work Down	1,366.676* (745.806)	860.652** (424.271)	472.787** (216.345)	538.300 (574.855)	10,145.838 (7,876.220)
Age 31-54 X Work Down	187.650 (120.037)	150.460*** (54.066)	147.489 (125.730)	517.543* (292.058)	197.412 (1,025.590)
Age 18-30 X New Child	-1,087.171*** (185.229)	-107.962 (155.158)	-750.477*** (150.214)	-1,066.734** (444.320)	-4,495.235 (2,767.821)
Age 31-54 X New Child	-194.442 (120.511)	-3.448 (49.816)	-304.385*** (101.473)	211.900 (292.896)	-2,575.911 (1,971.764)
Age 18-30 X Divorce	-126.187 (591.723)	-223.016** (107.749)	13.651 (207.196)	-612.917 (569.876)	15,502.454 (17,791.825)
Age 31-54 X Divorce	171.226 (117.865)	-57.286 (53.749)	173.342* (96.531)	922.971*** (345.087)	356.633 (1,386.681)
Age 18-30 X Marriage	532.321** (216.405)	-69.939 (112.795)	385.706** (191.061)	761.634* (454.666)	1,550.078 (1,845.707)
Age 31-54 X Marriage	397.127*** (126.351)	85.274* (49.428)	214.223** (87.748)	812.993** (339.808)	2,329.881 (1,672.536)
Constant	492.881*** (26.198)	64.525*** (20.196)	271.504*** (21.567)	1,086.870*** (62.211)	1,646.010*** (253.157)
Observations	205,098	44,269	108,000	42,563	10,266
R-squared	0.012	0.018	0.017	0.016	0.016
Demographic FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Table B.3: Life Events and Transfers by Wealth

Notes: This table reports the coefficients and standard errors from estimating equation 2 for a large set of life events. The dependent variable is total transfer amount (2024 USD). Job Loss, Work Down, New Child, Divorce, and Marriage are indicator variables equal to 1 when the recipient experienced each event between consecutive surveys.

	(1) Aggregate	(2) 0-25th	(3) 25-75th	(4) 75-95th	(5) >95th
Severe Inc Loss	657.956*** (147.912)	199.714* (103.630)	625.180*** (242.229)	897.215** (422.185)	2,012.645** (813.532)
New Child	79.203 (102.051)	261.393* (148.389)	-98.004 (89.836)	213.531 (242.193)	573.184 (811.984)
Divorce	454.280** (204.294)	281.425 (183.214)	495.941* (270.092)	594.854 (1,201.186)	991.940 (1,498.735)
Marriage	132.352 (130.174)	-211.826 (137.031)	225.512 (159.784)	211.799 (398.286)	503.763 (714.996)
Constant	496.186*** (31.224)	244.406*** (29.777)	428.933*** (42.094)	636.397*** (88.012)	1,281.233*** (168.102)
Observations	18,582	6,086	9,328	1,948	1,220
R-squared	0.015	0.024	0.019	0.017	0.120
Demographic FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Table B.4: Life Events and Transfers by Wealth, PSID

Notes: This table reports the coefficients and standard errors from estimating equation 2 for a large set of life events, while excluding age group indicators (due to lack of observations of older recipients). The dependent variable is total transfer amount (2024 USD). Severe Inc Loss is an indicator variable equal to 1 when the recipient's income dropped by more than 50% between consecutive surveys. New Child, Divorce, and Marriage are indicator variables equal to 1 when the recipient experienced each event between consecutive surveys.

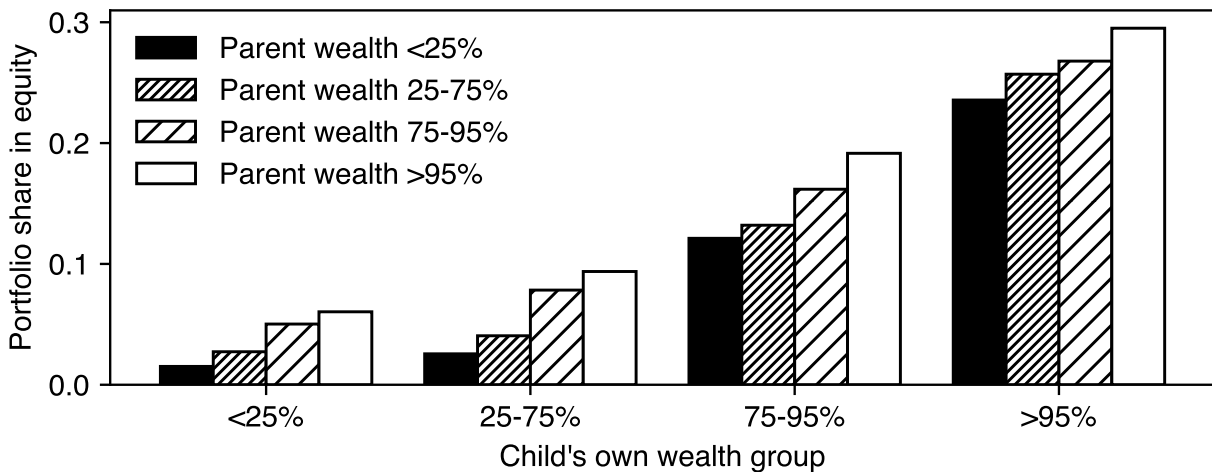


Figure B.1: Fraction of assets in equity by parental wealth group, by child's own wealth group

Notes: This figure plots the fraction of assets that are equity, broken out by child and parent wealth group.

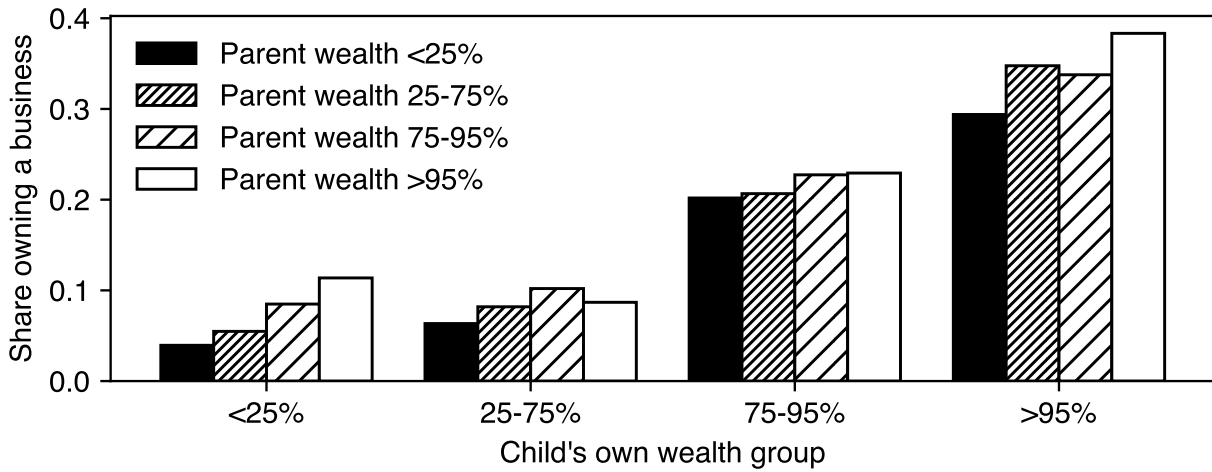


Figure B.2: Fraction of children owning a business by parental wealth group, by child's own wealth group

Notes: This figure plots the fraction of children owning a business, broken out by child and parent wealth group.

	(1) Self Employed	(2) Self Employed	(3) Self Employed
Parent Wealth 25-75th	0.016*** (0.005)	0.014*** (0.005)	0.004 (0.005)
Parent Wealth 75-95th	0.060*** (0.008)	0.053*** (0.008)	0.040*** (0.009)
Parent Wealth >95th	0.110*** (0.011)	0.097*** (0.011)	0.084*** (0.011)
Parent Self Employed		0.044*** (0.009)	0.047*** (0.009)
Constant	0.049*** (0.004)	0.047*** (0.004)	0.055*** (0.004)
Observations	24,800	24,800	24,736
R-squared	0.015	0.018	0.046
Parent Equity	No	Yes	Yes
Demographic FE	No	No	Yes
Year FE	No	No	Yes

Table B.5: Business Ownership and Parent Wealth

Notes: This table reports the coefficients and standard errors from estimating equation 3. The dependent variable is replaced with an indicator variable equal to 1 when the recipient owns a business.

C Appendix to section 4

C.1 Optimal decisions in retirement and the period before

In retirement. In retirement, the path of consumption satisfies the Euler equation

$$c_{t+1} = (\beta R_{j,t+1}(\omega))^{\eta_c} c_t \quad (\text{A.1})$$

and the budget constraint

$$a_t + c_t = R_{j,t}(\omega) a_{t-1} + \mathcal{S}(w_j h^p) + \tau_{j,t}(\omega). \quad (\text{A.2})$$

With these two equations and the terminal condition $a_{(T_{\ell,j}-1)} = 0$, we may solve for the path of consumption as a function of the starting level of assets $a_{(T_{w,j}-1)}$, the path of income, and the group-specific interest rates. For the purpose of cleaner notation, we'll suppress j subscripts and ω s throughout this derivation.

Solving the budget constraint forward, we obtain

$$c_{(T_{\ell}-1)} + \sum_{t=T_w}^{T_{\ell}-2} \left(\prod_{u=t+1}^{T_{\ell}-1} R_u \right) c_t = y_{(T_{\ell}-1)} + \sum_{t=T_w}^{T_{\ell}-2} \left(\prod_{u=t+1}^{T_{\ell}-1} R_u \right) y_t + \left(\prod_{t=T_w}^{T_{\ell}-1} R_t \right) a_{(T_w-1)}, \quad (\text{A.3})$$

where we define period income as

$$y_t = \mathcal{S}(w_j h^p) + \tau_{j,t}(\omega). \quad (\text{A.4})$$

Substituting the Euler equation (A.1) into (A.3), we find

$$c_{T_w} = \frac{y_{(T_{\ell}-1)} + \sum_{t=T_w}^{T_{\ell}-2} \left(\prod_{u=t+1}^{T_{\ell}-1} R_u \right) y_t + \left(\prod_{t=T_w}^{T_{\ell}-1} R_t \right) a_{(T_w-1)}}{\sum_{t=T_w+1}^{T_{\ell}-2} \left(\prod_{u=t+1}^{T_{\ell}-1} R_u \right) \left(\prod_{v=T_w+1}^t d_v \right) + \left(\prod_{u=T_w+1}^{T_{\ell}-1} R_u \right) + \left(\prod_{u=T_w+1}^{T_{\ell}-1} d_u \right)}, \quad (\text{A.5})$$

where the object d_t is

$$d_t = (\beta R_{j,t}(\omega))^{\eta_c}. \quad (\text{A.6})$$

We may also write (A.5) in terms of present discounted values, so

$$c_{T_w} = \frac{y_{T_w} + R_{T_w} a_{(T_w-1)} + \sum_{t=T_w+1}^{T_{\ell}-1} \left(\prod_{u=T_w+1}^t R_u^{-1} \right) y_t}{1 + \sum_{t=T_w+1}^{T_{\ell}-1} \left(\prod_{v=T_w+1}^t \frac{d_v}{R_v} \right)}. \quad (\text{A.7})$$

Further, the full sequence of consumption levels can be written in terms of c_{T_w} so

$$c_{T_w+u} = \left(\prod_{v=T_w+1}^{T_w+u} d_v \right) c_{T_w} \quad (\text{A.8})$$

and this means that the value starting at the beginning of retirement is linear in c_{T_w} . The full expression is

$$V_{T_w} = \left(1 + \sum_{u=1}^{T_\ell - T_w - 1} \beta^u \left(\prod_{v=T_w+1}^{T_w+u} d_v \right)^{\frac{\eta_c - 1}{\eta_c}} \right)^{\frac{\eta_c}{\eta_c - 1}} c_{T_w}. \quad (\text{A.9})$$

In terms of wealth and income, this is

$$V_{T_w} = \left(1 + \sum_{u=1}^{T_\ell - T_w - 1} \beta^u \left(\prod_{v=T_w+1}^{T_w+u} d_v \right)^{\frac{\eta_c - 1}{\eta_c}} \right)^{\frac{\eta_c}{\eta_c - 1}} \frac{y_{T_w} + R_{T_w} a_{(T_w-1)} + \sum_{t=T_w+1}^{T_\ell-1} \left(\prod_{u=T_w+1}^t R_u^{-1} \right) y_t}{1 + \sum_{t=T_w+1}^{T_\ell-1} \left(\prod_{v=T_w+1}^t \frac{d_v}{R_v} \right)}. \quad (\text{A.10})$$

With the knowledge that $\frac{d_t}{R_t} = \beta d_t^{\frac{\eta_c - 1}{\eta_c}}$, this may be simplified further as

$$V_{T_w} = \left(1 + \sum_{u=1}^{T_\ell - T_w - 1} \beta^u \left(\prod_{v=T_w+1}^{T_w+u} d_v \right)^{\frac{\eta_c - 1}{\eta_c}} \right)^{\frac{1}{\eta_c - 1}} \left[y_{T_w} + R_{T_w} a_{(T_w-1)} + \sum_{t=T_w+1}^{T_\ell-1} \left(\prod_{u=T_w+1}^t R_u^{-1} \right) y_t \right]. \quad (\text{A.11})$$

One period before. Knowing $y_{(T_w-1)} = w_j h^p \exp(\varepsilon) + \tau_{j,t}(\omega)$ and that, once the value of ε is realized, there is no more uncertainty in the model, we may extend equations (A.12),

(A.8), and (A.11) back by one period so

$$c_{(T_w-1)} = \frac{y_{(T_w-1)} + R_{(T_w-1)}a_{(T_w-2)} + \sum_{t=T_w}^{T_\ell-1} \left(\prod_{u=T_w}^t R_u^{-1} \right) y_t}{1 + \sum_{t=T_w}^{T_\ell-1} \left(\prod_{v=T_w}^t \frac{d_v}{R_v} \right)}. \quad (\text{A.12})$$

$$c_{(T_w+u-1)} = \left(\prod_{v=T_w}^{T_w+u-1} d_v \right) c_{(T_w-1)} \quad (\text{A.13})$$

$$V_{(T_w-1)} = \left(1 + \sum_{u=1}^{T_\ell-T_w} \beta^u \left(\prod_{v=T_w}^{T_w+u-1} d_v \right)^{\frac{\eta_c-1}{\eta_c}} \right)^{\frac{1}{\eta_c-1}} \left[y_{(T_w-1)} + R_{(T_w-1)}a_{(T_w-2)} + \sum_{t=T_w}^{T_\ell-1} \left(\prod_{u=T_w}^t R_u^{-1} \right) y_t \right]. \quad (\text{A.14})$$

Borrowing constraints. For the vast majority of parametrizations, the borrowing constraint will never bind during retirement; the drop off in income is simply too great. In the cases where it does, however, we can make adjustments to accommodate it.

C.2 Optimal decisions in one's work life

C.3 Optimal college attendance decision

The functions $\{W_j(h, z; \omega_j)\}_{j \in \{c, n\}}$ are given by equations (6) and (7). By standard results regarding GEV1 shocks, the probability that an agent goes to college, given their parameters, is

$$P(j = c \mid h, z, \Omega) = \left(1 + \exp \left(\frac{W_n(h, z; \omega_n) - W_c(h, z; \omega_c)}{\sigma} \right) \right)^{-1} \quad (\text{A.15})$$

and the expected value of having those particular parameters is given by

$$W(h, z, \Omega) = \sigma \log \left(\exp \left(\frac{W_c(h, z; \omega_c)}{\sigma} \right) + \exp \left(\frac{W_n(h, z; \omega_n)}{\sigma} \right) \right), \quad (\text{A.16})$$

where, in both cases, $\Omega = \{\omega_c, \omega_n\}$.

D Appendix to section 5

D.1 More details on processes and transfer types

D.2 Estimation procedure

Simulating a life, given initial conditions. Given a starting level of human capital h , learning rate z , transfer type ω , and education choice j , we can solve for the individual's policy functions for asset levels $a'_{j,t}(a_{t-1}, h_{t-1}, \varepsilon_t; z, \omega)$ and time allocation $i_{j,t}(a_{t-1}, h_{t-1}, \varepsilon_t; z, \omega)$. In the periods strictly before the period before retirement, these will be represented by Chebychev polynomials.

The steps for simulation starting in the period before retirement are much more straightforward. We can compute sequences of asset holdings and consumption immediately using the formulas of section C.1.

Computing conditional expectations. Let q_{65} be the parent's wealth quantile group at age 65. The moments we use to estimate the stochastic processes for human capital, learning ability, and transfer type require us to take expectations of the form $\mathbb{E}[y_t | q_{65}]$, where y_t is the value of the child's variable y at age t .

Simulation is not effective for computing these expectations inside of a minimum distance problem. It's noisy and inefficient. On the other hand, simulation is effective for computing the expectations $\mathbb{E}[y_t | h, z, \omega, j]$. For each (h, z, ω, j) combination, we can compute this expectation by simulating a large number of individuals with those initial conditions and taking the mean value for that panel.

By that principle, we can create N bins for the wealth levels a person can have at age 65 and use simulation to quickly compute $P(g_{a,65} = k | h, z, \omega, j)$, the probability that a person's wealth bin at age 65 $g_{a,65}$ is the k -th one.

The next step is to marginalize over one's education level j and value for ω . We evaluate

$$P(\omega_c, \omega_n, j | h, z) = \underbrace{P(j | \omega_c, \omega_n, h, z)}_{\text{Output of model solution}} \underbrace{Q_1(\omega_c | h, z) Q_2(\omega_n | h, z)}_{\text{Input processes}} \quad (\text{A.17})$$

$$\mathbb{E}[y_t | h, z] = \sum_{\omega_c, \omega_n, j} \underbrace{\mathbb{E}[y_t | h, z, \omega, j]}_{\text{Pre-computed via simulation}} P(\omega_c, \omega_n, j | h, z), \quad (\text{A.18})$$

which allows us compute $P(g_{a,65} = k | h, z)$ as well.

The Markov process $Q_0(h, z | h_p, z_p)$, which is an input we specify, implies a stationary

distribution $P(h, z)$, so we can compute the unconditional distribution $P(g_{a,65} = k)$ along with the unconditional expectation $\mathbb{E}[y_t]$. Then

$$k_q^* = \min k_q \quad (\text{A.19})$$

$$k_q = \left\{ \ell \left| \sum_{k=0}^{\ell} P(g_{a,65} = k) \geq q, \ell \in \{0, \dots, N-1\} \right. \right\} \quad (\text{A.20})$$

Then we know that $P(q_{65}) = P(g_{a,65} = k_q^*)$ and also that, for the conditional probability, $P(q_{65} | h, z) = P(g_{a,65} = k_q^* | h, z)$. Moreover, by Bayes' rule

$$P(h, z | q_{65}) = \frac{P(q_{65} | h, z) P(h, z)}{P(q_{65})}, \quad (\text{A.21})$$

so we conclude that

$$\mathbb{E}[y_t | q_{65}] = \sum_{h, z, h_p, z_p} \mathbb{E}[y_t | h, z] \underbrace{Q_0(h, z | h_p, z_p)}_{\text{Input process}} P(h_p, z_p | q_{65}). \quad (\text{A.22})$$

This particular procedure shows the case where the parents' wealth group is the top $(1 - q)\%$, but we can see how it may be extended quite easily to the other wealth groups we consider in the paper.

Computing the loss. Taking the model parameters in table 3 as given, the expectations $\mathbb{E}[y_t | h, z, \omega, j]$ and $P(j | \omega_c, \omega_n, h, z)$ can be pre-computed without any knowledge of Q_0 , Q_1 , or Q_2 . Then, for each evaluation of the loss function, we need only compute the conditional expectations for the relevant moments using the procedure above, which speeds estimation up considerably. It also eliminates simulation error in $(h, z, \omega_n, \omega_c, j)$, since we're able to use the exact distributions over these variables, which massively reduces the difficulty in finding the optimum in this very high-dimensional problem.

D.3 Additional moments

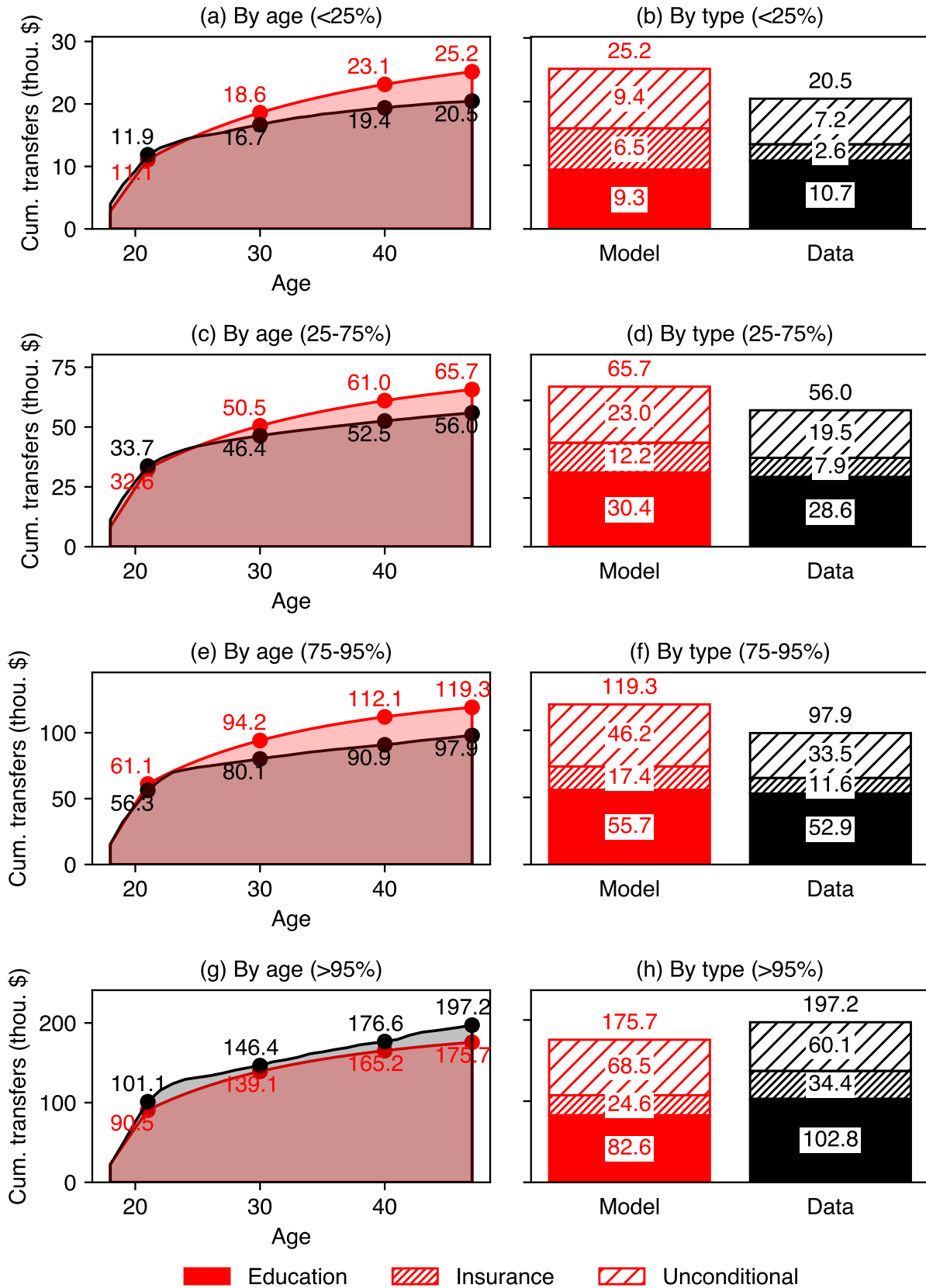


Figure D.1: Transfer paths and transfer mix, by parents' wealth group (model v. data)

E Appendix to section 5

E.1 Markov transition matrices with distribution of parent characteristics changing within parent group

		Baseline				No transfers (PE)			
<i>Child grp.</i>		<25%	25-75%	75-95%	>95%	<25%	25-75%	75-95%	>95%
<i>Parent grp.</i>	<25%	0.51	0.49	0.0	0.0	0.49 ↓	0.51 ↑	0.0 ↑	0.0 ↓
	25-75%	0.24	0.48	0.21	0.07	0.2 ↓	0.57 ↑	0.18 ↓	0.05 ↓
	75-95%	0.0	0.5	0.4	0.09	0.0 ↑	0.46 ↓	0.4 ↓	0.14 ↑
	>95%	0.0	0.64	0.33	0.03	0.0 ↓	0.48 ↓	0.49 ↑	0.03 ↑

Table E.1: Probability of child retirement wealth group, given retirement wealth group, baseline v. partial eq. counterfactual

		Baseline				No transfers (PE)			
<i>Child grp.</i>		<25%	25-75%	75-95%	>95%	<25%	25-75%	75-95%	>95%
<i>Parent grp.</i>	<25%	0.53	0.47	0.0	0.0	0.5 ↓	0.49 ↑	0.0 ↑	0.0 ↑
	25-75%	0.22	0.48	0.22	0.07	0.19 ↓	0.59 ↑	0.17 ↓	0.06 ↓
	75-95%	0.0	0.5	0.41	0.09	0.0 ↑	0.43 ↓	0.43 ↑	0.14 ↑
	>95%	0.0	0.66	0.31	0.03	0.0 ↓	0.51 ↓	0.46 ↑	0.03 ↑

Table E.2: Probability of child permanent income group, given parent's permanent income group, baseline v. partial eq. counterfactual

		Baseline				No transfers (GE)			
<i>Child grp.</i>		<25%	25-75%	75-95%	>95%	<25%	25-75%	75-95%	>95%
<i>Parent grp.</i>	<25%	0.51	0.49	0.0	0.0	0.56 ↑	0.41 ↓	0.03 ↑	0.0 ↑
	25-75%	0.24	0.48	0.21	0.07	0.22 ↓	0.51 ↑	0.21 ↑	0.06 ↓
	75-95%	0.0	0.5	0.4	0.09	0.01 ↑	0.5 ↓	0.41 ↑	0.08 ↓
	>95%	0.0	0.64	0.33	0.03	0.01 ↑	0.58 ↓	0.37 ↑	0.04 ↑

Table E.3: Probability of child retirement wealth group, given parent retirement wealth group, baseline v. general eq. counterfactual

		Baseline				No transfers (GE)			
<i>Child grp.</i>		<25%	25-75%	75-95%	>95%	<25%	25-75%	75-95%	>95%
<i>Parent grp.</i>	<25%	0.53	0.47	0.0	0.0	0.52 ↓	0.48 ↑	0.0 ↑	0.0 ↑
	25-75%	0.22	0.48	0.22	0.07	0.21 ↓	0.55 ↑	0.2 ↓	0.03 ↓
	75-95%	0.0	0.5	0.41	0.09	0.01 ↑	0.38 ↓	0.52 ↑	0.09 ↑
	>95%	0.0	0.66	0.31	0.03	0.0 ↑	0.29 ↓	0.44 ↑	0.26 ↑

Table E.4: Probability of child permanent income group, given parent permanent income group, baseline v. general eq. counterfactual