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Parental Death, Inheritance, and Labor Supply in the United States

by

Elif Taşar

A dissertation submitted in partial satisfaction of the

requirements for the degree of

Doctor of Philosophy

in

Agricultural and Resource Economics

in the

Graduate Division

of the

University of California, Berkeley

Committee in charge:

Professor Patrick Kline, Co-Chair

Professor James Sallee, Co-Chair

Professor Michael Anderson

Professor David Card

Spring 2026

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Abstract

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Throughout the world, population aging is reshaping workforces, pension systems, health-care, and wealth distributions. As larger cohorts reach old age, parental deaths—and any inheritances they trigger—will affect more households. There is little evidence on whether parental death is economically consequential for adult children. While wealth and income transfers often increase consumption of leisure, parental death may affect children’s economic well-being through other channels such as relief from eldercare obligations or grief. The aggregate impact of inheritances and corresponding earnings adjustments on wealth inequality is also ambiguous. In the United States, the absence of wealth and inheritance registries and barriers to constructing parent-child linkages in administrative data have constrained credible evidence on these questions. This dissertation studies how inheritances affect labor supply in the U.S. using large-scale administrative data. All three chapters are coauthored with John Voorheis at the U.S. Census Bureau.

Chapter 1 provides a theoretical framework for understanding how the receipt of an inheritance may affect labor supply, and describes the construction of a new dataset for studying the effects of parental death on adult children’s economic behavior. The canonical intertemporal labor supply model (Blundell and MaCurdy, 1999) assumes perfect foresight, implying that receipt of an inheritance has no impact on permanent income and therefore does not alter labor supply. To rationalize the possibility of earnings responses upon receiving an inheritance, we introduce a simple extension to the conventional model in which the timing of inheritance receipt is unknown. We show that, in the presence of timing uncertainty, the optimal choice of hours declines when the inheritance arrives. Next, the chapter discusses how we leverage federal tax and Social Security records for the universe of Social Security Number holders from 1994 to 2022 to build a panel of nearly two million adult children who lose their last living parent from 2005 to 2022. Finally, we discuss how variables in tax data can be used to partially infer inheritances.

Chapter 2 estimates behavioral responses to parental death using a staggered-adoption event study approach. Our results indicate that the death of a last parent causes sizable gains in investment income—our main proxy for inheritances—and proportionate reductions in labor supply. On average, annual per-adult investment income at the tax unit level increases by about \$300 (45 percent) and annual per-adult wage earnings decrease by \$600 (2 percent). Using capitalization methods from the literature, the impact on flow investment income corresponds to a per-adult stock of wealth of around \$13,900 and a total stock of \$20,500 at the tax unit-level. Investment income is an imperfect proxy for inheritances that reflects inherited housing incompletely and many other assets not at all. To account for the fact that many inherited assets do not generate investment income and the possibility that children immediately liquidate a portion of their inheritance to spend on consumption or debt, we benchmark our results to public data. Specifically, we combine results on child and parent investment income with information on the portfolio composition of parents in the Survey of Consumer Finances (SCF) who are observably similar to dying parents in our sample. From this exercise, we estimate that the implied stock value of our causal estimate for investment income captures between 13 and 38 percent of total inheritances.

Chapter 3 assesses the relative importance of income effects versus non-income mechanisms, estimates the marginal propensity to earn, and characterizes distributional effects of inheritances on investment income inequality. We study treatment effect heterogeneity along numerous dimensions and, across subsamples, find that earnings reductions generally mirror investment income gains, with both outcomes scaling markedly with parental income. Under strong assumptions and using an instrumental variables approach, we infer that a dollar of unearned income from inheritance leads to an 11 to 31 cent reduction in earnings. To the extent that the full inheritance is partially anticipated, these estimates understate the true earnings response to an exogenous shock to unearned income. Through heterogeneity analyses, we demonstrate that several non-income mechanisms such as the loss of informal childcare, compensatory labor supply to offset parent healthcare costs (i.e., added worker effects), and co-employment among children and parents are unlikely to play a significant role. By estimating the causal impact of parental death on the probability that a child's investment income falls below a set of fixed thresholds, we trace out effects on the cumulative distribution function and the associated Lorenz curve of child investment income. We find that parental death and associated inheritances slightly compress inequality in child investment income. This result is counterintuitive, but consistent with inheritances representing larger proportional increases in wealth for poorer individuals.

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Chapter 1

Inheritance and labor supply: theory and measurement

1.1 Introduction

This chapter lays the theoretical and empirical foundations for the rest of the dissertation. We begin by considering when economic theory predicts that inheritances should affect labor supply. Under the canonical intertemporal model with perfect foresight (Blundell and MaCurdy, 1999), any future inheritance is already incorporated into permanent income at birth, so its arrival triggers no adjustment in hours or consumption. This benchmark predicts a zero earnings response—a prediction we will find to be violated in the data.

To rationalize positive earnings responses, we extend the standard framework to allow uncertainty in the timing of inheritance receipt. We show that timing uncertainty implies a positive wealth shock at the moment an inheritance arrives. This prediction is reinforced if individuals also systematically underestimate the amount of the transfer, or face other frictions such as credit constraints or consumption commitments. The model thus provides a clear empirical prediction: parental death, to the extent it is accompanied by an inheritance, should cause a reduction in labor supply.

We then describe the data used to test this prediction. We construct a parent-child linked panel from federal tax and Social Security records for the near-universe of SSN holders from 1994 to 2022, yielding nearly two million adult children who lose their last living parent between 2005 and 2022. The dataset is, to our knowledge, the most comprehensive ever assembled for studying the economic consequences of parental death and inheritance in the United States. Section 1.2 presents the model. Section 1.3 describes the data, sample construction, key variables, and how we measure inheritances. Section 1.4 concludes.

1.2 Theoretical framework

In this section, we present the conventional intertemporal model of optimal labor-consumption choice with perfect foresight, following MaCurdy (1981). Next, we discuss how—absent perfect foresight, or due to violations of the permanent income hypothesis—inheritances may constitute a positive wealth shock that reduces labor supply.

With perfect foresight, an individual solves the following problem:

$$\max \sum_{t=0}^T \beta^t u(c_t, h_t)$$

subject to the budget constraint

$$a_{t+1} = (1 + r_{t+1})(a_t + w_t h_t - c_t) \quad (1.1)$$

which requires that the present value of permanent income equals the present value of lifetime consumption:

$$A_0 + \sum_{t=0}^T \left(\frac{w_t h_t}{\prod_{k=1}^t (1 + r_k)} \right) = \sum_{t=0}^T \left(\frac{c_t}{\prod_{k=1}^t (1 + r_k)} \right) \quad (1.2)$$

where β is the subjective discount factor, c is consumption, h is hours of work, a is assets, r is the real interest rate, and w is the real hourly wage. In this model, the present value of any inheritance is fully captured by the A_0 component of permanent income (initial assets). Therefore, receipt of an inheritance would not alter the optimal choice of hours or consumption at the time of inheritance or beyond.

In contrast, uncertainty in either the time of receipt or the amount of an inheritance can generate a positive surprise in the present value of permanent income. To see how timing uncertainty alone predicts a reduction in labor supply upon the arrival of an inheritance, consider a stylized case where an individual knows with certainty that she will receive a one-time inheritance $I > 0$ at an unknown date in the future. Let p denote the per-period arrival probability, and let a_t denote assets at the beginning of period t . For analytical tractability, we will move to an infinite horizon setting and assume additively separable utility with $u(c) = \ln(c)$ and $v(h) = \frac{1}{2}\chi h^2$. The individual's dynamic problem is:

$$V(a_t, 0) = \max_{c_t, h_t} \left\{ \ln(c_t) - \frac{1}{2}\chi h_t^2 + \beta[(1-p)V(a_{t+1}, 0) + pV(a_{t+1} + I, 1)] \right\} \quad (1.3)$$

$$V(a_t, 1) = \max_{c_t, h_t} \left\{ \ln(c_t) - \frac{1}{2}\chi h_t^2 + \beta V(a_{t+1}, 1) \right\} \quad (1.4)$$

where the budget constraint is:

$$a_{t+1} = (1 + r)(a_t + w h_t - c_t) \quad (1.5)$$

Equation (1.3) corresponds to the state where the individual has not yet received the inheritance. Equation (1.4) corresponds to the state where the individual has received the inheritance (i.e., the infinite horizon version of the above MaCurdy problem).

In both states, the FOCs take the same form. In state $s \in \{0, 1\}$:

$$\text{FOC for } c_t : \quad \frac{1}{c_t} = \beta R V'(a_{t+1}, s) \quad (1.6)$$

$$\text{FOC for } h_t : \quad \chi h_t = \beta R w V'(a_{t+1}, s) \quad (1.7)$$

where $R \equiv 1 + r$.

Dividing (1.7) by (1.6), the V' term cancels in both states, yielding the intratemporal condition:

$$h_t^* = \frac{w}{\chi c_t^*} \quad (1.8)$$

Note that, at $I = 0$, equations (1.3) and (1.4) are identical, so:

$$V(a_t, 0; 0) = V(a_t, 1), \quad c^*(a_t, 0; 0) = c^*(a_t, 1), \quad h^*(a_t, 0; 0) = h^*(a_t, 1)$$

PROPOSITION 1: For $I > 0$ and $\beta R^2 > 1$, the linearization of optimal hours around $I = 0$ satisfies

$$h_t^*(a_t + I, 1) - h_t^*(a_t, 0; I) \approx -h_t^*(a_t, 1) \cdot \frac{r}{r + p} \cdot \frac{(1 - \beta) I}{2c_t^*(a_t, 1) - a_t(1 - \beta)} < 0 \quad (1.9)$$

That is, optimal hours decline upon receipt of the inheritance.

PROOF: See Appendix A.

Note that the key assumptions for this result are stochastic arrival time of the inheritance and concave utility; we have not imposed an assumption of rational expectations over p . That is, the result does not depend on whether the true p equals the perceived p . From equation (1.9), underestimating p will yield a larger labor supply response by increasing the quantity $r/(r + p)$.

In reality, it is plausible that individuals systematically underestimate the *amount* of inheritance in addition to being surprised by its timing. One simple reason is that uncertainty in receipt timing may correspond to a positive surprise in the amount, since parents have less time to spend down their wealth before they die. A positive shock to the amount of the inheritance would also unambiguously cause labor supply to fall. Alternatively, individuals may be inattentive or myopic when it comes to preparing for a parent's death. Other frictions such as credit constraints or consumption commitments may also cause inheritances to reduce labor supply even under full anticipation and fully rational behavior.

1.3 Data

1.3.1 Data sources and sample construction

We link multiple administrative, Census and survey datasets using the Census Bureau’s data linkage infrastructure (Wagner and Layne, 2014). We start from a commingled set of federal tax information containing the universe of individuals who have a Social Security Number (SSN) from 1994 to 2022, similar to Chetty et al. (2020).¹ This dataset includes key fields from the IRS Form 1040 and the Social Security Administration’s Numident records provide sex and dates of birth and death. We link children to parents using fields on the 1040 that indicate dependent claiming. We define an individual’s parents to be the one or two individuals who claimed her as a dependent in the first year she was claimed. We restrict claimees to being under 24, the age limit for dependents, at the time they are claimed. We then construct a balanced panel of adult children with linked parents from 2005 to 2022, the years for which W-2 data are available.

To obtain our main estimation sample, we define treatment as experiencing the death of a parent who is age 65 or older and who is one’s last parent to die, including single parent deaths.² We then restrict to children who undergo treatment during the sample period. In our sample, only a very small share of individuals have a spouse who also loses an elderly, last parent during the sample period. We drop these individuals from the sample to guarantee that all married couples only undergo treatment, as we define it, once. We then link to the Census Bureau’s Environmental Impacts Frame (Voorheis et al., 2023), which provides harmonized address history information along with race and ethnicity for the near population sourced from administrative records and the Census Bureau’s Master Address File. To assign education and homeownership, we link to the short and long form Decennial Censuses and American Community Surveys from 2000 through 2022.

Our inability to observe dependent claiming prior to 1994 has important consequences for our sample. First, we only observe parent-child linkages for people whose parents were filing taxes when their children were age 24 or under. Second, the sample consists of adult children belonging to birth cohorts from 1971 to 1987, meaning that the oldest children we observe are only age 51 by 2022, the end of our sample period.³ As such, the dying parents we observe are necessarily either parents who had children relatively late in life or parents who die relatively early deaths, or both. We discuss this selection in Section 1.3.3.

1.3.2 Terminology and key variables

This section outlines the key variables used in our estimation. Further details on variable definitions can be found in Appendix D.

¹1994 is the earliest year of tax data in which dependent claiming fields are available.

²In heterogeneity analysis, we explore outcomes when treatment is defined as the death of a first (elderly) parent.

³The range of birth cohorts among dying parents is 1916 to 1957.

Some economic outcomes are reported at the tax unit level and cannot be attributed to a specific individual for married couples. Therefore, for consistent comparison of all outcomes across both single and married tax units, unless otherwise noted we report outcomes on a per-adult basis by normalizing them by the number of adults in the tax unit. Following Golosov et al. (2024) and others, we define this number as two for individuals with filing status “married filing jointly” and one otherwise. Therefore, single person tax units include non-filers and filers who do not file jointly. We obtain filing status and spouse identity from the 1040.

Tax variables. *Wage earnings* or simply *earnings* refers to the sum of pre-tax wages, tips, salary taxable fringe benefits paid by all employers (i.e., the sum of earnings across W-2 forms) for an individual in a given year. It does not include self-employment income (i.e., self-employment business, farm, or partnership income). We define *investment income* as the sum of taxable and tax-exempt interest income, taxable dividend income, and gross rental income in a given year. For non-filers, we set these quantities equal to \$0. *Adjusted gross income*, or AGI, is the sum of total labor earnings, investment income, pension and retirement income, taxable Social Security payments, capital gains, unemployment compensation, business income, farm income, royalties, and real estate income in a given year and is net of above-the-line deductions.⁴ We report all monetary values in inflation-adjusted 2022 U.S. dollars using the Consumer Price Index for All Urban Consumers (CPI-U) to adjust.⁵ We also use indicators for the receipt of certain information returns, described in Chapter 2, as outcome variables.

Research design variables. The *treatment year* is the year of death of the individual’s elderly, last parent. We refer to all individuals who experience the death of such a parent in the same year as a *treatment cohort*. The *baseline year* is defined as one year prior to the treatment year. Unless otherwise noted, the *baseline mean* of a given variable is its mean in the baseline year among treatment cohorts for which we estimate treatment effects. The *event time* ℓ for treatment cohort c is the calendar year $t = c + \ell$, where ℓ may be positive or negative.

1.3.3 Descriptive statistics

Column 1 of Table 1.1 reports a set of summary statistics for individuals and parents in our sample—that is, the sample of individuals with at least one linked parent who lose an elderly, last parent during the sample period. Our final sample consists of nearly two million unique adult children and 1.4 million parent deaths from 2010–2022. All summary statistics are measured in their baseline year, i.e., one year prior to parent death. Each statistic is a weighted average using cohort size as weights. We find that, consistent with the selection described above, individuals in our sample lose their last parent when both they and the parent are relatively young, about 38 years old and 73 years old, respectively. Appendix Table B.1 reproduces the Social Security Administration’s cohort life table for the closest

⁴Real estate income includes but is not limited to rental income.

⁵We winsorize monetary variables at the 0.1 and 99.9th percentiles.

available cohort (1940) to the average parent birth cohort in our sample (1943). The table suggests that, approximately, male (female) dying parents in our sample belong to the first one half (one third) of their birth cohort to die.

In column 2, we present corresponding summary statistics for a randomly drawn 10 percent sample of all individuals belonging to the same birth cohorts as those in our sample and with at least one linked parent (unconditional on parental death). Individuals and parents in our sample earn less and have lower investment income than their counterparts in the any parent sample, consistent with early (parental) mortality being more prevalent among lower income groups. In the case of parents, lower AGI and lower investment income among parents in our main sample reflects not just lower socioeconomic status but also the fact that parent tax units in the main sample consist of only the sole remaining parent. In spite of these differences, the final four rows of Table 1.1 demonstrate that individuals in our sample are well represented in each quartile of the earnings distribution of the any parent sample.

Identifying parent linkages requires parents to have filed taxes in the 1990s, and filers are higher income than non-filers on average. Appendix Table B.2 reproduces key summary statistics for our main sample and compares them to summary statistics from a randomly drawn 10 percent sample of all individuals belonging to the same birth cohorts, unconditional on linkage to any parent. The table illustrates that median wage earnings in our main sample are only slightly lower than in the full population of SSN-holders belonging to the same birth cohorts. Employment shares are comparable across the two samples. Strikingly, the Black share of our main sample remains substantially higher than that of the full population, indicating the extent to which early mortality varies by race. In combination with Table 1.1, Appendix Table B.2 illustrates that, while conditioning on linkage to a parent selects for higher socioeconomic status than the full population, conditioning on linkage to a parent who dies early results in a sample that is slightly disadvantaged relative to the full population.

1.3.4 Measuring inheritances

Institutional background. In the U.S., there is no requirement that parents bequeath assets to their children upon death. There are, however, benefits to bequeathing wealth to one's children upon death rather than during one's lifetime. Namely, bequeathed wealth is generally not taxed due to the tax code's step-up basis feature and absence of meaningful estate taxation. The step-up basis stipulates that when an heir inherits an asset the asset's value is reset to its fair market value at the time of the original owner's death, rather than the value it had when it was originally purchased by the decedent.

With a filing threshold of \$28M for married couples as of 2025, the federal estate tax binds for only about 0.1 percent of decedents (Alvaredo et al., 2017).⁶ The few states that impose estate or inheritance taxes also have large exemptions. Inter vivos gifts are generally also

⁶Each spouse has an exemption of \$14 million; any unused portion of the first deceased spouse's exemption can be preserved and added to the surviving spouse's exemption.

not taxed, but any sale of assets to facilitate such gifts is subject to capital gains taxation. Only annual gifts above \$38,000 per married couple are reportable (in 2025). Amounts exceeding this exclusion amount are subject to taxation only if they also exceed a lifetime gift exemption, which is equal to the estate tax exemption and therefore seldom binds.

While the transfer of inherited assets is typically not taxed, distributions from inherited tax-deferred retirement accounts are taxable as ordinary income. Non-spouse beneficiaries listed on retirement accounts must contact the account-holder’s financial institution or plan administrator to establish an “inherited account” into which funds are transferred. In addition to taxes on retirement withdrawals, individuals face taxes on income earned from inherited financial assets, investment properties, or other sources. Life insurance death benefits are generally tax-exempt.

When a parent dies, any debts are paid from their estate, and only what remains can be inherited. Heirs do not personally inherit those debts. The main exception is secured debts such as mortgages and car loans. If heirs wish to retain the assets in such cases (e.g., keep the family home), they must continue making loan payments or refinance.

Proxies for inheritances. As mentioned in Section 1.3.2, our main proxy for inheritances—investment income—reflects returns on dividends, interest income, and rental income from financial assets and investment properties. To the extent that financial assets are liquidated or drawn down (for consumption or to pay down debt) investment income underestimates inheritances. To the extent that assets such as retirement accounts or proceeds from house sales are reinvested in financial assets, investment income reflects these components of inheritances. This is unlikely in the case of retirement assets, since retirement is a highly tax-advantaged means of holding wealth. In Chapter 2, we will show that comparisons to public data imply that investment income captures between 13 and 38 percent of total inheritances.

We also measure additional signals of receiving an inheritance in the form of indicators for the receipt of information returns, known as 1099 forms (or Form 1098 in the case of the form issued by mortgage interest payments). Like W-2s, these forms are filed with the IRS by firms (financial institutions or closing agents in the case of the 1099-S) and appear in our data regardless of whether individuals file taxes in a given year. Our data include indicators for receiving Form 1099-R, which reports retirement account distributions or rollovers; Forms 1099-INT and 1099-DIV, which indicate receipt of annual interest or dividend income; Form 1099-S, which documents proceeds from real estate transactions; and Form 1098, which reports mortgage interest payments.

Children who inherit retirement accounts should nearly universally receive Form 1099-R in at least one year of our post-period. The reason is that, after parental death, a listed child beneficiary must open an inherited retirement account, into which funds are transferred, with the relevant financial institution or employer plan administrator. During our sample period, IRS rules stipulated that child beneficiaries of retirement accounts either begin taking annual required minimum distributions (RMDs) by December 31 of the year following the parent’s death or withdraw the full account balance within five years.

With respect to housing, closing agents generally must file Form 1099-S for home sales but are exempt from this requirement if sellers certify their property as a primary residence and the property meets certain excludability criteria regarding the sale price and capital gain.⁷ During our sample period, median house sale prices imply that many sales by owner-occupiers would not be reported.⁸ In contrast, heirs who sell an inherited house typically would receive the form since in most cases the house would not have been their primary residence. Mortgage servicers issue Form 1098 to borrowers except in rare cases (namely, when interest paid is under \$600 per year).

Forms 1099-INT and 1099-DIV are issued to individuals holding financial assets unless those assets generate under \$10 in interest or dividend income per year. The primary form of non-income bearing financial assets held by households are traditional checking and savings accounts, which yield little to no interest. However, based on the 2010–2016 average national interest rate for checking accounts of 0.06 percent, balances of roughly \$17,000 would suffice to generate at least \$10 in interest, implying limited scope for receipt of these forms to underestimate inheritances from financial assets (Federal Deposit Insurance Corporation).⁹

These details, along with other components of inheritances that are captured by neither investment income nor information returns (namely, business income and non-housing durable goods such as vehicles), are summarized in Appendix Table B.3.

⁷More precisely, the house must have been a primary residence for two of the prior five years. In addition, both the sale price and gain must be below \$250,000 (for single sellers) or \$500,000 (for married sellers). In practice, absent such certification, closing agents often issue the form by default.

⁸During our sample period, the median U.S. home price in nominal terms ranged from about \$220,000 to \$310,000 (Federal Reserve Bank of St. Louis).

⁹The average national savings rate was higher, about 0.10 percent, during this time period.

Table 1.1: Summary statistics

	Main sample (last parent dies) (1)	Any linked parent (10% sample) (2)
<i>Children</i>		
Age	38.26	36.03
Birth year	1979	1981
Female	0.49	0.49
Married	0.37	0.45
White	0.57	0.65
Black	0.21	0.14
Hispanic	0.15	0.15
Number of linked parents	1.47	1.69
Has female linked parent	0.76	0.90
Has male linked parent	0.71	0.79
Has positive wage earnings	0.74	0.79
Wage earnings	\$42,300	\$50,140
Wage earnings (median)	\$27,890	\$36,890
Wage earnings (cond. on positive)	\$57,510	\$63,440
Tax unit investment income	\$1,583	\$2,020
Tax unit investment income (median)	\$0	\$0
Relative Q1 earnings share	0.31	0.25
Relative Q2 earnings share	0.26	0.25
Relative Q3 earnings share	0.22	0.25
Relative Q4 earnings share	0.20	0.25
<i>Parents</i>		
Dying parent age at death	73.59	73.33
Dying parent female	0.55	0.54
Oldest parent birth year	1943	1952
Oldest parent number of kids	1.95	2.48
1994 tax unit AGI	\$71,580	\$95,030
1994 tax unit AGI (median)	\$51,910	\$73,690
Tax unit investment income	\$3,478	\$8,249
Tax unit investment income (median)	\$0	\$0.53
Number of unique individuals	1,939,000	4,655,000
Number of unique parent deaths	1,416,000	216,000

Notes: This table presents, in column 1, descriptive statistics for our main estimation sample of individuals who lose an elderly, last parent. All monetary values are reported in 2022 U.S. dollars. In the upper section of the table, we report mean characteristics for children (except where otherwise noted). All values in column 1 are measured one year prior to parental death and reported as cohort size-weighted averages. Column 2 reports the same statistics for all individuals in the same birth cohorts as our main sample (1971–1987) to whom we can link at least one parent. We also construct earnings quartiles of the any parent sample for each calendar year. In the middle section of the table, we report mean characteristics for parents (except where otherwise noted). Source: Census Environmental Impacts Frame, Master Address File, Decennial Census (2000, 2010), American Community Survey (2000–2022); IRS 1040s, W-2s (2005–2022); SSA Numident (1994–2022).

1.4 Conclusion

This chapter has established two building blocks for the empirical analysis in Chapters 2 and 3. First, we showed that the standard intertemporal labor supply model, once extended to allow uncertainty in inheritance timing, predicts that receipt of an inheritance will reduce labor supply. This prediction arises from timing uncertainty and is reinforced by any tendency to underestimate the amount of the transfer or by credit constraints.

Second, we described a uniquely rich administrative dataset—linking federal tax records to Social Security, Census, and survey data—covering nearly two million adult children who lose a last, elderly parent between 2005 and 2022. The dataset allows us to observe investment income, a proxy for inherited wealth, alongside labor earnings, at the individual and household level over nearly three decades. We also described the institutional landscape governing inheritance in the U.S. and our proxies for wealth transfers, including investment income flows and information returns associated with retirement, housing, and financial assets.

Chapter 2 takes these theoretical predictions to the data, presenting our research design and main empirical results on how parental death affects investment income and earnings.

Chapter 2

Behavioral responses to parental death

2.1 Introduction

Building on the dataset and theoretical framework developed in Chapter 1, this chapter estimates the causal effect of losing a last, elderly parent on the economic behavior of adult children. The core identification challenge is that individuals who lose parents at different points in time may differ systematically in ways that also affect their economic outcomes. We address this using a stacked differences-in-differences design that compares individuals in a given treatment cohort to individuals who will lose a parent in a later cohort. This approach exploits the imprecise timing of parental death as a source of quasi-random variation, and avoids comparisons of treated individuals to previously treated individuals—the contamination problem that afflicts the traditional two-way fixed effects estimator.

We find that the death of an elderly, last parent causes a sizable and sustained increase in per-adult investment income—about \$300 per year on average, a 45 percent gain relative to the baseline mean—consistent with children inheriting meaningful wealth. Simultaneously, parental death reduces per-adult earnings by about \$600 per year, roughly 2 percent of the baseline mean. These earnings effects are large relative to the implied wealth transfer, and 60 percent of the initial reduction persists after six years. On the extensive margin, the share of tax units with positive investment income rises by about three percentage points, while the effect on employment is negligible. Effects on other labor market outcomes, marriage, divorce, and geographic mobility are small.

Section 2.2 presents the research design. Section 2.3 documents the main results, quantifies the share of total inheritances captured by investment income, and characterizes the distribution of inheritances across socioeconomic groups. Section 2.4 concludes.

2.2 Research design

Our parameter of interest is a treatment cohort-weighted average treatment effect of losing a last, elderly parent on a given outcome as measured in post-death year $c + \ell$. To recover our parameter of interest, we make use of the quasi-random timing of parental death in a staggered adoption event study by comparing outcomes for individuals who lose a parent in a given treatment cohort to outcomes for individuals who lose a parent in a later treatment cohort. Following Fadlon and Nielsen (2021) and Nekoei and Seim (2023), we impose that control individuals for a given treatment cohort undergo treatment within δ years of that treatment cohort. We set $\delta = 6$ in order to enable evaluation of treatment effects up to $\ell = 5$.¹

We additionally require that controls belong to the same pre-treatment earnings tercile, racial/ethnic group (white/non-white), and birth cohort as the treatment cohort.² Conditioning on pre-treatment earnings and racial group limits comparisons of individuals whose earnings are evolving differently prior to treatment; conditioning on birth cohort limits the potential for age effects to confound our results. Our identification assumption, therefore, is that, in the absence of treatment, the outcomes of treated individuals would have followed the same trend as the outcomes of individuals belonging to the same demographic group who lose their last, elderly parent within six years. Our justification for making this (conditional) parallel trends assumption is that parental death is universal, and its precise timing generally cannot be foreseen.

We implement our approach using the stacked differences-in-differences estimator, first developed by Cengiz et al. (2019).³ Relative to the traditional two-way fixed effects DiD estimator, stacking avoids comparisons of treated individuals to previously treated individuals. For each treatment cohort $c \in [2010, 2016]$, the subset of treatment cohorts that are balanced in event time for $\ell \in [-5, 5]$, we form multiple “stacks.” Each stack consists of all observations with $t \in [c_i - 5, c_i + 5]$ for all individuals i in treatment cohort c_i who belong to a given demographic cell, as well as all available not-yet-treated observations for individuals $i \in$ treatment cohorts $[c_i + 1, c_i + 6]$.⁴ We vertically concatenate all stacks and estimate the following event study equation on this stacked dataset:

$$Y_{its} = \sum_{\ell \neq -1} \beta_{\ell} D_{its}^{\ell} + \alpha_{is} + \psi_{ts} + \epsilon_{its} \quad (2.1)$$

¹Our results are not sensitive to larger choices of δ .

²Henceforth we use the term “racial group,” where white includes white Hispanic and non-white includes non-white Hispanic.

³Using the Callaway and Sant’Anna (2021) estimator yields very similar point estimates. Relative to that estimator, the stacked approach greatly simplifies inference, especially when conducting heterogeneity analyses.

⁴In heterogeneity analyses, we additionally include any characteristics that we condition on in the stack definition. Note that, given the construction of stacks, conditioning on time-varying characteristics in $\ell = -1$ requires all individuals in a stack to share these characteristics in the calendar year prior to parental death for the *treated* cohort. Conditioning in this way avoids mean reversion.

where Y_{its} is the realized outcome of individual i at calendar year t for stack s . $D_{its}^\ell = 1(t - c_i = \ell)$ is an indicator for individual i at year t for stack s is treated ℓ periods from now. α_{is} and ψ_{ts} represent a set of individual $\times$ stack and calendar year $\times$ stack fixed effects, respectively. In all regressions, we normalize the baseline year, $\ell = -1$, to 0 and cluster standard errors at the level of the dying parent.

When reporting event time parameter estimates, we report the number of unique individuals in the regression and the number of stacks. Our main sample consists of 714 stacks corresponding to the combination of the seven treatment cohorts for which we estimate treatment effects, 17 birth cohorts, three income terciles, and two racial groups. Appendix Figure C.1 reports the count of unique individuals per treatment cohort in our main sample.

2.3 Behavioral responses to parental death

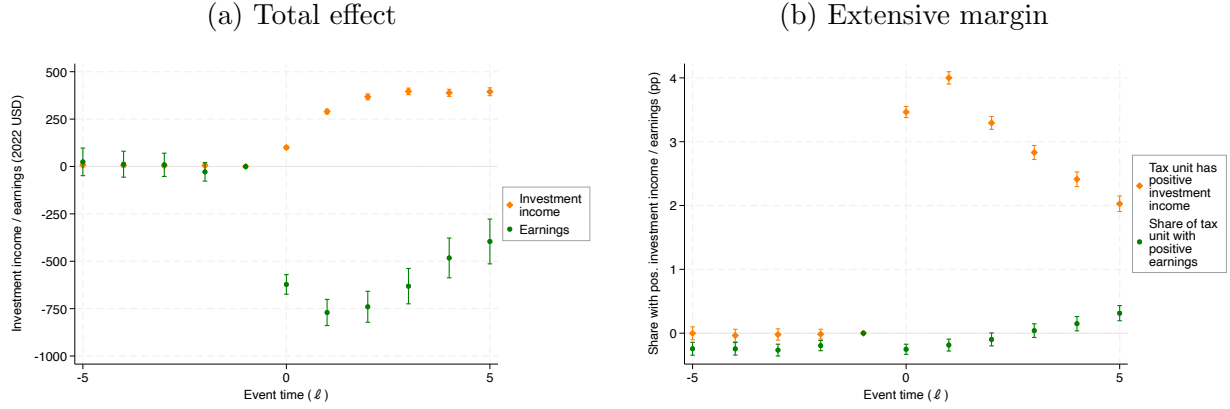
2.3.1 Investment income and earnings responses

In panel (a) of Figure 2.1 we plot our estimated event time coefficients β_ℓ from equation 2.1 for our two main outcomes: per-adult investment income and per-adult earnings at the level of the tax unit. There is no evidence of differential trends between current and later treated individuals in pre-treatment event times -5 to -2 for either outcome, supporting the common trends assumption. The series labeled “Investment income” illustrates that, over the five year post-period, investment income of treated individuals increases by about \$300 a year on average relative to that of later treated individuals. This increase represents a 45 percent gain relative to the baseline mean. The second series in panel (a) shows that annual earnings of treated individuals fall by about \$600, or about 1.8 percent of the baseline mean.

We report event time and DiD coefficients for investment income and earnings in Appendix Table B.5. In Appendix Figure C.2, as a robustness check, we report results from fitting a Poisson model to the data. The coefficient estimates imply similar percentage changes in per-adult investment income and earnings as those implied by Figure 2.1. Our results are not impacted by the omission of parent deaths or observations during the years of the Covid pandemic (2020–2021).

Since investment income is flow income generated by underlying assets, we interpret the observed spike in investment income as evidence of new wealth from inheritances. Event study results for the constituent components of investment income can be found in Appendix Figure C.3. Taxable interest income, tax-exempt income, dividend income, and rental income are primarily generated by debt instruments, municipal bonds, corporate stocks and mutual funds, and investment properties, respectively. The plot illustrates that gains in investment income are driven by increases in dividends and rental income, which roughly flatten in the third year following parental death. Using annual asset class-specific capitalization factors from Saez and Zucman (2016) for 2010–2016, we estimate that the observed overall investment income flow of \$300 corresponds to a stock of roughly \$13,900. The capitalization factors we use can be found in Appendix Table B.6.

Figure 2.1: Effect of last parent death on investment income and labor supply



Notes: This figure presents estimates of the effect of losing a last parent on four outcomes, based on estimating equation 2.1. Panel (a) illustrates that, at the tax unit level, per-adult investment income rises by \$312 on average while wage earnings fall by \$622. Panel (b) shows that the share of tax units with any positive investment income increases by three percentage points on average, while effects on the share of tax unit members with any positive earnings are negligible. 95 percent confidence intervals are displayed, clustering on dying parent. We use $c - 1$ as the omitted event time. Source: Census Environmental Impacts Frame, Master Address File, Decennial Census (2000, 2010), American Community Survey (2000–2022); IRS 1040s, W-2s (2005–2022); SSA Numident (1994–2022).

Panel (b) illustrates that the effect of parental death on the share of individuals whose tax unit records any positive investment income is about three percent, averaging across post-period years, relative to a baseline mean of about 20 percent. The impact on the share of an individual's tax unit with any positive earnings (i.e., the share that is employed) is negligible. This is intuitive, given that the average value of the transfer is small relative to a stream of future earnings and individuals in our sample are only 38 years old on average, far from retirement age.

Table 2.1 reports impacts on the probability of switching employers, the number of W-2s received, and W-2 deferred compensation (generally contributions to 401(k)s). Parental death causes small increases in the first two outcomes, suggesting that switching jobs or shifting to more part-time employment may be a channel through which individuals reduce hours. The effect on deferred compensation is insignificant, implying it is not the case that individuals maintain their baseline earnings but augment retirement saving.

With respect to dynamics, in panel (a) we see that earnings losses peak in the year after parental death, consistent with behavioral responses occurring mostly in the year of death for those bereaved early in the year and mostly in the following year for those bereaved later. In panel (b), the impact on the share of individuals with positive (tax unit-level) investment income also peaks in $\ell = 1$. As with earnings, within-year timing can explain this peak: parents who die midway through a given year may still earn investment income up until their death. Such income is reported on the parent's final income return (usually filed by an executor, next-of-kin, or legal heir) rather than the child's.

Table 2.1: DiD estimates for additional labor supply outcomes

	Employer mobility (1)	W-2 form count (2)	Deferred compensation (3)
DiD estimate	.0052 (.0006)	.0124 (.0010)	-2.191 (2.666)
Baseline mean	.2126	1.055	950.06
N individuals	774,000	1,939,000	1,939,000

Notes: This table reports DiD estimates for the probability of switching employers, per-adult count of W-2 forms received, and W-2 deferred compensation. For employer mobility, we restrict the sample to individuals with an Employer Identification Number (EIN) populated in every year. Employers are identified by the EIN on the individual’s largest W-2. When computing standard errors (reported in parenthesis), we cluster on dying parent. Source: Census Environmental Impacts Frame, Master Address File, Decennial Census (2000, 2010), American Community Survey (2000–2022); IRS 1040s, W-2s (2005–2022); SSA Numident (1994–2022).

The longer lag before the peak in the total effect on investment income likely reflects delays in the transfer of assets. Probate, the legal process that authorizes the distribution of assets in a will, or non-trivial estates with no will, can range in duration from a few months to a few years.⁵ The duration of closing a trust, an estate planning tool used by middle- and higher-income households, depends on its complexity; various law firm websites suggests an average of about one year.⁶ Financial assets in trusts are often disbursed quickly, but a trust cannot be closed until real estate is transferred. After trust settlement, selling property and reinvesting proceeds into a taxable account would create a lag before investment income peaks.

In Appendix Table B.7, we examine other margins of adjustment to parental death beyond earnings that we can observe in our data: marriage, divorce, and geographic mobility. We find trivial impacts on the probability of new marriage and new divorce, and a small increase in the probability of changing Census tracts.

2.3.2 Share of inheritances captured by investment income gains

Above, we documented an average annual increase in per-adult investment income of \$312 across our sample. The total investment income gain at the tax unit level is \$461, corresponding to a stock of about \$20,500 using an asset class-averaged capitalization factor of 44.46 (see Appendix B.6). Since each tax unit undergoes exactly one last parent death, this

⁵The probate court of Fulton County, Georgia, indicates that its process “has an average range of 6 to 12 months,” while that of Harris County, Texas, states that “simple cases may resolve in a few months; more complex estates can take a year or longer” (Fulton County Probate Court; Harris County Public Probate Administrator).

⁶See Parker Law Offices; The Legacy Lawyers; Geiger Law Office; Moran & Associates; SSR Elder Law & Estate Planning.

stock represents the portion of inheritance from one last parent that generates investment income. As described in Section 1.3.4, many assets comprising an inheritance either do not generate investment income or may be liquidated upon receipt. To interpret the labor supply responses we observe, we would like to know what share of the total average inheritance from a last parent \$20,500 represents.

One approach to estimating this parameter is to benchmark to inheritances in the SCF, a cross-sectional survey that asks households whether they have ever received an inheritance and, if so, its total value and source. Using the SCF waves that align with our sample period—2010, 2013, and 2016—we attempt to construct a sample of children that is comparable to our main sample by restricting to households where either the respondent or spouse is in the birth cohort range of our sample and has no living parents. In this SCF sample we find an unconditional mean inheritance of \$43,200, suggesting that our DiD estimate captures 47 percent of the total inheritance. Details are described in Appendix E.

We believe this estimate is unreliable and likely overestimates the true share. First, the SCF sample consists of only 2,300 households and the estimate of the unconditional mean is highly sensitive to sample restrictions. Second, the SCF does not allow us to condition on parental age at death. Third, a share of 47 percent implies that the share of investment income-bearing assets in total assets held by parents in our main sample approaches that of the top 0.1 percent of the overall U.S. wealth distribution, according to the Federal Reserve’s Distributional Financial Accounts.⁷ We therefore employ two alternative approaches to establish approximate bounds.

Method 1: Comparison of DiD to baseline parent investment income. Table 1.1 documents that, in the baseline year, the dying parent’s tax unit recorded \$3,478 in investment income. If all parent assets bear investment income and all are bequeathed to children, then the share of the average total inheritance captured by our DiD estimate is:

$$\frac{\text{DiD estimate} \times \text{number of children per parent}}{\$3,478}$$

Table 1.1 reports that dying parents in our sample on average have 1.95 children. However, children above the age of 18 during the early years for which dependent claiming information is available are unobserved. Using the average number of children reported for single parents age 65 and above in the 2010–2016 SCF waves, 2.85, this approach yields an upper bound of 38 percent.

Method 2: Benchmarking to parent-reported balance sheets. The SCF also surveys households about the composition and magnitude of their assets and liabilities across different asset classes. Using the 2010–2016 waves, we restrict to respondents who are age 65 or above, unmarried or widowed, and have adult children away from home. In this sample, we find that assets that generate investment income represent 35 percent of inheritable net worth. Appendix F describes details.

⁷See Board of Governors of the Federal Reserve System (2025).

Re-scaling Method 1 to account for the share of total parent assets that bear investment income yields a lower bound of 13 percent. In summary, our preferred range of estimates of the share of total inheritances captured by investment income gains is 13 to 38 percent.

$$\frac{\text{DiD estimate} \times \text{number of children per parent}}{\$3,478} \times \frac{\text{assets bearing investment income}}{\text{net worth}}$$

2.3.3 Causal and survey evidence on the distribution of inheritances

The distribution of causal effects on investment income is not econometrically identified without the implausible assumption of rank invariance.⁸ Our data do allow us to obtain causal evidence on heterogeneity in the *probability* of receiving an inheritance across socioeconomic and demographic groups. To do so, we use the proxies for wealth transfers discussed in Section 2.3.1 to construct indicator variables for undergoing a change in wealth attributable to various sources. These indicators are defined by the appearance of retirement distributions, housing sales, or notable changes in investment income. Appendix D provides further details on the construction of these change in wealth variables.

We then estimate a simple difference in means for these variables using our stacked dataset. That is, we estimate:

$$Y_{is} = \alpha + \beta D_{is} + \epsilon_{is} \quad (2.2)$$

where Y_{is} is an indicator for individual i for stack s undergoing a change in wealth and D_{is} is an indicator for whether the individual is treated in stack s . We cluster standard errors at the level of the dying parent. The difference in means for treated and control units represents the share of individuals who receive an inheritance from a given source.

Our results are summarized in Table 2.2. Because our approach cannot pick up all measures of inheritances, these shares underestimate true inheritance shares. However, because these proxies span a broad set of asset classes, this measurement error is unlikely to cause significant bias in heterogeneity across subsamples.

The key result of Table 2.2 is that the probability of receiving an inheritance from a last parent is nearly eight times higher among children with parents in the top 1994 AGI quartile than those in the bottom. This finding is consistent with a highly skewed distribution of inheritances and broader patterns of wealth inequality. In Appendix Table B.4, we show corresponding shares for the union of indicators for experiencing a change in wealth from different sources.

⁸Rank invariance implies that every individual's potential outcome in the treated state is a (weakly) increasing function of their potential outcome in the control state.

Table 2.2: Share of individuals who receive an inheritance from a last parent

	Control (1)	Treated (2)	Difference (3)	N individuals
Main sample	0.2041 (0.0003)	0.3280 (0.0007)	0.1239 (0.0007)	1,939,000
Male	0.2027 (0.0004)	0.3219 (0.0009)	0.1192 (0.0010)	992,000
Female	0.2057 (0.0004)	0.3344 (0.0009)	0.1287 (0.0010)	947,000
No college	0.1901 (0.0008)	0.3041 (0.0018)	0.1140 (0.0019)	237,000
College	0.2565 (0.0009)	0.4788 (0.0021)	0.2224 (0.0023)	199,000
White	0.2128 (0.0004)	0.3886 (0.0010)	0.1758 (0.0010)	1,112,000
Black	0.1572 (0.0007)	0.2035 (0.0015)	0.0462 (0.0016)	288,000
Hispanic	0.2112 (0.0006)	0.2691 (0.0013)	0.0579 (0.0014)	412,000
Parent 1994 AGI Q1	0.1680 (0.0006)	0.2036 (0.0011)	0.0356 (0.0012)	446,000
Parent 1994 AGI Q2	0.1952 (0.0006)	0.2802 (0.0013)	0.0850 (0.0014)	444,000
Parent 1994 AGI Q3	0.2167 (0.0006)	0.3819 (0.0015)	0.1652 (0.0016)	443,000
Parent 1994 AGI Q4	0.2507 (0.0006)	0.5202 (0.0017)	0.2695 (0.0017)	442,000

Notes: This table reports means and difference in means for treated and control individuals across different subsamples, based on equation 2.2 and using an indicator for undergoing a change in wealth from retirement distributions. When computing standard errors (reported in parenthesis), we cluster on dying parent. Source: Census Environmental Impacts Frame, Master Address File, Decennial Census (2000, 2010), American Community Survey (2000–2022); IRS 1040s, W-2s (2005–2022); SSA Numident (1994–2022).

2.4 Conclusion

This chapter has documented the main empirical facts about the economic consequences of parental death. Using a stacked differences-in-differences design that exploits the quasi-random timing of parental death, we find that loss of a last, elderly parent causes a sizable and sustained increase in investment income—a 45 percent gain relative to baseline—accompanied by a 2 percent reduction in earnings that is large relative to the implied wealth transfer. These effects are consistent with the theoretical prediction from Chapter 1 that inheritances reduce labor supply when their timing is uncertain.

We also documented that investment income captures between 13 and 38 percent of total inheritances, that inheritances are highly concentrated among children of wealthy parents, and that parental death has modest effects on other dimensions of behavior. The propor-

tionality between investment income gains and earnings reductions across groups already hints that income effects are the dominant mechanism—a hypothesis we examine rigorously in Chapter 3.

Chapter 3

The role of inheritance in earnings responses

3.1 Introduction

Chapter 2 established that the investment income and earnings responses to parental death scale strongly with parental income. These patterns are suggestive of income effects from inheritances driving the labor supply response, but they do not rule out other channels: grief, the loss of informal childcare, relief from eldercare obligations, co-employment disruptions, or added worker effects could each contribute. This chapter evaluates the relative importance of these mechanisms, quantifies the aggregate earnings response per dollar of unearned income, and assesses the distributional consequences of inheritances.

We first examine treatment effect heterogeneity in detail, showing that investment income and earnings responses mirror each other closely across over a dozen socioeconomic and demographic dimensions, with both scaling markedly with parental income. We formalize this symmetry through a visual instrumental variables analysis that implies a marginal propensity to earn in the range of -0.11 to -0.31 under our preferred assumptions.

We then investigate non-income mechanisms. We rule out childcare loss, added worker effects, and co-employment as important drivers. Comparing own versus spousal responses casts doubt on grief as a persistent mechanism, though it may operate in the year of death. The one group that significantly increases earnings after parental death—children who co-habit with their parent—provides strong evidence that eldercare release is an important channel for those living in close proximity. A short-lived psychological or logistical component appears to explain the universal earnings decline in the year of death across all subgroups.

Having established that inheritances are the primary channel through which parental death affects labor supply, we estimate the marginal propensity to earn (MPE), finding a range of -0.11 to -0.31, broadly consistent with lottery and cash-transfer studies. We also show that, despite the stark inequality in who receives inheritances, parental death slightly

compresses the distribution of investment income.

Our paper is the first to document behavioral responses to inheritances in the U.S. using comprehensive administrative data. The most similar study to ours, Nekoei and Seim (2023), examines responses to parental death in Sweden, a setting with different inequality dynamics, a stronger social safety net, and higher labor force participation than the U.S. The authors find that labor earnings initially decline by one percent following parental death and fully recover within seven years, a similar result to ours. By our calculations, their results indicate an annualized earnings response to an extra dollar of unearned income similar to the range we estimate. Recent work by Brülhart et al. (2025) documents long-lasting earnings reductions in response to moderately-sized inheritances in one Swiss canton. Building on these papers, we provide precise heterogeneity results that allow us to explore dimensions of inequality and mechanisms underlying the earnings response to parental death in the U.S., the world’s richest country by total household wealth. In doing so, we also shed light on direct earnings effects of parental death, a virtually universal but understudied life event relative to others such as child-bearing and own health shocks.

Within the U.S., existing work on labor supply responses to inheritances is limited to studies that use either survey data from the Panel Study on Income Dynamics (PSID) or one percent samples of estate tax returns that capture only the largest inheritances for a small number of years in the 1980s (Holtz-Eakin et al., 1993; Joulfaian and Wilhelm, 1994). Unlike these papers, we directly quantify earnings responses for a large, representative sample of the U.S. population using a granular dataset and a credible control group. To our knowledge, the only other study to examine the labor supply impacts of inheritances in the U.S. is Brown et al. (2010), who show that inheritances increase the probability of retirement among older workers using Health and Retirement Survey data.

Our paper also complements previous work on labor supply responses to windfall income, chiefly lottery winnings (Cesarini et al., 2017; Picchio et al., 2018; Bulman et al., 2021; Golosov et al., 2024) and, more recently, unconditional transfers in two U.S. states (Vivalt et al., 2025). In this literature, a key parameter is the marginal propensity to earn (MPE), which represents the decrease in annual earnings associated with an annual dollar increase in unearned income for the rest of one’s life. Estimating an MPE using our results requires stronger assumptions than in these settings, since we do not directly observe total inheritances and cannot identify the unanticipated portion of inheritances. Imposing these additional assumptions yields the -11 to -31 cent range noted above, the upper end of which aligns with recent estimates by Golosov et al. (2024) and Vivalt et al. (2025). In addition, like Golosov et al. (2024) we find that earnings reductions are increasing in baseline earnings.

Finally, our paper brings new evidence to bear on a long-standing literature concerning the contribution of inherited wealth to aggregate private wealth (Kotlikoff and Summers, 1981; Modigliani, 1986; Alvaredo et al., 2017). This literature has historically assumed inelastic labor supply with respect to inheritances. The large labor supply responses we document imply that past estimates may be upwardly biased, since inheritances reduce the accumulation of wealth that would otherwise be attributed to life-cycle saving. Our study also complements a related literature that studies intergenerational wealth elasticities and

bequest patterns (Black et al., 2020; Adermon et al., 2018; Wolff, 2002; Bernheim, 1991) by documenting stark heterogeneity in inheritances by different measures of parental income.

Section 3.2 presents the income effects analysis. Section 3.3 examines non-income mechanisms. Section 3.4 estimates the MPE. Section 3.5 documents distributional effects. Section 3.6 concludes.

3.2 Income effects

3.2.1 Treatment effect heterogeneity

In Section 2.3.1, we established that investment income and earnings of treated individuals demonstrate divergent patterns after parental death. In Figure 3.1, we examine heterogeneity in these effects along three dimensions: own and parental income, own demographic characteristics, and parental demographic characteristics. As with other results, we condition on own characteristics but report outcomes on a per-adult basis. We report own outcomes, which are very similar, in Appendix Tables B.9–B.13. All time-varying characteristics pertain to the year prior to the parent’s death (with the exception of parent age, which is age at death).

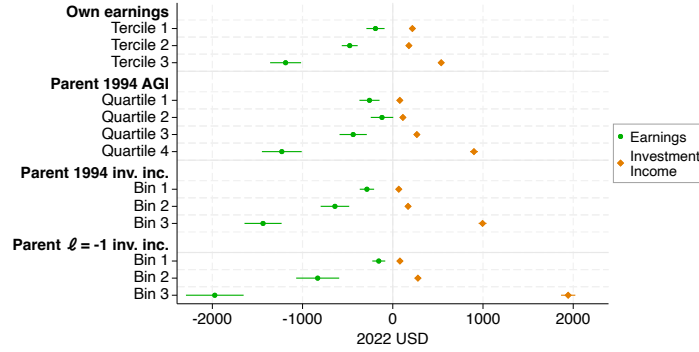
In panel (a), we consider heterogeneity by own wage earnings tercile in the year prior to parent death and three measures of parental income, all of which are at the level of the dying parent’s tax unit: AGI in 1994 (the first year in which we observe parents), investment income in 1994, and investment income in the baseline year.¹ We divide parental AGI into quartiles. Since the investment income distribution of parents (as well as children) is very skewed, we divide this variable into a bin for having \$0 investment income in a given year (bin 1) and bins for below- or above-median conditional on having non-zero investment income (bins 2 and 3). We find that, across virtually every measure, income is highly predictive of both investment income and earnings responses, which display striking symmetry across subsamples. This result is consistent with studies documenting strong intergenerational transmission of wealth, and supports the hypothesis that income effects drive the observed labor supply response (Charles and Hurst, 2003; Killewald et al., 2017; Black et al., 2020). Appendix Figure C.4 reproduces panel (a) in proportional terms, scaling by baseline mean investment income and earnings.

In panel (b), we find a close mirroring of earnings and investment income responses across groups defined by sex, race, age, and college attendance. The relative magnitudes of investment income effects by group follow broader trends in wealth inequality, reflecting a stark racial wealth gap and disparities by college attendance. We discuss heterogeneity by geographical distance to parent in Section 3.3, as the dynamics are notable. Panel (c) documents a weaker relationship between the two outcomes when conditioning on demo-

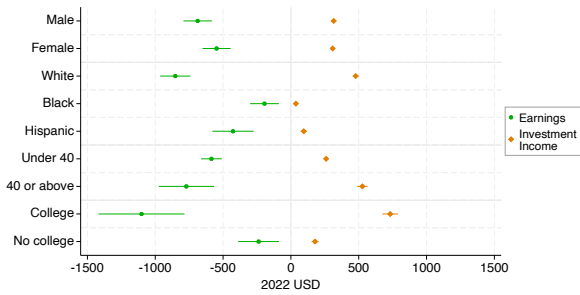
¹We use AGI rather than wage earnings as our main measure of parental income because W-2s are not available prior to 2005.

Figure 3.1: DiD estimates across outcomes and heterogeneity dimensions

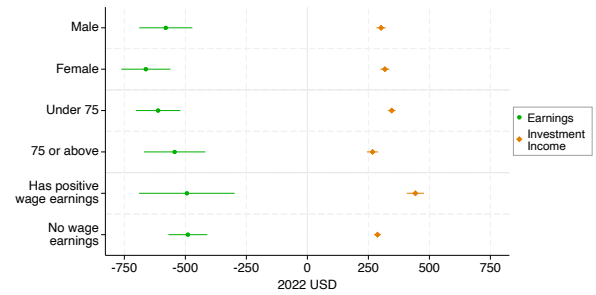
(a) Own and parental income



(b) Own demographic characteristics



(c) Parent demographic characteristics



Notes: This figure presents DiD estimates for investment income and earnings across groups defined by different socioeconomic and demographic characteristics. 95 percent confidence intervals are displayed, clustering on dying parent. All time-varying characteristics pertain to the year prior to the parent's death (with the exception of parent age, which is age at death). Source: Census Environmental Impacts Frame, Master Address File, Decennial Census (2000, 2010), American Community Survey (2000–2022); IRS 1040s, W-2s (2005–2022); SSA Numident (1994–2022).

graphic characteristics of the dying parent, though earnings results are less precise and do not preclude symmetric responses.

We report additional heterogeneity analyses based on current and childhood household characteristics in Appendix Figure C.5. Interestingly, investment income decreases monotonically with number of siblings. Aggregate investment income gains across siblings are similar for only children and those with two siblings, and slightly higher for those with one sibling. In contrast, investment income gains are slightly larger among younger children than older children.²

Overall, Figure 3.1 and Appendix Figure C.5 illustrate a strong inverse relationship between investment income and earnings across many, but not all, demographic and socioeco-

²A limitation of our data is that we cannot observe siblings who were over 24, the age limit for dependent claiming, in 1994.

nomic dimensions. Measures and correlates of own and parental income are especially strong predictors of both outcomes.

3.2.2 Instrumental variables analysis

Next, in a complementary attempt to understand the extent to which income effects explain the observed labor supply response, we construct the plot shown in Figure 3.2. To make this plot, we estimate effects for our two main outcomes in sixteen different subsamples defined by the interaction of three key heterogeneity dimensions: sex, 1994 parent AGI quartile, and racial group (white/non-white). We then plot DiD coefficients for earnings against coefficients for investment income, and fit a line of best fit through these points, using weighted least squares with the number of individuals per group as weights. Thus, the x-axis of the plot is analogous to the first-stage and the y-axis to the reduced form of an overidentified two-stage least squares regression of earnings on investment income, where the instruments are interactions of an indicator for being treated in the post-period and indicators for belonging to each subsample.

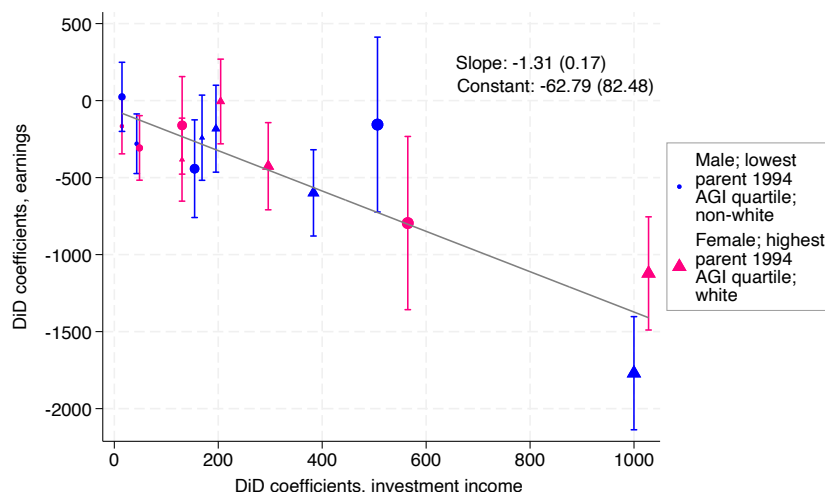
This figure provides a few useful insights. First, it formalizes the symmetry in earnings and investment income responses we observed in Section 3.2.1. Because we created this plot using group-level effects rather than two-stage least squares estimates, we are able to visualize the line of best fit’s constant and confirm that it is near but not equal to zero (when the exclusion restriction is assumed to be true, the constant is zero by construction). That is, on average over six years, tax units receiving zero investment income have only small reductions in earnings. Appendix Table B.14 presents results from estimating this system via two-stage least squares. We find that the overidentification test’s p-value is 0.012. Since the J-test is insignificant at the one percent level and the constant from our visual IV is indistinguishable from zero, we interpret the slope of the line of best fit as the causal effect of investment income on earnings.

The line’s slope indicates that, for every dollar of flow investment income that is derived from inheritances over this period, on average tax units drop their earnings by \$1.31.³ Under the assumption that the share of inheritances captured by investment income is constant across groups, and using the range of parameter estimates for this share established in Section 2.3.2, this slope implies that a dollar gain in unearned income from inheritance leads to a 17 to 49 cent reduction in earnings. Our finding that the earnings response is linear in investment income is consistent with Stone-Geary preferences (Deaton and Muellbauer, 1980).

While Figure 3.2 documents that parental income is a strong predictor of investment income and earnings reductions, it does not elucidate whether high or low-income children of wealthy parents drive the average earnings response. To explore heterogeneity by own income, we repeat the exercise among terciles of the distribution of children’s own earnings

³The slope reflects a relationship at the tax unit, rather than individual, level because both the y- and x-axis are per-adult responses.

Figure 3.2: Visual IV estimates of the effect of investment income on earnings



Notes: This figure plots DiD estimates for earnings against DiD estimates for investment income for sixteen different subsamples, as detailed in Section 3.2.2. The constant of the line of best fit is near zero, suggesting that children who do not gain investment income barely decrease their earnings over the post-period. Whiskers mark 95 percent confidence intervals for the earnings estimates. Source: Census Environmental Impacts Frame, Master Address File, Decennial Census (2000, 2010), American Community Survey (2000–2022); IRS 1040s, W-2s (2005–2022); SSA Numident (1994–2022).

in the baseline year. We present regression statistics for these plots in Table 3.1; Appendix Figure C.6 presents corresponding heterogeneity figures. Like Golosov et al. (2024), we find that earnings responses are increasing in baseline income.

Table 3.1: Summary of visual IV results across subsamples

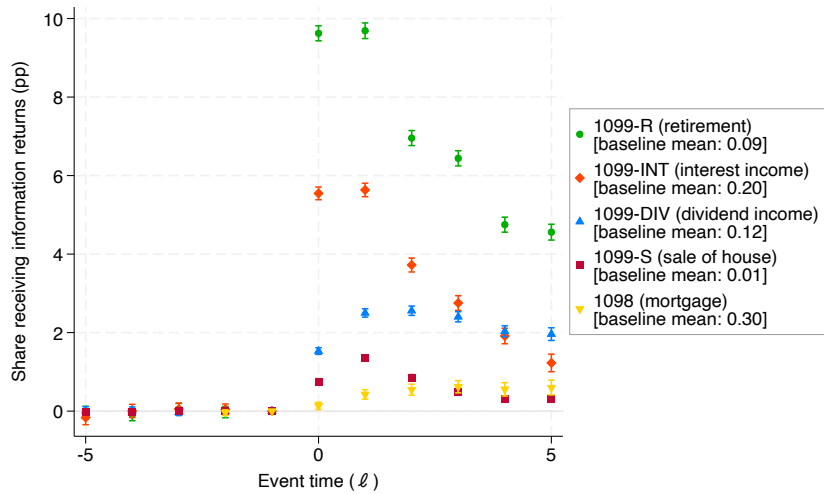
	Full sample	Tercile 1	Tercile 2	Tercile 3
	(1)	baseline earnings	baseline earnings	baseline earnings
	(1)	(2)	(3)	(4)
Slope	-1.31 (0.17)	-0.88 (0.21)	-1.02 (0.25)	-1.34 (0.29)
Constant	-62.79 (82.48)	123.50 (83.79)	-187.70 (79.64)	-245.10 (205.00)
R ²	0.82	0.55	0.54	0.61
N individuals	1,774,000	725,000	860,500	765,000

Notes: This table reports regression statistics associated with Figure 3.2 and Appendix Figure C.6. Source: Census Environmental Impacts Frame, Master Address File, Decennial Census (2000, 2010), American Community Survey (2000–2022); IRS 1040s, W-2s (2005–2022); SSA Numident (1994–2022).

3.2.3 Additional evidence on inheritances

We have presented evidence that income effects from receiving an inheritance are the leading mechanism through which parental death affects labor supply. To obtain a more complete picture of inheritances, and insights into how individuals use them, we study the effect of parental death on the probability of undergoing certain changes in wealth that are indicated by information returns. In Figure 3.3 we plot these effects, which represent impacts in a given year relative to the baseline share, not cumulative impacts.

Figure 3.3: Effect on additional wealth-related outcomes



Notes: This figure presents estimates of the effect of losing a last parent on indicator variables that correspond to tax-reportable changes in wealth, based on estimating equation 2.1. 95 percent confidence intervals are displayed, clustering on dying parent. We use $\ell = -1$ as the omitted event time. 1099 and 1098 indicators are available beginning in 2010 and 2013, respectively. We therefore estimate treatment effects only for the 2015 and 2016 treatment cohorts. Source: Census Environmental Impacts Frame, Master Address File, Decennial Census (2000, 2010), American Community Survey (2000–2022); IRS 1040s, W-2s (2005–2022); SSA Numident (1994–2022).

Interest and dividends. Parental death raises the probability of receiving a 1099-INT and 1099-DIV by about six and three percentage points by $\ell = 1$, respectively, a roughly 30 percent increase relative to the baseline mean in both cases. A natural reconciliation of the extensive- and intensive-margin patterns is heterogeneity: many heirs receive small inheritances that trigger a 1099 flag but are quickly depleted, while wealthier heirs keep their wealth intact and drive the total effect.

Housing. The probability of receiving a 1099-S roughly doubles for treated individuals in each of the three years following parental death relative to its baseline mean of one percent. Even accounting for the tax code's step-up basis, which favors retaining inherited housing as a rental property, the absolute impact on house sales is puzzlingly small. We discuss possible reasons in the main paper.

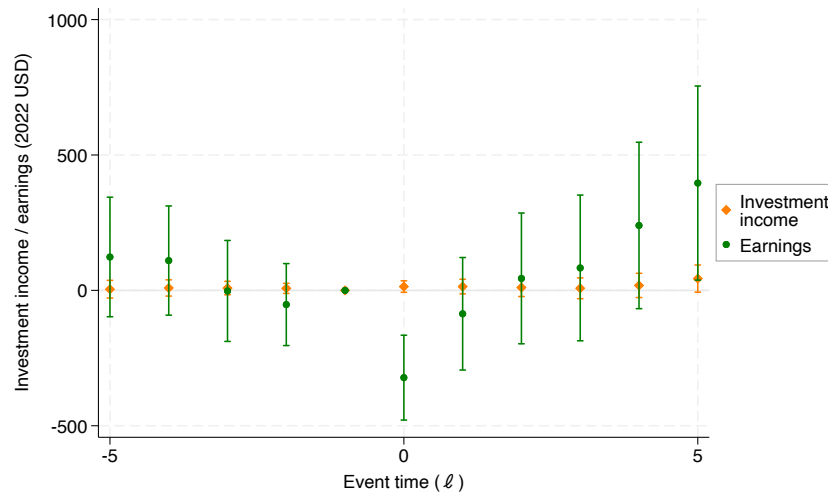
Retirement accounts. The impact of parental death on the probability of receiving a 1099-R is equal in magnitude to the baseline mean in the first two years of parental death. Given that children in our sample are not of retirement age, the nine percent baseline mean likely reflects early withdrawals and account rollovers. The declining pattern indicates that most individuals liquidate their parent’s retirement accounts, consistent with credit constraints.

In summary, we find that parental death has a sizable and significant impact on the probability of receiving most information returns that an inheritance might trigger.

3.2.4 Earnings responses when parents have no wealth

To further explore the extent to which earnings responses are driven by inheritances, in Figure 3.4 we present effects for our two main outcomes among the subsample of individuals whose dying parents have no observable wealth in our data prior to death. We define having no observable wealth as not receiving a 1099-R, having zero investment income, and not being a homeowner in 2010.

Figure 3.4: Effects among subsample whose parents have no wealth at $\ell - 1$



Notes: This figure presents estimates of the effect of losing a last parent on two outcomes, based on estimating equation 2.1, among individuals whose last parent has no apparent wealth in our tax data. In this subsample, earnings reductions are virtually indistinguishable from zero after the year of parent death. 95 percent confidence intervals are displayed, clustering on dying parent. We use $c - 1$ as the omitted event time. Source: Census Environmental Impacts Frame, Master Address File, Decennial Census (2000, 2010), American Community Survey (2000–2022); IRS 1040s, W-2s (2005–2022); SSA Numident (1994–2022).

Figure 3.4 demonstrates that individuals whose parents had no observable wealth at baseline, about one fifth of the sample, do not gain any investment income after the parent’s death. Earnings fall significantly only in the year of parent death; the reduction in all other years is virtually indistinguishable from 0. The magnitude of the earnings drop in the year of death is about half that of our headline findings in Figure 2.1. From this plot, we infer

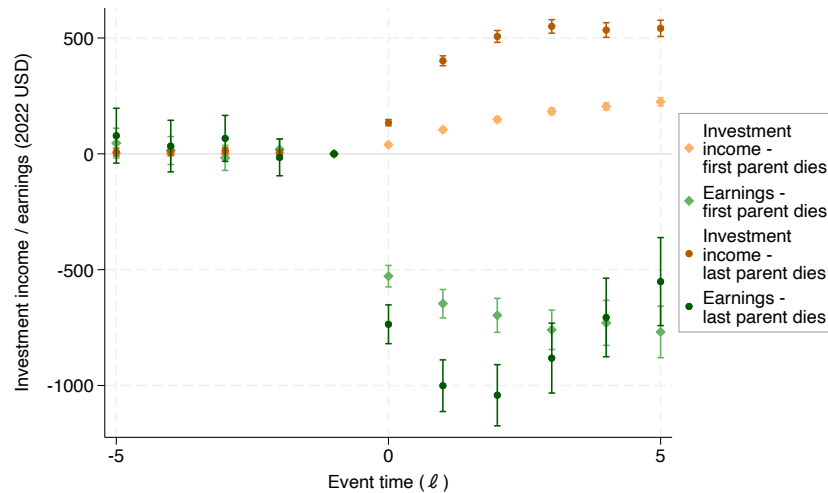
that parental death affects earnings primarily through inheritances, but that non-income channels have a temporary, smaller negative effect.

3.2.5 Responses to the death of a first parent

We examine outcomes among children who lose a first parent, who should receive much smaller inheritances on average. For this comparison, we restrict to the set of individuals with two linked parents, such that first and last parent to die are mutually exclusive.

Figure 3.5 shows that the effect on per-adult investment income of a first parent's death is much more muted than that of a last parent's death. This pattern is consistent with first parent assets frequently passing to the surviving spouse rather than children. However, although the gain in investment income among children who lose a first parent is at most 40 percent that of children who lose a last parent (in $\ell = 5$), children of first parents drop their earnings in the year of death by 70 percent as much as children of last parents, and do not display the same earnings recovery.

Figure 3.5: Responses to first parent death versus last parent death



Notes: This figure presents estimates of the effect of losing a parent on two outcomes, based on estimating equation 2.1, for two samples: the sample of individuals with two linked parents who lose a first, elderly parent and the sample of individuals with two linked parents who lose a last, elderly parent. 95 percent confidence intervals are displayed, clustering on dying parent. We use $c - 1$ as the omitted event time. Source: Census Environmental Impacts Frame, Master Address File, Decennial Census (2000, 2010), American Community Survey (2000–2022); IRS 1040s, W-2s (2005–2022); SSA Numident (1994–2022).

One explanation for these effects that is consistent with a pure income effects story is that the degree of anticipation matters greatly and varies substantially across first and last parent deaths. As shown in Section 1.2, in a conventional labor supply model the change in hours resulting from an exogenous shock to assets is proportional to the unanticipated portion of the shock. It is plausible that the unanticipated portion of small inheritances from

a first parent may be nearly as large as that of larger inheritances from a second parent, since parent deaths occur at a relatively young age and are less likely to be accompanied by clear estate plans (Hurd and Smith, 2001).

3.3 Non-inheritance mechanisms

Social and economic ties between parents and adult children are, of course, complex. The sociology literature on intergenerational family relations documents strong affective ties among American parents and children and largely episodic material support such as financial transfers, access to professional networks, lodging, transportation, child care or eldercare, and household help (Swartz, 2009; Silverstein and Bengtson, 1997). Here we review whether proxies in our data for various forms of intergenerational solidarity influence the earnings response to parental death.

Loss of child care. We view loss of childcare as unlikely to drive earnings reductions for three reasons. First, women’s average earnings reductions are slightly smaller than men’s in both absolute and proportional terms. Second, the earnings response does not vary with the sex of the dying parent, whereas grandmothers provide the majority of grandparent-provided child care (Pew Research Center, 2013; U.S. Census Bureau, 2024). Third, filers with dependents exhibit a slightly *smaller* earnings reduction than filers with no dependents (panel (a) of Appendix Figure C.5).

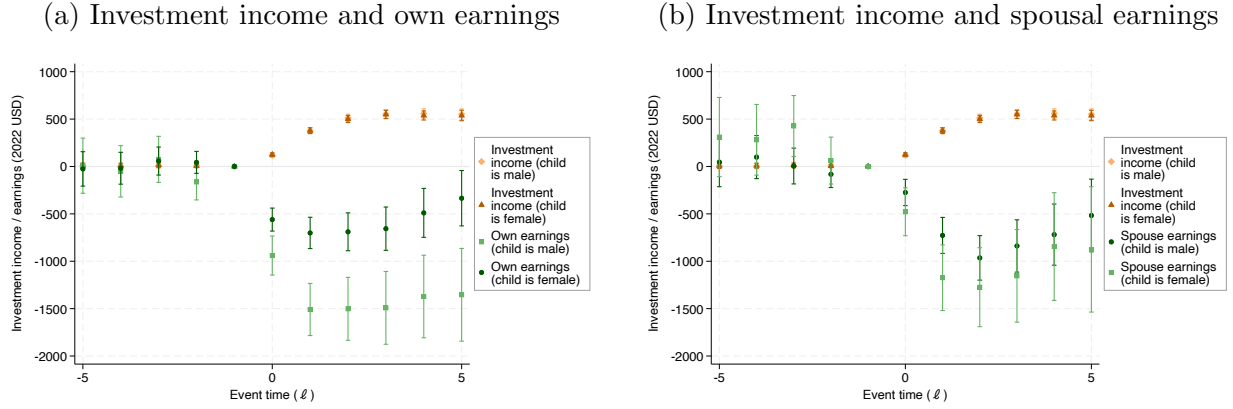
Added worker effects. Could parental illness be a negative income shock that induces children to work more leading up to the death, resulting in a sharp earnings decline after death? If so, we would expect added worker effects to be muted among children of higher income parents (Blundell et al., 2016; Autor et al., 2019; Stephens, 2002). We find the opposite: earnings reductions consistently scale with parent income. The absence of pre-trends in our event study also casts doubt on this explanation.

Co-employment. We view co-employment disruptions as unlikely to be driving our results, since only 30 percent of children in our sample have a dying parent who is employed at all, and earnings responses do not vary with whether the parent was employed (panel (c) of Figure 3.1). Furthermore, prior work suggests that co-employment effects are concentrated early in a child’s career—at ages well below the average in our sample (Staiger, 2025).

Grief. We investigate grief by analyzing own versus spousal responses (separated by sex) in Figure 3.6.

Across-panel comparisons illustrate that the death of a parent and the death of a parent-in-law have similar effects on earnings. The DiD coefficient for men is -\$1,332 when their own parent dies versus -\$1,162 when their spouse’s parent dies. The corresponding coefficients for women are -\$594 and -\$676. The main exception is in the year of parent death: for both men and women, the $\ell = 0$ coefficient is about twice as big when a parent dies as when a spouse’s parent dies. We interpret these results as evidence that grief is not a major driver

Figure 3.6: Effects by relation to parent and sex



Notes: Panel (a) presents estimates of effects on per-adult investment income and own earnings for male and female children. Panel (b) presents estimates of effects on per-adult investment income and earnings of the same children's spouses. To obtain these estimates, we restrict the sample to individuals who are married in the year prior to parent death and use estimating equation 2.1. 95 percent confidence intervals are displayed, clustering on dying parent. We use $c - 1$ as the omitted event time. Source: Census Environmental Impacts Frame, Master Address File, Decennial Census (2000, 2010), American Community Survey (2000–2022); IRS 1040s, W-2s (2005–2022); SSA Numident (1994–2022).

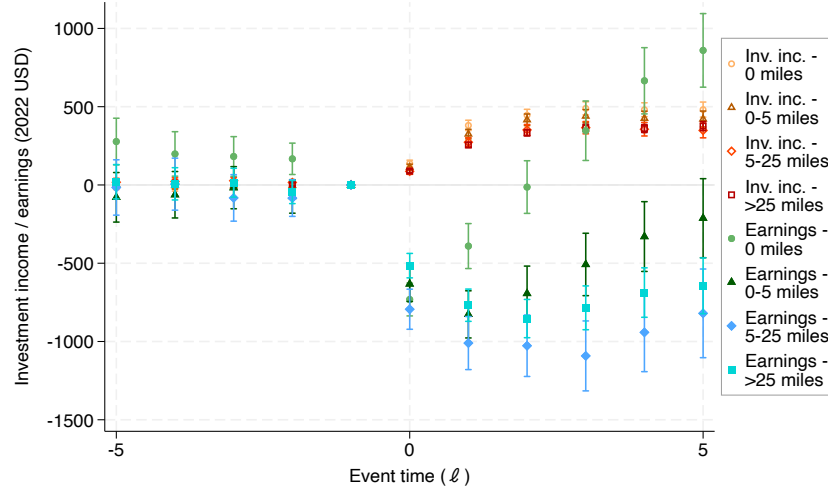
of the earnings response, except possibly in the year of death, and as support for the unitary household model (Lundberg and Pollak, 1996).

Eldercare. Given that geographic proximity to parents strongly predicts eldercare provision, in Figure 3.7 we investigate heterogeneity by distance to dying parent in the year prior to death.

We find that children in all distance bins reduce earnings in the year of parent death. Subsequently, individuals who cohabit with parents, who represent about one fifth of the sample, markedly increase their earnings and, by $\ell = 5$ earn \$860 more than in the baseline year. Across all subsamples in our entire analysis, cohabitators are the only group to significantly increase their earnings. What's more, they exhibit a modest negative pre-trend in the years leading up to the baseline year, consistent with reducing hours to provide additional care as a parent's health conditions worsen (Wolff et al., 2025).

In summary, our findings cast doubt on foregone child care, added worker effects, or co-employment as explanations for the earnings response to parental death, while providing strong evidence that eldercare plays a role among cohabitators. Grief appears unlikely to have lasting effects, but may contribute to the earnings decline in the year of parental death. The presence of a statistically significant drop in earnings in the year of death across *all* subsamples suggests there is a short-lived psychological or logistical element to the earnings response. Although our data cannot unpack this mechanism, the emotional shock of bereavement and the time demands of funeral planning, probate and estate settlement, and selling property are common-sense explanations with anecdotal support.

Figure 3.7: Effects by distance to parent



Notes: This figure presents estimates of the effect of losing a last parent on two outcomes, based on estimating equation 2.1, for four samples of individuals based on geographical distance to their dying parent in the baseline year. The distance bins are 0 miles (cohabitators); (0,5] miles; (5, 25] miles, and >25 miles. In contrast to all other subsamples in this study, children cohabiting with their parents prior to parent death decrease their earnings during the pre-period and increase their earnings over the post-period. 95 percent confidence intervals are displayed, clustering on dying parent. We use $c - 1$ as the omitted event time. Source: Census Environmental Impacts Frame, Master Address File, Decennial Census (2000, 2010), American Community Survey (2000–2022); IRS 1040s, W-2s (2005–2022); SSA Numident (1994–2022).

3.4 Comparison to estimates of marginal propensity to earn

Having established that income effects are the dominant driver of earnings reductions, additional assumptions allow us to perform a back-of-the-envelope calculation to estimate a marginal propensity to earn (MPE). Assuming that our estimate for the earnings reduction approximates the average lifetime earnings response and that our estimate for investment income captures a constant share of inheritances, the slope from our visual IV in Section 3.2.2 represents the dollar-for-dollar reduction in earnings in response to investment income over the post-period.

The MPE is usually considered to be a parameter representing lifetime behavior. To approximate annual unearned income, we annuitize our capitalized per-adult DiD estimate using the standard formula for an annuity and the interest rate implied by our average capitalization factor, 2.2 percent:

$$\eta = \frac{r}{1+r} \left(1 - \left(\frac{1}{1+r} \right)^{T-k+1} \right)^{-1} L \quad (3.1)$$

where L is the stock of inherited wealth, η is unearned income, r is the discount rate, k is age, and $T - k$ is remaining years of life.⁴ We set $k = 39$, the average at parent death in our sample and $T = 80$, matching Golosov et al. (2024).

Appendix Figure C.7 plots the implied return on assets from annuitization against our DiD and event study estimates for investment income over the six year post-period.

The bounds on the investment income share of inheritance from Section 2.3.2 imply a range of MPEs from -0.11 to -0.31. These bounds are largely within the range of other household-level, pre-tax estimates from recent studies based on lotteries (Golosov et al., 2024) and randomized cash transfers (Vivalt et al., 2025) in the U.S. and inheritances in Sweden (Nekoei and Seim, 2023). These comparisons are summarized in Appendix Table B.15.

Since our calculation treats the full inheritance amount as exogenous unearned income, our estimate understates the true MPE to the extent that inheritances are unanticipated. We also note that our calculation does not account for the fact that, if individuals forecast foregone wage growth, the observed earnings reduction would overestimate the MPE, or that individuals close to retirement have limited scope to adjust earnings.⁵

3.5 Distributional effects of inheritances

Next, we assess the impact of inheritances on investment income inequality. We obtain DiD estimates for the probability of recording investment income less than or equal to specific cut points. We define these points to be the 80th, 85th, 90th, 94th, and 95th percentiles of the $\ell = -1$ distribution of investment income among 2010–2016 treatment cohorts. For each cut point, we use our DiD estimates to compute fitted and counterfactual values of the outcome among treated individuals within each stack, then average these values across stacks using the number of treated individuals in each stack as weights. The resulting estimates trace out approximations of the CDF of investment income. From these CDFs, we back out associated Lorenz curves, assuming the investment income held by each cut point interval is the midpoint of that interval.

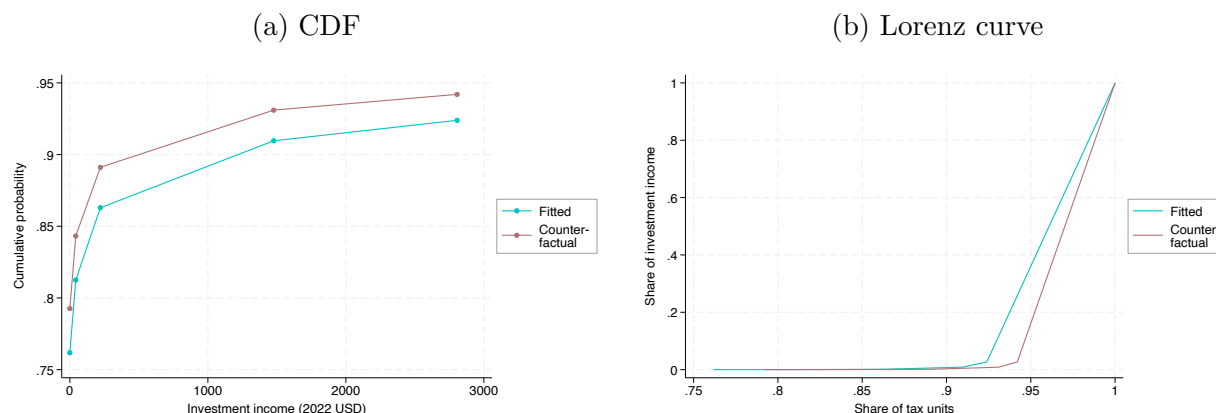
The results indicate that, on average over the six years following parent death, inheritances have a slight equalizing effect on the distribution of investment income among children. The CDF shifts to the right and the Lorenz curve shifts inward, with the Gini coefficient falling from 0.940 to 0.921. Appendix Figure C.8 shows the corresponding probability mass functions.

Although investment income is only one component of wealth, this finding accords with prior evidence from the U.S. and Sweden that inheritances exert an equalizing short-run effect on wealth inequality (Wolff, 2002; Wolff and Gittleman, 2011; Nekoei and Seim, 2023). The main intuition is that, although inheritances increase absolute wealth inequality, inheritance inequality (the share bequeathed by wealthy parents) is less pronounced than wealth inequality. Formally, Nekoei and Seim (2023) show that the effect of inheritances on wealth

⁴Golosov et al. (2024) use an interest rate of 2.5 percent, which yields similar results.

⁵To our knowledge, no prior study that estimates the MPE has addressed these considerations.

Figure 3.8: Impact of inheritances on CDF and Lorenz curve for investment income



Notes: Panel (a) of this figure presents averages of fitted and counterfactual values for investment income among treated individuals, tracing out a cumulative distribution function. Panel (b) presents the corresponding Lorenz curves. These figures indicate that inheritances slightly reduce inequality in the distribution of child investment income over the post-period. Source: Census Environmental Impacts Frame, Master Address File, Decennial Census (2000, 2010), American Community Survey (2000–2022); IRS 1040s, W-2s (2005–2022); SSA Numident (1994–2022).

inequality is increasing in inheritance inequality and decreasing in intergenerational wealth mobility.

3.6 Conclusion

This chapter examined the mechanisms behind the earnings response to parental death, estimated the marginal propensity to earn, and documented the distributional consequences of inheritances. Our analysis established that income effects are large and are the dominant channel through which parental death reduces labor supply. Non-income mechanisms play a limited role overall, though we find strong evidence that elimination of eldercare responsibilities explains the positive earnings responses among children who cohabited with their parents. Finally, we showed that inheritances have a slight equalizing effect on the distribution of investment income.

Despite the robust evidence we find that inheritances reduce labor supply, our ability to precisely estimate the magnitude, composition, and depletion rate of inheritances is limited. Future work should further examine the share of housing and retirement wealth in inheritances. These questions could feasibly be answered using proprietary property tax data along with long histories of mortgage interest payments and parent retirement contributions and withdrawals. Such an analysis would offer clearer insight into the relative contribution of housing and retirement to overall inheritance amounts, as well as the share of liquidated inheritances that are spent on consumption versus used to deleverage. Another ambitious but valuable contribution would be to link tax data to loan-level credit bureau or mortgage

servicing data to better understand the impact of inheritances on financial distress.

Bibliography

- Adermon, A., M. Lindahl, and D. Waldenström (2018, July). Intergenerational wealth mobility and the role of inheritance: Evidence from multiple generations. *The Economic Journal* 128(612), F482–F513.
- Alvaredo, F., B. Garbinti, and T. Piketty (2017). On the share of inheritance in aggregate wealth: Europe and the usa, 1900–2010. *Economica* 84(334), 239–260.
- Autor, D., A. Kostøl, M. Mogstad, and B. Setzler (2019). Disability Benefits, Consumption Insurance, and Household Labor Supply. *American Economic Review* 109(5), 1537–1575.
- Benveniste, L. M. and J. A. Scheinkman (1979). On the differentiability of the value function in dynamic models of economics. *Econometrica* 47(3), 727–732.
- Bernheim, B. D. (1991). How strong are bequest motives? evidence based on estimates of the demand for life insurance and annuities. *Journal of Political Economy* 99(5), 899–927.
- Black, S. E., P. J. Devereux, P. Lundborg, and K. Majlesi (2020). Poor little rich kids? the role of nature versus nurture in wealth and other economic outcomes and behaviours. *Review of Economic Studies* 87(4), 1683–1725.
- Blundell, R. and T. MaCurdy (1999). Labor supply: A review of alternative approaches. In O. C. Ashenfelter and D. Card (Eds.), *Handbook of Labor Economics*, Volume 3, Chapter 27, pp. 1559–1695. Elsevier.
- Blundell, R., L. Pistaferri, and I. Saporta-Eksten (2016). Consumption Inequality and Family Labor Supply. *American Economic Review* 106(2), 387–435.
- Board of Governors of the Federal Reserve System (2025). Distributional financial accounts: Compare Wealth Components across Groups. Data visualization, last updated September 19, 2025.
- Brown, J. R., C. C. Coile, and S. J. Weisbenner (2010). The effect of inheritance receipt on retirement. *The Review of Economics and Statistics* 92(2), 425–434.
- Brühlhart, M., A. Eyquem, I. Z. Martínez, and E. Rubolino (2025). The output cost of inheritance. Technical report. Working paper.

- Bulman, G., R. Fairlie, S. Goodman, and A. Isen (2021). Parental Resources and College Attendance: Evidence from Lottery Wins. *American Economic Review* 111(4), 1201–1240.
- Callaway, B. and P. H. Sant’Anna (2021). Difference-in-Differences with Multiple Time Periods. *Journal of Econometrics* 225(2), 200–230.
- Cengiz, D., A. Dube, A. Lindner, and B. Zipperer (2019). The Effect of Minimum Wages on Low-Wage Jobs. *The Quarterly Journal of Economics* 134(3), 1405–1454.
- Cesarini, D., E. Lindqvist, M. J. Notowidigdo, and R. Östling (2017). The Effect of Wealth on Individual and Household Labor Supply: Evidence from Swedish Lotteries. *American Economic Review* 107(12), 3917–3946.
- Charles, K. K. and E. Hurst (2003). The correlation of wealth across generations. *Journal of Political Economy* 111(6), 1155–1182.
- Chetty, R., N. Hendren, M. R. Jones, and S. R. Porter (2020, May). Race and economic opportunity in the united states: An intergenerational perspective. *Quarterly Journal of Economics* 135(2), 711–783.
- Deaton, A. and J. Muellbauer (1980). *Economics and Consumer Behavior*. Cambridge: Cambridge University Press.
- Fadlon, I. and T. H. Nielsen (2021). Family Labor Supply Responses to Severe Health Shocks: Evidence from Danish Administrative Records. *American Economic Journal: Applied Economics* 13(3), 1–30.
- Federal Deposit Insurance Corporation (2025). Historical rates prior rule (excel). Excel file. Accessed September 25, 2025.
- Federal Reserve Bank of St. Louis (2025). U.S. Census Bureau and U.S. Department of Housing and Urban Development, Median Sales Price of Houses Sold for the United States. Retrieved from FRED. Accessed September 23, 2025.
- Fulton County Probate Court (n.d.). Frequently asked questions: How long does probate take? <https://www.fultonprobatega.org/FAQ.aspx?QID=68>. Accessed: 2025-09-12.
- Geiger Law Office (n.d.). How Long Does It Take to Settle a Trust in California? <https://www.geigerlawoffice.com/blog/how-long-does-it-take-to-settle-a-trust-in-california-.cfm>. Accessed: 2025-09-12.
- Golosov, M., M. Graber, M. Mogstad, and D. Novgorodsky (2024). How Americans Respond to Idiosyncratic and Exogenous Changes in Household Wealth and Unearned Income. *The Quarterly Journal of Economics* 139(2), 1321–1395.
- Harris County Public Probate Administrator (n.d.). Frequently asked questions. <https://ppa.harriscountytexas.gov/Frequently-Asked-Questions>. Accessed: 2025-09-12.

- Holtz-Eakin, D., D. Joulfaian, and H. S. Rosen (1993). The Carnegie Conjecture: Some Empirical Evidence. *The Quarterly Journal of Economics* 108(2), 413–435.
- Hurd, M. D. and J. P. Smith (2001). Anticipated and actual bequests. In D. A. Wise (Ed.), *Themes in the Economics of Aging*, pp. 357–392. University of Chicago Press.
- Joulfaian, D. and M. O. Wilhelm (1994). Inheritance and Labor Supply. *The Journal of Human Resources* 29(4), 1205–1234.
- Killewald, A., F. T. Pfeffer, and J. N. Schachner (2017). Wealth inequality and accumulation. *Annual Review of Sociology* 43, 379–404.
- Kotlikoff, L. J. and L. H. Summers (1981). The role of intergenerational transfers in aggregate capital accumulation. *Journal of Political Economy* 89(4), 706–732.
- Lundberg, S. and R. A. Pollak (1996). Bargaining and distribution in marriage. *Journal of Economic Perspectives* 10(4), 139–158.
- MaCurdy, T. E. (1981). An empirical model of labor supply in a life-cycle setting. *Journal of Political Economy* 89(6), 1059–1085.
- Modigliani, F. (1986). Life cycle, individual thrift, and the wealth of nations. *American Economic Review* 76(3), 297–313.
- Moran & Associates (n.d.). What is the typical timeline for trust administration in palm beach county after a death? <https://moran.law/what-is-the-typical-timeline-for-trust-administration-in-palm-beach-county-after-a-death/>. Accessed: 2025-09-12.
- Nekoei, A. and D. Seim (2023). How Do Inheritances Shape Wealth Inequality? Theory and Evidence from Sweden. *Review of Economic Studies* 90(1), 463–498.
- Parker Law Offices (n.d.). How long does trust administration usually take? <https://www.estateandtrustlawyer.com/how-long-does-trust-administration-usually-take/>. Accessed: 2025-09-12.
- Pew Research Center (2013). Grandparents living with or serving as primary caregivers for their grandchildren. Technical report, Pew Research Center, Social and Demographic Trends. Accessed: 2025-09-14.
- Picchio, M., S. Suetens, and J. C. Van Ours (2018). Labour Supply Effects of Winning a Lottery. *The Economic Journal* 128(611), 1700–1729.
- Saez, E. and G. Zucman (2016, May). Wealth Inequality in the United States since 1913: Evidence from Capitalized Income Tax Data. *The Quarterly Journal of Economics* 131(2), 519–578.

- Silverstein, M. and V. L. Bengtson (1997). Intergenerational solidarity and the structure of adult child–parent relationships in american families. *American Journal of Sociology* 103(2), 429–460.
- Smith, M., O. Zidar, and E. Zwick (2023). Top wealth in America: New estimates under heterogeneous returns. *The Quarterly Journal of Economics* 138(1), 515–573.
- SSR Elder Law & Estate Planning (n.d.). Trust administration. <https://ssrlawoffice.com/trust-administration/>. Accessed: 2025-09-12.
- Staiger, M. (2025, April). The intergenerational transmission of employers and the earnings of young workers. Working paper, Opportunity Insights and Harvard University. Preprint, 77 pages.
- Stephens, M. J. (2002). Worker Displacement and the Added Worker Effect. *Journal of Labor Economics* 20(3), 504–537.
- Swartz, T. T. (2009). Intergenerational family relations in adulthood: Patterns, variations, and implications in the contemporary united states. *Annual Review of Sociology* 35, 191–212.
- The Legacy Lawyers (n.d.). How long does a trustee have to distribute assets? <https://www.thelegacylawyers.com/blog/how-long-does-a-trustee-have-to-distribute-assets/>. Accessed: 2025-09-12.
- U.S. Census Bureau (2024). Grandparents and their coresident grandchildren: 2021. Technical Report P20-588, U.S. Census Bureau. Accessed: 2025-09-14.
- U.S. Social Security Administration (2005). Cohort life table for the 1950 birth cohort. https://www.ssa.gov/oact/NOTES/as120/LifeTables_Tbl_7_1950.html. From *Actuarial Study No. 120: Life Tables for the United States Social Security Area 1900–2100*.
- Vivalt, E., E. Rhodes, A. Bartik, D. Broockman, P. Krause, and S. Miller (2025). The employment effects of a guaranteed income: Experimental evidence from two U.S. states. *Working Paper*.
- Voorheis, J., J. Colmer, K. Houghton, E. Lyubich, M. Munro, C. Scalera, and J. Withrow (2023, April). Building the prototype census environmental impacts frame. Census Working Paper CES-23-20, U.S. Census Bureau.
- Wagner, D. and M. Layne (2014, July 1). The Person Identification Validation System (PVS): Applying the Center for Administrative Records Research and Applications’ (CARRA) Record Linkage Software. Working Paper CARRA WP 2014-01, U.S. Census Bureau.

- Wolff, E. N. (2002, May). Inheritances and Wealth Inequality, 1989–1998. *American Economic Review* 92(2), 260–264.
- Wolff, E. N. and M. Gittleman (2011, February). Inheritances and the Distribution of Wealth or Whatever Happened to the Great Inheritance Boom? Results from the SCF and PSID. *NBER Working Paper Series* (16840). National Bureau of Economic Research, Working Paper No. 16840.
- Wolff, J. L., J. C. Cornman, and V. A. Freedman (2025). The Number of Family Caregivers Helping Older U.S. Adults Increased from 18 Million to 24 Million, 2011–22. *Health Affairs* 44(2), 187–195.

Appendix A

Proof of Proposition 1

A.1 Analytical solution for $h^*(a_t, 1)$

We can solve analytically for $c_t^*(a_t + I, 1)$. First, applying the envelope theorem for stochastic dynamic programming problems (Benveniste and Scheinkman, 1979) to equation (1.4) and combining with equation (1.6), yields:

$$V'(a_t, 1) = \frac{1}{c_t^*(a_t, 1)} \quad (\text{A.1})$$

Advancing one period and substituting back into equation (1.6) (suppressing arguments for brevity) yields the Euler equation:

$$\frac{1}{c_t} = \frac{\beta R}{c_{t+1}} \implies c_{t+1}^* = \beta R c_t^* \quad (\text{A.2})$$

Next, we impose the transversality condition:

$$\lim_{T \rightarrow \infty} \beta^T \cdot V'(a_T, 1) \cdot a_T = 0 \quad (\text{A.3})$$

Combining with equation (A.1), we have:

$$\lim_{T \rightarrow \infty} \frac{\beta^T \cdot a_T}{c_T^*} = 0 \quad (\text{A.4})$$

By the Euler equation, we have:

$$c_T = (\beta R)^{T-t} c_t \quad (\text{A.5})$$

Combining equations (A.4) and (A.5) yields:

$$\lim_{T \rightarrow \infty} \frac{a_T}{R^T} = 0 \quad (\text{A.6})$$

Next, we can write the intertemporal budget constraint by rewriting the within-period budget constraint as:

$$c_t - wh_t = a_t - \frac{a_{t+1}}{R} \quad (\text{A.7})$$

Combining within-period constraints up to period T yields the intertemporal budget constraint:

$$\sum_{k=0}^{\infty} \frac{c_{t+k} - wh_{t+k}}{R^k} = a_t - \lim_{T \rightarrow \infty} \frac{a_T}{R^T} \quad (\text{A.8})$$

Substituting in equation (A.6), we have:

$$\sum_{k=0}^{\infty} \frac{c_{t+k} - wh_{t+k}}{R^k} = a_t \quad (\text{A.9})$$

Substituting the Euler path $c_{t+k} = (\beta R)^k c_t$ and $h_{t+k} = w/(\chi(\beta R)^k c_t)$:

$$\sum_{k=0}^{\infty} \frac{c_{t+k}}{R^k} = c_t \sum_{k=0}^{\infty} \beta^k = \frac{c_t}{1 - \beta} \quad (\text{A.10})$$

$$\sum_{k=0}^{\infty} \frac{wh_{t+k}}{R^k} = \frac{w^2}{\chi c_t} \sum_{k=0}^{\infty} (\beta R^2)^{-k} = \frac{w^2}{\chi c_t} \cdot \frac{\beta R^2}{\beta R^2 - 1} \quad (\text{A.11})$$

The final equality holds if $\beta R^2 > 1$. This condition ensures the present value of labor income converges: with log utility of consumption and quadratic disutility of labor, labor income is proportional to $1/c_t$. Plugging in the Euler equation, labor income shrinks at rate $1/(\beta R)$ per period. Combined with discounting at rate $1/R$, the present value of labor income is a geometric series with common ratio $1/(\beta R^2)$ and converges iff $\beta R^2 > 1$.¹

We can rewrite the intertemporal budget constraint in equation (A.9) as:

$$a_t = \frac{c_t}{1 - \beta} - \frac{w^2 \beta R^2}{(\beta R^2 - 1) \chi c_t} \quad (\text{A.12})$$

$$= \frac{c_t^*}{1 - \beta} - \frac{K}{c_t^*} \quad (\text{A.13})$$

where $K \equiv \frac{w^2 \beta R^2}{(\beta R^2 - 1) \chi}$. This expression can be rearranged to solve for $c_t^*(a_t, 1)$, which by equation (1.8) recovers $h_t^*(a_t, 1)$. In contrast, $c_t^*(a_t, 0)$ does not have an analytical solution. However, at $I = 0$ the two states coincide. Therefore, to compare $h_t^*(a_t + I, 1)$ and $h_t^*(a_t, 0)$, we will develop an approximation of $h_t^*(a_t, 0)$ in terms of $h_t^*(a_t, 1)$ by linearizing $h_t^*(a_t, 0)$ in the inheritance amount I .

¹More generally, with $v(h) = \chi h^{1+\gamma}/(1+\gamma)$ (Frisch elasticity $1/\gamma$), the analogous convergence condition would be $\beta R^{1+\gamma} > 1$. Quadratic disutility corresponds to a Frisch elasticity of 1.

A.2 First-order expansion of $V(a, 0; I)$

The Taylor expansion around $I = 0$ is:

$$V(a_t, 0; I) \approx V(a_t, 1) + I \cdot \Omega(a_t) + O(I^2),$$

where $\Omega(a_t) \equiv \partial V(a_t, 0; I) / \partial I|_{I=0}$.

Applying the envelope theorem to equation (1.3) with respect to the parameter I and denoting the optimal next-period assets $a_{t+1}^* = R(a_t + wh^*(a_t, 1) - c^*(a_t, 1))$:

$$\Omega(a_t) = \beta p V'(a_{t+1}^* + I, 1)|_{I=0} + \beta(1-p) \Omega(a_{t+1}^*) = \frac{\beta p}{c^*(a_{t+1}^*, 1)} + \beta(1-p) \Omega(a_{t+1}^*)$$

Using equation (A.2), the state-1 Euler equation, to simplify the first term:

$$\Omega(a_t) = \frac{p}{R c^*(a_t, 1)} + \beta(1-p) \Omega(a_{t+1}^*) \quad (\text{A.14})$$

Solving the recursion. Guess $\Omega(a_t) = \lambda / c^*(a_t, 1)$. Substituting into equation (A.14) and again using the Euler equation on the right-hand side:

$$\frac{\lambda}{c^*(a_t, 1)} = \frac{p}{R c^*(a_t, 1)} + \beta(1-p) \cdot \frac{\lambda}{\beta R c^*(a_t, 1)}$$

Multiplying through by $c^*(a_t, 1)$ and collecting:

$$\lambda R = p + (1-p)\lambda \implies \lambda(R - 1 + p) = p \implies \lambda = \frac{p}{r + p}$$

Therefore:

$$\Omega(a_t) = \frac{p}{r + p} \cdot \frac{1}{c^*(a_t, 1)} = \frac{p}{r + p} \cdot V'(a_t, 1) \quad (\text{A.15})$$

A.3 Post-inheritance hours are lower than pre-inheritance hours

The envelope theorem gives $V'(a, s; I) = 1/c^*(a, s; I)$ in *both* states (Appendix A.1 derives this for state 1; the same argument applied to (1.3) and (1.6) gives $V'(a, 0; I) = 1/c^*(a, 0; I)$). Combining with the intratemporal condition (1.8):

$$h^*(a, s; I) = \frac{w}{\chi} \cdot V'(a, s; I) \quad (\text{A.16})$$

So the difference in hours between the post- and pre-inheritance states is proportional to the difference in the marginal value of assets:

$$h^*(a_t + I, 1) - h^*(a_t, 0; I) = \frac{w}{\chi} [V'(a_t + I, 1) - V'(a_t, 0; I)] \quad (\text{A.17})$$

Step 1: Linearize $V'(a_t, 0; I)$ in I . Differentiating the expansion $V(a_t, 0; I) \approx V(a_t, 1) + I \Omega(a_t)$ with respect to a_t :

$$V'(a_t, 0; I) \approx V'(a_t, 1) + I \cdot \Omega'(a_t) = V'(a_t, 1) + \frac{p}{r+p} I \cdot V''(a_t, 1) \quad (\text{A.18})$$

where the last equality uses $\Omega(a_t) = \frac{p}{r+p} V'(a_t, 1)$ from (A.15).

Step 2: Linearize $V'(a_t + I, 1)$ in I .

$$V'(a_t + I, 1) \approx V'(a_t, 1) + I \cdot V''(a_t, 1) \quad (\text{A.19})$$

Step 3: Subtract. Taking equation (A.19) minus equation (A.18):

$$V'(a_t + I, 1) - V'(a_t, 0; I) \approx I \cdot V''(a_t, 1) \cdot \left(1 - \frac{p}{r+p}\right) = I \cdot V''(a_t, 1) \cdot \frac{r}{r+p} \quad (\text{A.20})$$

Step 4: Express $V''(a_t, 1)$ in closed form. Differentiating $V'(a_t, 1) = 1/c^*(a_t, 1)$:

$$V''(a_t, 1) = -\frac{dc_t^*(a_t, 1)/da_t}{c^*(a_t, 1)^2} \quad (\text{A.21})$$

Implicit differentiation of (A.13) with respect to a_t gives:

$$1 = \frac{dc_t^*(a_t, 1)}{da_t} \cdot \left(\frac{1}{1-\beta} + \frac{K}{c_t^*(a_t, 1)^2}\right) \implies \frac{dc_t^*(a_t, 1)}{da_t} = \frac{(1-\beta)c_t^*(a_t, 1)^2}{c_t^*(a_t, 1)^2 + K(1-\beta)} \quad (\text{A.22})$$

Rearranging (A.13) yields:

$$K(1-\beta) = c_t^*(a_t, 1)^2 - a_t(1-\beta)c_t^*(a_t, 1) \quad (\text{A.23})$$

So:

$$\frac{dc_t^*(a_t, 1)/da_t}{c_t^*(a_t, 1)} = \frac{1-\beta}{2c_t^*(a_t, 1) - a_t(1-\beta)} \quad (\text{A.24})$$

Substituting equation (A.24) into equation (A.21) yields:

$$V''(a_t, 1) = -\frac{1}{c^*(a_t, 1)} \cdot \frac{1-\beta}{2c^*(a_t, 1) - a_t(1-\beta)} \quad (\text{A.25})$$

Step 5: Combine. Substituting equations (A.20) and (A.25) into equation (A.17), and using $h^*(a_t, 1) = w/(\chi c^*(a_t, 1))$ from equation (1.8):

$$h^*(a_t + I, 1) - h^*(a_t, 0; I) \approx -h^*(a_t, 1) \cdot \frac{r}{r+p} \cdot \frac{(1-\beta)I}{2c^*(a_t, 1) - a_t(1-\beta)} \quad (\text{A.26})$$

The denominator $2c^*(a_t, 1) - a_t(1-\beta)$ can be rewritten using equation (A.13) as $c^*(a_t, 1) + K(1-\beta)/c^*(a_t, 1)$, which is strictly positive under our assumption that $\beta R^2 > 1$. Hence $h^*(a_t + I, 1) - h^*(a_t, 0; I) < 0$, establishing Proposition 1. $\square$

The difference decomposes into two offsetting effects:

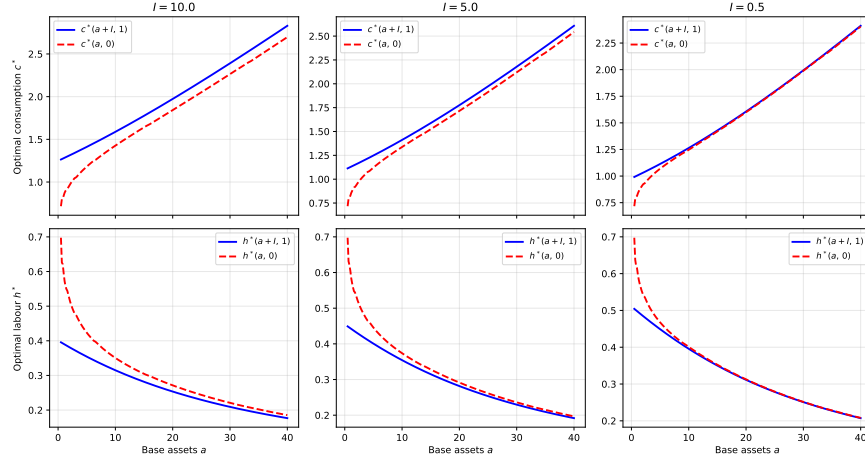
$$h^*(a_t + I, 1) - h^*(a_t, 0; I) = \underbrace{h^*(a_t + I, 1) - h^*(a_t, 1)}_{\text{direct wealth effect: } < 0} + \underbrace{h^*(a_t, 1) - h^*(a_t, 0; I)}_{\text{anticipation effect: } > 0}.$$

From equations (A.19), (A.18), and (A.17), the direct wealth effect has magnitude $\frac{(1-\beta)I}{2c_t^*(a_t, 1) - a_t(1-\beta)}$ and the anticipation effect has magnitude $\frac{p}{r+p} \cdot \frac{(1-\beta)I}{2c_t^*(a_t, 1) - a_t(1-\beta)}$. Since $p/(r+p) < 1$, the direct wealth effect strictly dominates. Note that as $p \rightarrow 0$, the hours reduction vanishes, consistent with the agent smoothing fully under near-certain timing.

A.4 Numerical verification

This approximation holds exactly at $I = 0$ and for small $I > 0$. We can also verify that this local approximation holds for discrete I by solving numerically for $h^*(a_t, 0)$. Figure A.1 shows the results of applying value function iteration to solve for $c_t^*(a_t, 0)$ and plotting it against $c_t^*(a_t + I, 1)$, with standard calibration parameters.

Figure A.1: Optimal consumption and hours in pre- and post-inheritance states



Notes: This figure presents the optimal policy functions for consumption and hours for the dynamic problem described by equations (1.3) and (1.4). The following parameter calibrations are used: $\beta = 0.95$; $R = 1.04$; $w = 1.0$; $\chi = 2.0$; and $p = 0.1$.

The top row of Figure A.1 illustrates that, when the inheritance is large relative to baseline assets, optimal consumption in the post-inheritance state lies above optimal consumption in the pre-inheritance state. Only when the inheritance is very small relative to baseline assets, as shown in the third column, do the two policy functions converge. The bottom row shows the corresponding result that optimal post-inheritance hours lie below optimal pre-inheritance hours except when the inheritance is very small relative to baseline assets.

Appendix B

Appendix Tables

Table B.1: Social Security Administration cohort life table

Expected share of 1940 birth cohort surviving to age x		
x	Male	Female
60	0.776	0.855
65	0.720	0.815
70	0.644	0.756
75	0.545	0.674
80	0.424	0.564
85	0.281	0.421
90	0.139	0.252

Notes: This table reproduces the SSA's cohort life tables by sex for the closest available birth year to the average parent birth cohort in our sample and for older ages. Source: U.S. Social Security Administration (2005).

Table B.2: Additional summary statistics for children

	Main sample (last parent dies) (1)	Unconditional on parent linkage (10% sample) (2)
Age	38.26	37.87
Birth year	1979	1979
Female	0.49	0.50
Married	0.37	0.43
White	0.57	0.59
Black	0.21	0.14
Hispanic	0.15	0.18
Has positive wage earnings	0.74	0.73
Wage earnings	\$42,300	\$46,360
Wage earnings (median)	\$27,890	\$31,560
Wage earnings (cond. on positive)	\$57,510	\$63,340
Tax unit investment income	\$1,583	\$2,103
Tax unit investment income (median)	\$0	\$0
Number of unique individuals	1,939,000	7,198,000

Notes: This table reproduces, in column 1, descriptive statistics from Table 1.1 for our main estimation sample of individuals who lose an elderly, last parent. All monetary values are reported in 2022 U.S. dollars, using the Consumer Price Index to adjust for inflation. All values in column 1 are measured one year prior to parental death (the baseline year) and reported as cohort size-weighted averages. Column 2 reports the same set of descriptive statistics for all individuals in the same birth cohorts as our main estimation sample (1971-1987). All values are reported as averages across calendar years that correspond to the baseline year in the main sample, using treatment cohort shares in the main sample as weights. Source: Census Environmental Impacts Frame, Master Address File, Decennial Census (2000, 2010), American Community Survey (2000-2022); IRS 1040s, W-2s (2005-2022); SSA Numident (1994-2022).

Table B.3: Inheritance components captured by our IRS data

Category	Captured by information return flag	Captured by investment income
Most financial assets, if retained	1099-INT + 1099-DIV	✓
Housing that is individually owned & rented	x	✓
Retirement accounts	1099-R	If reinvested in financial assets (unlikely)
Housing that is sold	1099-S (partial coverage)	If reinvested in financial assets
Financial assets that are liquidated	x	x
Financial assets that bear < \$10 income	x	x
Housing that is neither sold nor rented	x	x
Business income	x	x
Non-housing durables	x	x

Notes: This table summarizes the fields in our tax data that indicate underlying wealth, and which we use as proxies for inheritances. Details are described in Section 1.3.4.

Table B.4: Share of individuals who receive an inheritance from a last parent based on union across change in wealth outcomes

	Control (1)	Treated (2)	Difference (3)	N individuals
Main sample	0.3963 (0.0003)	0.5001 (0.0007)	0.1038 (0.0008)	1,939,000
Male	0.3859 (0.0005)	0.4874 (0.0010)	0.1015 (0.0010)	992,000
Female	0.4071 (0.0005)	0.5134 (0.0010)	0.1062 (0.0010)	947,000
No college	0.3601 (0.0009)	0.4749 (0.0019)	0.1148 (0.0020)	237,000
College	0.5339 (0.0010)	0.6950 (0.0019)	0.1612 (0.0021)	199,000
White	0.4381 (0.0005)	0.5829 (0.0010)	0.1448 (0.0010)	1,112,000
Black	0.3055 (0.0009)	0.3473 (0.0018)	0.0418 (0.0019)	288,000
Hispanic	0.3338 (0.0007)	0.3970 (0.0014)	0.0633 (0.0015)	412,000
Parent 1994 AGI Q1	0.3139 (0.0007)	0.3573 (0.0013)	0.0433 (0.0014)	446,000
Parent 1994 AGI Q2	0.3609 (0.0007)	0.4458 (0.0014)	0.0849 (0.0015)	444,000
Parent 1994 AGI Q3	0.4165 (0.0007)	0.5636 (0.0015)	0.1471 (0.0016)	443,000
Parent 1994 AGI Q4	0.5132 (0.0007)	0.7124 (0.0015)	0.1991 (0.0015)	442,000

Notes: This table reports means and difference in means for treated and control individuals across different subsamples, based on equation 2.2 and using an indicator for undergoing a change in wealth from retirement distributions, housing sales, or new investment income, as described in Section 2.3.3. When computing standard errors (reported in parenthesis), we cluster on dying parent. Source: Census Environmental Impacts Frame, Master Address File, Decennial Census (2000, 2010), American Community Survey (2000-2022); IRS 1040s, W-2s (2005-2022); SSA Numident (1994-2022).

Table B.5: Effect of last parent death on investment income and labor supply

Event year	Per-adult investment income	Tax unit investment income	Tax unit has positive investment income	Per-adult earnings
	(1)	(2)	(3)	(4)
-5	7.823 (5.247)	14.2 (7.985)	-.0000242 (.0005165)	24.31 (37.15)
-4	6.383 (4.958)	12.42 (7.475)	-.0003545 (.0004914)	11.98 (34.94)
-3	4.786 (4.436)	10.41 (6.611)	-.0002135 (.0004546)	8.757 (31.34)
-2	5.875 (3.525)	8.979 (5.24)	-.0001585 (.0003939)	-28.42 (24.89)
-1	0 (0)	0 (0)	0 (0)	0 (0)
0	100.1 (4.169)	144.1 (6.137)	.03465 (.0004438)	-622.3 (26.4)
1	289.6 (6.355)	423.9 (9.426)	.04 (.0004933)	-770.3 (35.3)
2	367.4 (7.666)	545.2 (11.6)	.03294 (.0005147)	-740.2 (41.63)
3	396.3 (8.675)	593.3 (13.29)	.02831 (.0005596)	-631.4 (47.58)
4	388.6 (9.493)	583.7 (14.72)	.02412 (.0005849)	-482.5 (53.58)
5	394.3 (10.55)	587.7 (16.47)	.02027 (.0006219)	-395.7 (60.27)
DiD estimate	311.7 (6.749)	461.2 (10.49)	.03077 (.0003847)	-621.6 (37.69)
Baseline mean	695	1151	.1974	35230
N individuals	1.939M	1.939M	1.939M	1.939M

Notes: This table presents estimates of the effect of losing a last parent on various outcomes, based on estimating equation 2.1. When computing standard errors (reported in parenthesis), we cluster on dying parent. We use $c - 1$ as the omitted event time. Source: Census Environmental Impacts Frame, Master Address File, Decennial Census (2000, 2010), American Community Survey (2000-2022); IRS 1040s, W-2s (2005-2022); SSA Numident (1994-2022).

Table B.5: Effect of last parent death on investment income and labor supply (continued)

Event year	Own earnings	Has positive earnings	Tax unit earnings	Share of tax unit with positive earnings
	(5)	(6)	(7)	(8)
-5	-67.06 (39.05)	-.00348 (.0005388)	162.1 (61.06)	-.002443 (.0005173)
-4	-74.38 (36.53)	-.00325 (.0005219)	108.4 (56.94)	-.002454 (.0004999)
-3	-49.99 (32.64)	-.003084 (.0004943)	82.18 (50.55)	-.002654 (.0004727)
-2	-44.12 (25.49)	-.002357 (.0004287)	-22.06 (40.46)	-.001948 (.0004092)
-1	0 (0)	0 (0)	0 (0)	0 (0)
0	-695.9 (27.3)	-.002574 (.0004256)	-829.4 (43.16)	-.002524 (.0004059)
1	-813 (37.29)	-.002112 (.0005029)	-1087 (57.76)	-.001863 (.0004779)
2	-743.8 (44.96)	-.001049 (.0005447)	-1103 (68.51)	-.0009807 (.0005165)
3	-670.5 (51.55)	.0003353 (.0005751)	-985.7 (78.83)	.0003946 (.000546)
4	-541.5 (58.3)	.001321 (.0006039)	-842.3 (89.24)	.001487 (.0005728)
5	-454.4 (65.83)	.002852 (.0006384)	-754.9 (100.9)	.003129 (.0006052)
DiD estimate	-616.8 (42.06)	.002054 (.0004308)	-1008 (63.67)	.001659 (.0004011)
Baseline mean	35000	.7189	53560	.7175
N individuals	1.939M	1.939M	1.939M	1.939M

Notes: This table presents estimates of the effect of losing a last parent on various outcomes, based on estimating equation 2.1. When computing standard errors (reported in parenthesis), we cluster on dying parent. We use $c - 1$ as the omitted event time. Source: Census Environmental Impacts Frame, Master Address File, Decennial Census (2000, 2010), American Community Survey (2000-2022); IRS 1040s, W-2s (2005-2022); SSA Numident (1994-2022).

Table B.6: DiD estimates for components of investment income and capitalization factors

	DiD point estimates for each investment income asset class	Saez and Zucman (2016) average capitalization factors
Taxable interest	\$33.13	77.9
Tax-exempt interest	\$14.72	36.4
Taxable dividend	\$117.5	42.5
Gross rental	\$146.4	39.3

Notes: This table presents, in the left column, our DiD point estimates for the components of investment income. The right column contains the average of Saez and Zucman (2016)'s annual capitalization factors from 2010-2016 (the years corresponding to treatment cohorts in our sample), using the number of individuals in each treatment cohort as weights. Source: Census Environmental Impacts Frame, Master Address File, Decennial Census (2000, 2010), American Community Survey (2000-2022); IRS 1040s, W-2s (2005-2022); SSA Numident (1994-2022).

Table B.7: DiD estimates of additional behavioral outcomes

	New marriage	New divorce	Changed Census tract
	(1)	(2)	(3)
DiD estimate	0.0010 (0.0005)	0.0021 (0.0008)	0.0046 (0.0005)
Baseline mean	0.0000	0.0000	0.2037
N individuals	1,365,000	800,000	1,127,000

Notes: This table reports DiD estimates for marriage, divorce, and geographic mobility. To study the effect on marriage (divorce), we restrict the sample to individuals who were unmarried (married) individuals who are tax filers in the baseline year, and define our outcome of interest to be a time-varying indicator equal to one if the winner is married (unmarried). Restricting to tax filers makes the two subsamples more comparable since, as described in Section 1.3.2, married individuals in our sample are tax filers by definition. To study geographic mobility, we define indicators for the probability of moving to a different Census tract. We restrict the sample to individuals who have a populated Census tract in all 18 years of the data. Results shown in this table are own outcomes for the child of the deceased parent, rather than per-adult outcomes. When computing standard errors (reported in parenthesis), we cluster on dying parent. Source: Census Environmental Impacts Frame, Master Address File, Decennial Census (2000, 2010), American Community Survey (2000-2022); IRS 1040s, W-2s (2005-2022); SSA Numident (1994-2022).

Table B.8: Baseline shares of children and children with parents receiving information returns

	Children		Parents		
	<u>Mean</u>	<u>SD</u>	<u>Mean</u>	<u>SD</u>	<u>N individuals</u>
1099-R (retirement)	.0931	.2906	.5317	.4990	1,609,000
1099-INT (interest income)	.1957	.3968	.2726	.4453	1,609,000
1099-DIV (dividend income)	.1179	.3225	.1635	.3698	1,609,000
1099-S (sale of house)	.0101	.1002	.0150	.1220	1,609,000
1098 (mortgage)	.3005	.4585	.2575	.4372	992,000

Notes: This table presents baseline shares of children receiving various information returns for tax-reportable changes in wealth, and corresponding shares of children with a dying parent who receives these forms. 1099 indicators are available in our data beginning in 2010 and the 1098 indicator is available beginning in 2013. For consistency with our event studies for these outcomes (see Figure 3.3), we estimate means for the 2015 and 2016 treatment cohorts only. Source: Census Environmental Impacts Frame, Master Address File, Decennial Census (2000, 2010), American Community Survey (2000-2022); IRS 1040s, W-2s (2005-2022); SSA Numident (1994-2022).

Table B.9: DiD estimates across outcomes by own and parental income

Sample	Own earnings		Per-adult earnings		Per-adult investment income		N individuals
	Estimate	(1) Baseline mean	Estimate	(2) Baseline mean	Estimate	(3) Baseline mean	
<i>Own earnings</i>							
Tercile 1	16.48 (42.15)	190.7	-191.7 (51.4)	8074	217.2 (10.81)	575.3	809,000
Tercile 2	-426.1 (45.11)	21060	-477.3 (45.05)	24060	178.6 (7.611)	300	945,000
Tercile 3	-1429 (107.6)	83610	-1188 (87.51)	73440	536.9 (14.52)	1208	822,000
<i>Parent 1994 AGI</i>							
Quartile 1	-247.9 (62.13)	24820	-258.4 (56.91)	25060	78.02 (8.601)	371.9	434,000
Quartile 2	-42.59 (69.16)	29280	-119.6 (63.44)	29640	112.3 (9.793)	431.1	439,000
Quartile 3	-482.3 (85.32)	36380	-439 (77.03)	36600	267.1 (12.81)	650	447,000
Quartile 4	-1332 (128.6)	52080	-1230 (112.6)	52140	899.9 (22.52)	1370	454,000
<i>Parent 1994 inv. inc.</i>							
Bin 1	-238.4 (44.27)	26250	-286.6 (40.61)	26530	66.71 (5.798)	322.2	1,047,000
Bin 2	-580.1 (89.77)	39880	-641.2 (80.68)	40180	169.5 (11.85)	673.6	448,000
Bin 3	-1568 (119.4)	50640	-1438 (104.9)	50680	995.1 (22.42)	1591	445,000
<i>Parent $\ell = -1$ inv. inc.</i>							
Bin 1	-127.8 (40.04)	29360	-155.3 (36.6)	29660	79.36 (5.066)	414.9	1,506,000
Bin 2	-919.9 (138.1)	48200	-832.4 (121.6)	48370	278.8 (17.75)	900.2	473,000
Bin 3	-2163 (187.8)	56990	-1973 (163)	56870	1944 (40.44)	2238	353,000

Notes: This table, which corresponds to panel (a) of Figure 3.1, presents DiD estimates for own and per-adult earnings and per-adult investment income in different subsamples defined by own earnings and different measures of parental income. Note that, in our data, earnings are measured at the individual level and investment income is measured at the tax unit level. When computing standard errors (reported in parenthesis), we cluster on dying parent. Outcomes and baseline means are reported in 2022 U.S. dollars. Source: Census Environmental Impacts Frame, Master Address File, Decennial Census (2000, 2010), American Community Survey (2000-2022); IRS 1040s, W-2s (2005-2022); SSA Numident (1994-2022).

Table B.10: DiD estimates across outcomes by own demographic characteristics

Sample	Own earnings		Per-adult earnings		Per-adult investment income		N individuals
	Estimate	(1) Baseline mean	Estimate	(2) Baseline mean	Estimate	(3) Baseline mean	
Male	-799 (67.17)	40090	-687.4 (53.38)	34720	315.7 (9.467)	699.1	992,000
Female	-436.1 (48.95)	29690	-547.7 (52.65)	35760	307.8 (9.084)	690.7	947,000
White	-844.8 (64.51)	41280	-852.2 (56.82)	41710	477.4 (10.74)	944.4	1,112,000
Black	-157 (56.7)	24140	-194.7 (54.04)	24110	36.84 (6.235)	216.2	412,000
Hispanic	-376.6 (81.89)	26450	-426.8 (77.56)	26430	94.88 (11.8)	351.8	288,000
Under 40	-563.6 (43.36)	31180	-585.7 (39.04)	31490	259.6 (6.761)	531.8	1,709,000
40 or above	-837 (118)	50430	-770.5 (103.9)	50340	527.3 (19.62)	1354	557,000
No college	-1219 (187)	58520	-1101 (161.7)	58150	731.9 (29.55)	1576	199,000
College	-246.4 (83.33)	28010	-237.9 (77.07)	28740	178 (13.22)	371	237,000
Lives with parent	-79.82 (81.87)	28160	-89.77 (76.28)	28220	401 (16.47)	512.2	489,000
0-5m from parent	-477.2 (90.97)	35300	-505.4 (80.28)	35520	352.6 (16.51)	633.2	464,000
5-25m from parent	-923.8 (101.3)	40790	-915.7 (89.79)	41280	275.5 (15.43)	719.7	469,000
>25m from parent	-701.7 (63.25)	35300	-709.7 (56.48)	35490	283.4 (9.252)	763.8	1,201,000

Notes: This table, which corresponds to panel (b) of Figure 3.1, presents DiD estimates for own and per-adult earnings and per-adult investment income in different subsamples defined by own demographic characteristics. We define distance bins, the last four rows of the table, based on miles. Note that, in our data, earnings are measured at the individual level and investment income is measured at the tax unit level. When computing standard errors (reported in parenthesis), we cluster on dying parent. Outcomes and baseline means are reported in 2022 U.S. dollars. Source: Census Environmental Impacts Frame, Master Address File, Decennial Census (2000, 2010), American Community Survey (2000-2022); IRS 1040s, W-2s (2005-2022); SSA Numident (1994-2022).

Table B.11: DiD estimates across outcomes by parent demographic characteristics

Sample	Own earnings		Per-adult earnings		Per-adult investment income		N individuals
	Estimate	(1) Baseline mean	Estimate	(2) Baseline mean	Estimate	(3) Baseline mean	
Male	-575 (62.27)	34690	-580.3 (55.47)	34760	302.2 (9.827)	717.3	873,000
Female	-665.1 (57)	35290	-662 (51.38)	35650	317.7 (9.286)	674.9	1,066,000
Under 75	-631.9 (51.8)	35250	-611.7 (46.45)	35470	345.7 (8.121)	664.9	1,175,000
75 or above	-477.9 (71.68)	34470	-543.9 (64.24)	34730	267.1 (11.93)	758.2	764,000
No wage earnings	-507.8 (45.12)	34010	-489.8 (40.61)	34270	287.4 (7.299)	671.8	1,555,000
Has positive wage earnings	-445.4 (113.8)	39970	-493.9 (99.92)	40030	442.6 (17.95)	811.2	657,000

Notes: This table, which corresponds to panel (c) of Figure 3.1, presents DiD estimates for own and per-adult earnings and per-adult investment income in different subsamples defined by characteristics of the dying parent. Note that, in our data, earnings are measured at the individual level and investment income is measured at the tax unit level. When computing standard errors (reported in parenthesis), we cluster on dying parent. Outcomes and baseline means are reported in 2022 U.S. dollars. Source: Census Environmental Impacts Frame, Master Address File, Decennial Census (2000, 2010), American Community Survey (2000-2022); IRS 1040s, W-2s (2005-2022); SSA Numident (1994-2022).

Table B.12: DiD estimates across outcomes by current household characteristics

Sample	Own earnings		Per-adult earnings		Per-adult investment income		N individuals
	Estimate	(1) Baseline mean	Estimate	(2) Baseline mean	Estimate	(3) Baseline mean	
Unmarried	-421.8 (40.99)	25520	-413.8 (40.55)	25520	258 (7.478)	361.3	1,365,000
Unmarried filer	-698.1 (59.71)	37130	-692.2 (58.92)	37130	365.9 (11.29)	600.3	992,000
Married (filer)	-943.9 (93.27)	53600	-922.1 (76.41)	54270	426.7 (12.9)	1349	800,000
Filer with dependent(s)	-699.2 (72.65)	44780	-701.5 (60.63)	45330	312.1 (10.37)	959.7	951,000
Filer with no dependent(s)	-844.6 (79.23)	44560	-819.4 (74.42)	44500	551.1 (14.86)	920.9	883,000

Notes: This table, which corresponds to panel (a) of Appendix Figure C.5, presents DiD estimates for own and per-adult earnings and per-adult investment income in different subsamples defined by characteristics of the child's current household. Note that, in our data, earnings are measured at the individual level and investment income is measured at the tax unit level. When computing standard errors (reported in parenthesis), we cluster on dying parent. Outcomes and baseline means are reported in 2022 U.S. dollars. Source: Census Environmental Impacts Frame, Master Address File, Decennial Census (2000, 2010), American Community Survey (2000-2022); IRS 1040s, W-2s (2005-2022); SSA Numident (1994-2022).

Table B.13: DiD estimates across outcomes by childhood household characteristics

Sample	Own earnings		Per-adult earnings		Per-adult investment income		N individuals
	Estimate	(1) Baseline mean	Estimate	(2) Baseline mean	Estimate	(3) Baseline mean	
Only child	-607.5 (62.5)	37600	-595.4 (56)	37850	411.4 (10.21)	771.9	817,000
1 sibling	-679.5 (77.91)	35630	-679.7 (69.97)	35810	302.5 (12.95)	718.3	635,000
2 siblings	-403 (109.3)	30620	-486 (97.32)	30980	143.8 (15.69)	554.1	301,000
1st of 2 kids	-791.5 (99.07)	35390	-761.3 (88.57)	35510	249.4 (14.78)	704.6	365,000
2nd of 2 kids	-557.6 (121.5)	35960	-595.2 (109.2)	36230	370.8 (18.7)	737.2	270,000
Boy in boy+girl HH	-700.4 (118.1)	36890	-625.8 (94.7)	32060	233.4 (15.54)	619.6	336,000
Girl in boy+girl HH	-327.3 (79.73)	26770	-453.4 (85.03)	31980	206.7 (13.48)	583.2	362,000

Notes: This table, which corresponds to panel (b) of Appendix Figure C.5, presents DiD estimates for own and per-adult earnings and per-adult investment income in different subsamples defined by characteristics of the child's household of origin. The last two rows of the table correspond to subsamples of adult children whose dying parent has at least one male and at least one female child. Note that, in our data, earnings are measured at the individual level and investment income is measured at the tax unit level. When computing standard errors (reported in parenthesis), we cluster on dying parent. Outcomes and baseline means are reported in 2022 U.S. dollars. Source: Census Environmental Impacts Frame, Master Address File, Decennial Census (2000, 2010), American Community Survey (2000-2022); IRS 1040s, W-2s (2005-2022); SSA Numident (1994-2022).

Table B.14: IV estimates of the effect of investment income on earnings

	Main sample
Per-adult earnings	-1.399 (.1157)
F-statistic	146.2
J-statistic	30.06
J-statistic p-value	.0117
N individuals	1.939M

Notes: This table reports 2SLS estimates and test statistics for an overidentified model where the outcome is per-adult earnings, the endogenous variable is per-adult investment income, and instrument sets are constructed by interacting 1(treated for stack) $\times$ 1(post-treatment for stack) and group dummies. Groups are defined by the interaction of sex, 1994 parent AGI quartile, and racial group. We include individual $\times$ stack and calendar year $\times$ stack fixed effects as in equation 2.1. When computing standard errors (reported in parenthesis), we cluster on dying parent. The small discrepancy between our main estimate and the slope in Figure 3.2 reflects slight differences in the number of observations contributing to each stack when estimating the model using the full microdata versus subsamples. Source: Census Environmental Impacts Frame, Master Address File, Decennial Census (2000, 2010), American Community Survey (2000-2022); IRS 1040s, W-2s (2005-2022); SSA Numident (1994-2022).

Table B.15: Comparison of MPE estimates across studies

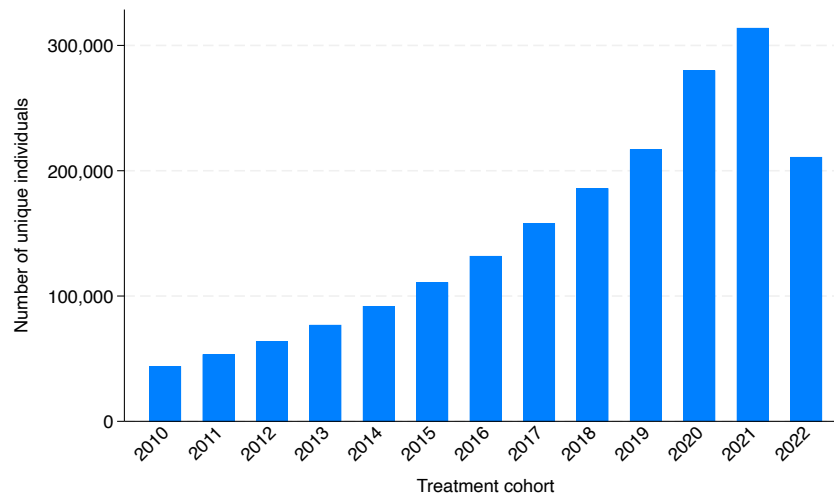
	Setting	Mean effect of an extra dollar of unearned income (MPE)
This paper	Inheritances (U.S.)	-0.11 - -0.31 (0.10)
Nekoei & Seim (2023)	Inheritances (Sweden)	-0.28 (Not reported)
Golosov et al. (2024)	Lottery winnings (U.S.)	-0.33 (Not reported)
Vivalt et al. (2025)	Cash transfers (Texas & Illinois)	-0.35 - -0.44 (Not reported)

Notes: This table reports pre-tax, household- or tax unit-level MPE estimates from this study and other papers. The standard error reported for our study is equal to the standard error for the slope of the line of best fit from our visual IV, scaled by the annuity payout associated with a \$1 stock of wealth. Our approach closely matches that of Golosov et al. (2024). Neither Golosov et al. (2024) nor Vivalt et al. (2025), who do not report standard errors for these estimates. Nekoei and Seim (2023) report annual MPEs as the ratio of event time estimates for earnings to unearned income; the estimate shown above is a simple average of annual MPEs across their post-period. Since estimates across event times are not independent and identically distributed, we cannot report a standard error for their mean.

Appendix C

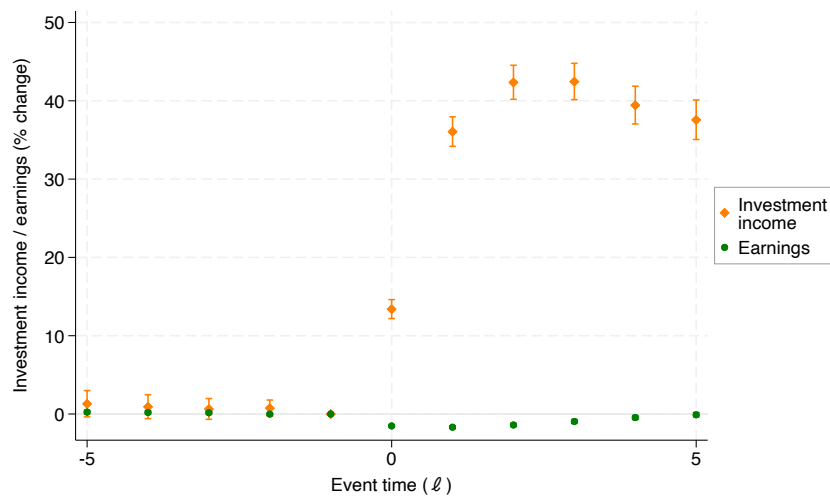
Appendix Figures

Figure C.1: Unique individuals per treatment cohort



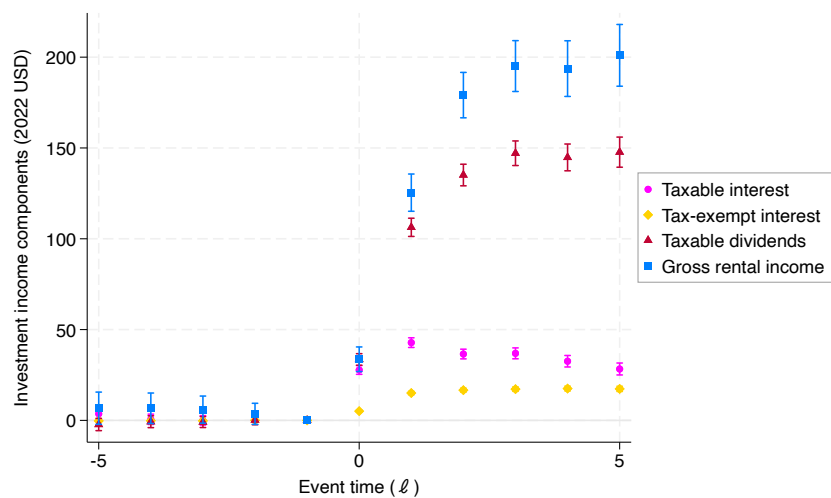
Notes: This figure displays the number of unique individuals belonging to each treatment cohort in our main estimation sample. We estimate treatment effects for cohorts 2010-2016, while cohorts 2017-2022 serve as controls for certain treatment cohorts, as described in Section 2.2. Source: Census Environmental Impacts Frame, Master Address File, Decennial Census (2000, 2010), American Community Survey (2000-2022); IRS 1040s, W-2s (2005-2022); SSA Numident (1994-2022).

Figure C.2: Effect of last parent death across outcomes: Poisson model



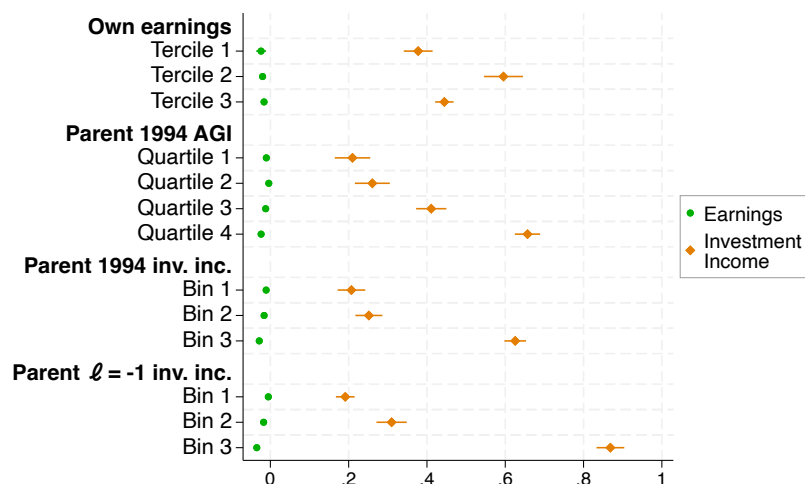
Notes: This figure presents estimates of the effect of losing a last parent on two outcomes, based on estimating a Poisson version of equation 2.1. 95 percent confidence intervals are displayed, clustering on dying parent. We use $c - 1$ as the omitted event time. Source: Census Environmental Impacts Frame, Master Address File, Decennial Census (2000, 2010), American Community Survey (2000-2022); IRS 1040s, W-2s (2005-2022); SSA Numident (1994-2022).

Figure C.3: Effect of last parent death on components of investment income



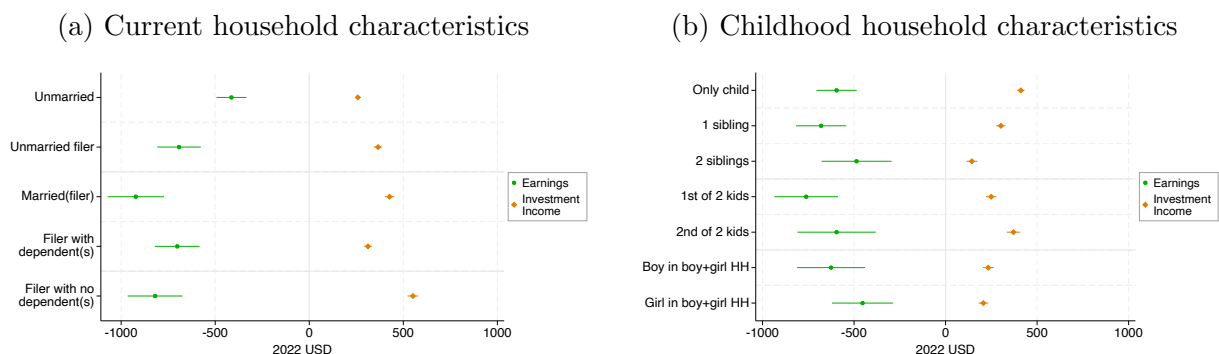
Notes: This figure presents estimates of the effect of losing a last parent on the four income variables whose sum we defined to be investment income, based on estimating equation 2.1. 95 percent confidence intervals are displayed, clustering on dying parent. We use $c - 1$ as the omitted event time. Source: Census Environmental Impacts Frame, Master Address File, Decennial Census (2000, 2010), American Community Survey (2000-2022); IRS 1040s, W-2s (2005-2022); SSA Numident (1994-2022).

Figure C.4: Proportional responses across outcomes, by own and parental income



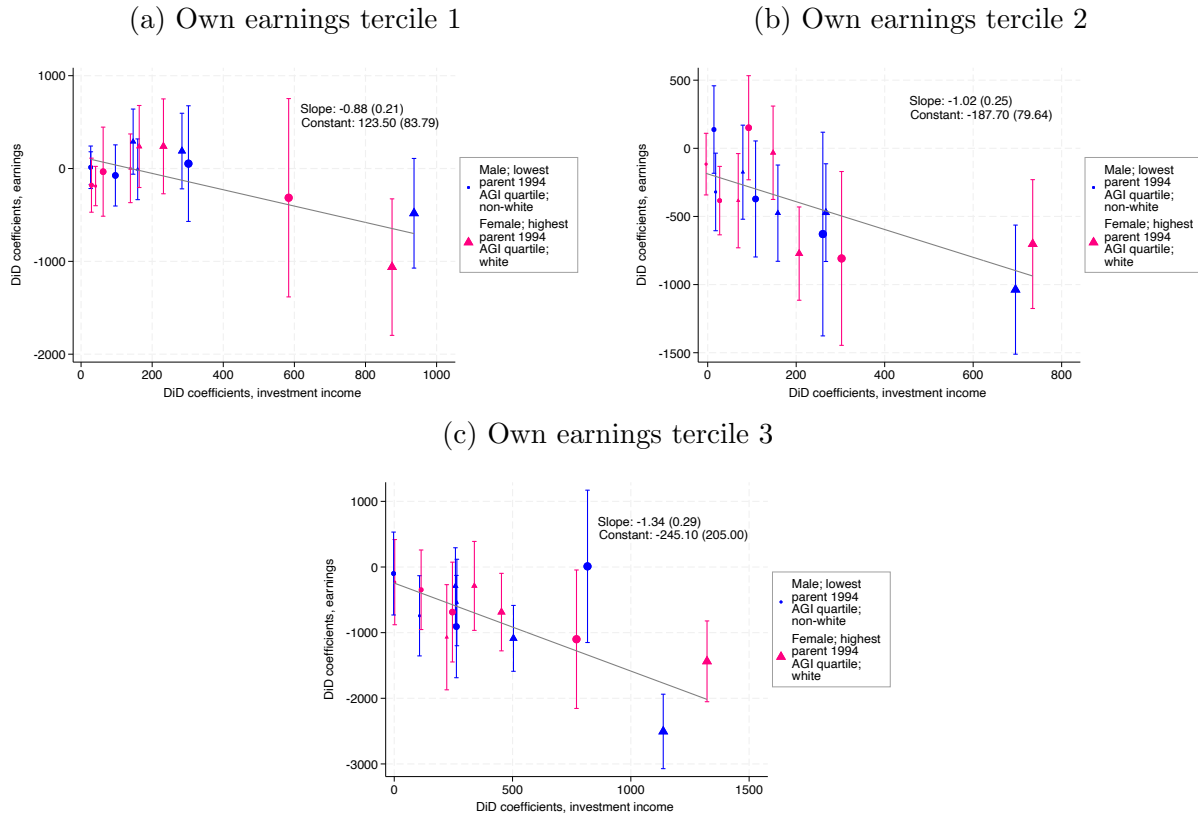
Notes: This figure presents proportional impacts on investment income and earnings—that is, DiD estimates for these outcomes scaled by their baseline means—across groups defined by baseline own earnings and different measures of parental income. Group definitions are described in Section 3.2.1. 95 percent confidence intervals are displayed, clustering on dying parent. Source: Census Environmental Impacts Frame, Master Address File, Decennial Census (2000, 2010), American Community Survey (2000-2022); IRS 1040s, W-2s (2005-2022); SSA Numident (1994-2022).

Figure C.5: DiD estimates across outcomes and household characteristics



Notes: This figure presents DiD estimates for investment income and earnings across groups defined by different socioeconomic and demographic characteristics. 95 percent confidence intervals are displayed, clustering on dying parent. All time-varying characteristics pertain to the year prior to the parent's death (with the exception of parent age, which is age at death). Source: Census Environmental Impacts Frame, Master Address File, Decennial Census (2000, 2010), American Community Survey (2000-2022); IRS 1040s, W-2s (2005-2022); SSA Numident (1994-2022).

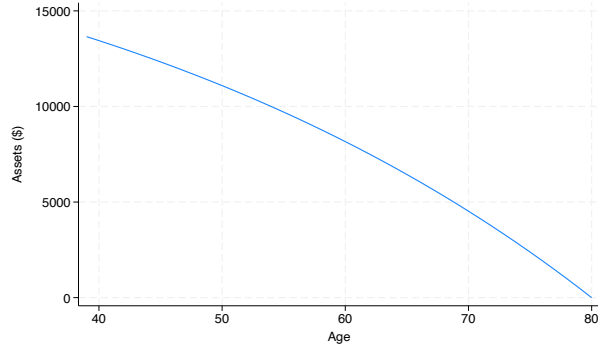
Figure C.6: Visual IV estimates of the effect of investment income on earnings, by earnings tercile



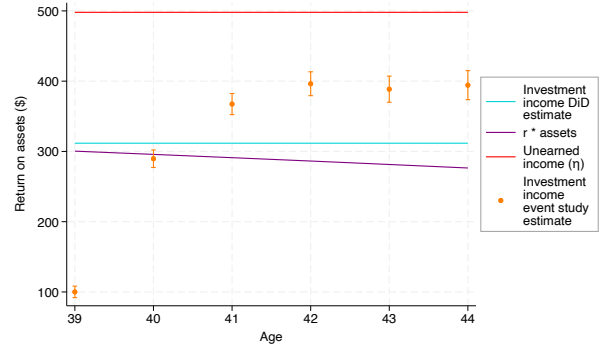
Notes: Each panel plots DiD estimates for earnings against DiD estimates for investment income for sixteen different subsamples, as detailed in Section 3.2.2, within a given tercile of baseline own earnings. Whiskers mark 95 percent confidence intervals for the earnings estimates. Source: Census Environmental Impacts Frame, Master Address File, Decennial Census (2000, 2010), American Community Survey (2000-2022); IRS 1040s, W-2s (2005-2022); SSA Numident (1994-2022).

Figure C.7: Asset and return paths from annuitizing investment income gains

(a) Path of assets until end of life

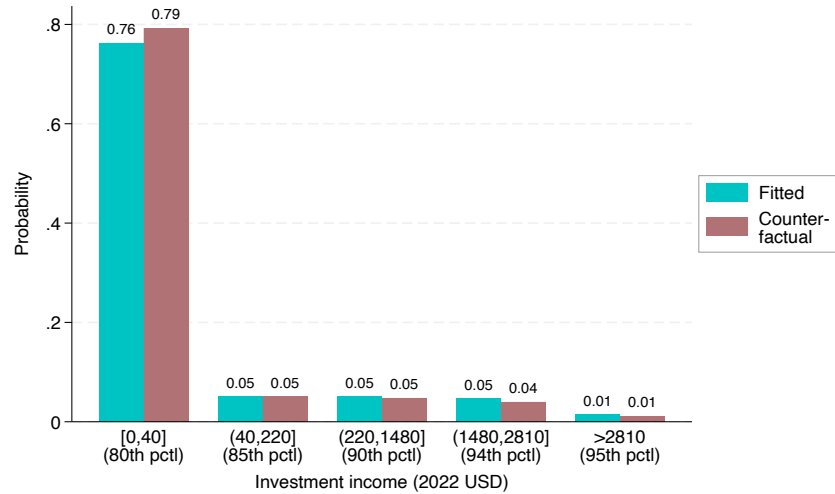


(b) Returns from annuitization and event study



Notes: Panel (a) plots the path of assets over the remainder of life implied by the annuitization formula (equation 3.1), when using treating our capitalized DiD estimate as the stock of wealth and other parameters defined in Section 3.4. Restricting to the first six remaining years of life after parent death (i.e., our event study post-period), panel (b) plots unearned income; returns from the asset balance in panel (a) using the interest rate applied in our annuitization (0.022); and our DiD and event study estimates for investment income.

Figure C.8: Effect of inheritances on PMF of investment income



Notes: This figure presents the probability mass function associated with the cumulative distribution function in Figure 3.8. To build this plot, we follow the procedure described in Section 3.5. Source: Census Environmental Impacts Frame, Master Address File, Decennial Census (2000, 2010), American Community Survey (2000-2022); IRS 1040s, W-2s (2005-2022); SSA Numident (1994-2022).

Appendix D

Variable Definitions

Here we define variables not already described in Sections 1.3.1 and 1.3.2.

1099-R: An indicator for receipt of a 1099-R information return (this return is issued to an individual plan-holder).

1099-INT: An indicator for receipt of a 1099-INT information return, either by an individual or their spouse (this return is often issued to only one member of a married tax unit).

1099-DIV: An indicator for receipt of a 1099-DIV information return, either by an individual or their spouse (this return is often issued to only one member of a married tax unit).

1099-S: An indicator for receipt of a 1099-S information return, either by an individual or their spouse (this return is often issued to only one member of a married tax unit).

1098: An indicator for receipt of a 1098 information return, either by an individual or their spouse (this return is often issued to only one member of a married tax unit).

2010 homeownership: An indicator for being a head of household or spouse or partner of a head of household in the 2010 Decennial in a household where the householder is a homeowner (either owning free and clear or with a mortgage).

Census tract: The Census tract (Census-defined geographic aggregation) corresponding to an individual's home address in a given year.

EIN: For individuals linked to a single firm through Form W-2, this is the identity of their employer. For individuals linked to multiple firms through Form W-2, this is the identity of the highest-paying employer.

College: An indicator for having a bachelor's degree or higher in the 2000 Decennial or 2001-2020 ACS surveys (the 2010 Decennial does not include data on college attendance).

Distance to parent: Distance of child's home address to home address of the dying parent, in miles, as calculated by Stata's geodist package.

Having dependents: An indicator for claiming a child at home or child away exemption on Form 1040.

Number of siblings: The number of other children claimed by one's parent from 1951-2007, covering births up to 20 years before and 20 years after the birth year range of children in our sample (1971-1987).

Birth order: The relative birth year order among children claimed by one's parent from 1951-2007, a 20 year range surrounding the minimum and maximum birth year of children in our sample.

Having no wealth (dying parents): An indicator for not recording receipt of a 1099-R, having 0 investment income, and not being a homeowner in 2010.

Wealth change due to retirement: A binary indicator for recording receipt of a 1099-R in $\ell \in \{0, 1, 2\}$.

Wealth change due to housing: A binary indicator for recording receipt of a 1099-S in $\ell \in \{0, 1, 2\}$.

Wealth change due to investment income: A binary indicator equal to the union of the following binary indicators:

- A binary indicator for recording receipt of a 1099-DIV or 1099-INT in $\ell \in \{0, 1, 2\}$ having not received one in $\ell \in \{-3, -2, -1\}$
- A binary indicator for recording investment income in $\ell \in \{0, 1, 2\}$ in a category (taxable and tax-exempt interest income, taxable dividend income, or gross rental income) that was not recorded in $\ell \in \{-3, -2, -1\}$.
- A binary indicator for recording at least 50 percent higher investment income in $\ell \in \{0, 1, 2\}$ in a given category than was recorded in the same category in $\ell \in \{-3, -2, -1\}$.
- A binary indicator for recording at least 50 percent higher total investment income in $\ell \in \{0, 1, 2\}$ than total investment income recorded in $\ell \in \{-3, -2, -1\}$.

Wealth change due any source: A binary indicator equal to the union of wealth change due to retirement, wealth change due to housing, and wealth change due to investment income.

Appendix E

Child-Reported Inheritances in the Survey of Consumer Finances

The SCF contains a section called “Inheritances and Charitable Contributions” which asks respondents: “*Including any gifts or inheritances you may have already told me about, have you (or your husband/wife/partner/ spouse) ever received an inheritance, or been given substantial assets in a trust or in some other form?*” For up to three such “inheritances, gifts, or transfers,” the survey subsequently asks respondents to provide information on the type of transfer (whether an inheritance, trust, or transfer/gift); the approximate value at the time the transfer was received, the year of receipt, and from whom the transfer was received.

The same section also asks “How much altogether were any others you have received?” but there are no questions on transfer type, year of receipt, or source associated with this question. This section of the SCF is intended to encompass all inheritances, but other sections contain a few more questions about whether specific assets were received as inheritances. However, these sections do not distinguish between gifts and inheritances and lack information on the source of the inheritance (i.e. whether from parents or another entity). Wolff and Gittleman (2011) show that nearly all respondents who report having received specific assets also report these assets in the general section on inheritances. For these reasons, we restrict attention to the general questions.

We pool 2010-2016 SCF waves and restrict to households where at least one member (respondent or spouse) has no living parent and was born in the same birth cohort range as children in our main estimation sample (1971-1987). These choices reflect a compromise between approximating our sample selection, given that the SCF lacks information on parental death year, and maintaining sample size, which would be sharply reduced by fine-grained re-weighting. We inflation adjust values so that all inheritances amounts are measured in USD 2022. The resulting sample has similar per-adult wage earnings and ages as our main estimation sample in the baseline year (see Appendix Table B.5). The survey permits dollar-valued responses of up to one billion, such that top-coding does not constrain the upper tail of reported values.

Table E.1: SCF subsample inheritance statistics (2010-2016)

	Statistic	SD
Mean inheritance	\$43,189	\$7,706
Median inheritance	\$0	N/A
Inheritance share	.1888	.0149
Cond. mean inheritance	\$228,752	\$38,074
Cond. median inheritance	\$89,648	\$25,032
Mean per-adult wage earnings	\$43,934	\$5,082
Median per-adult wage earnings	\$29,438	\$1,140
Mean respondent age	41.02	0.3037
Mean spouse age	37.20	0.2364
N respondents	2,367	

Notes: This table presents descriptive statistics from the 2010, 2013, and 2016 SCF surveys, as described above. Dollar amounts are reported in 2022 USD.

Appendix F

Parent Asset Portfolios in the Survey of Consumer Finances

We pool 2010-2016 SCF waves and restrict to respondents who are age 65 or above, unmarried or widowed, and have children away from home who are age 18 or older (a proxy for having adult children). Like Smith et al. (2023) and other papers that use the SCF to decompose wealth, we merge to the SCF’s “Bulletin” extract file which contains variables representing categories of assets and liabilities, summarized at a high level here: <https://www.federalreserve.gov/econres/files/Networth%20Flowchart.pdf>. These categories allow us to determine the value of assets that generate investment income, all assets that can be inherited, and debt. We inflation adjust values so that all variables are measured in USD 2022.

Defining investment income-bearing assets. The definition of investment income in our tax data maps fairly cleanly onto the SCF bulletin concepts. We include all bulletin concepts for financial assets that typically generate interest or dividends. We omit checking account balances under \$17,000 from the category `liq` (liquid assets), since the taxable interest these generate would generally be under the \$10 exemption for a 1099-INT form and therefore are unlikely to be reported on tax forms (see Section 1.3.4). We define these small balances as their own category, `checking_small`. Since investment income includes rental income, but the SCF bulletin concepts do not distinguish between investment properties versus other non-primary residence properties, we define a category called `rental` that sums the value of directly-owned, non-primary properties that respondents indicate generate rental income. In summary, we define investment income-bearing assets as:

```
asset_invinc = (liq - checking_small) + cds + nmmf + savbnd + stocks + bond
               + trusts + rental
```

Defining inheritable assets. We define inheritable assets as the sum of investment income-bearing assets and all other bulletin asset categories, including equity in primary residences and quasi-liquid retirement accounts. Like the Bulletin extract, we omit defined benefit

pension entitlements since children typically cannot inherit them. Although vehicles are often omitted from definitions of net worth, we maintain them in our definition of inheritable assets. The SCF uses vintage, make, and model-specific market values to calculate the asset value of vehicles, such that these values likely approximate their value to heirs. Our definition is thus:

```
asset_inheritable = asset_invinc + cashli + annuit + retqliq + othfin + vehic
                  + houses + bus + othnfin + checking_small
```

We can then define inheritable net worth as:

```
inheritable_net_worth = asset_inheritable - debt
```

Using these definitions and a few additional variables in the SCF, we obtain summary statistics—presented below in Tables F.1 and F.2—for parents who are broadly similar to those in our main sample (setting aside their mortality risk, which is unobservable in the SCF).

Table F.1: SCF subsample parent asset statistics (2010-2016)

	Statistic	SD
Investment income-bearing assets	\$200,144	\$16,198
Inheritable assets	\$601,453	\$27,019
Debt	\$36,508	\$2,458
Interest & dividend income	\$3,605	\$299
Median interest & dividend income	\$0	N/A
Age	76.18	0.1687
Number of adult children	2.847	0.0327
N respondents	6,456	

Notes: This table presents descriptive statistics from the 2010, 2013, and 2016 SCF surveys. All statistics are means unless otherwise noted. Dollar amounts are reported in 2022 USD.

Table F.2: SCF subsample parent asset shares (2010-2016)

	Share of inheritable assets	Share of inheritable net worth
Investment income-bearing assets	0.3328	0.3542
Quasi-liquid retirement assets	0.1134	0.1208
Vehicles	0.0201	0.0214
Primary residences	0.3066	0.3263
Businesses	0.1073	0.1143
Other assets	0.1198	0.1275
Total	1	1.065
N respondents	6,456	

Notes: This table presents the share of different asset categories in total inheritable assets and inheritable net worth from the 2010, 2013, and 2016 SCF surveys.