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INTERGENERATIONAL MOBILITY AND LONG-TERM CARE

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Intergenerational Mobility and Long-Term Care*

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Abstract

This paper investigates how long-term care risk facing elderly adults impacts the intergenerational mobility of children in the United States. I show that the long-term care needs of grandparents impact both time and monetary investments families make in children. Motivated by these data patterns, I develop and estimate an overlapping generations model in which parents and grandparents interact with limited commitment to make long-term care, childcare, saving, and human capital investment choices. I find that the presence of long-term care needs decreases intergenerational mobility by 12%. Policies that provide coverage for formal long-term care costs increase intergenerational mobility whereas policies that provide payments for informal caregivers decrease intergenerational mobility. These effects are driven by changes in the time and monetary investments families make in their children as a result of these policy changes.

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1 Introduction

One of the largest risks facing elderly adults in the United States is developing long-term care needs. Nearly 70% of adults who reach age 65 will need long-term care at some point, 69% of which is provided informally by family members (Gruber et al., 2023). This care can impose significant time and financial costs to families and social programs such as Medicaid. Moreover, 1 in 5 elder caregivers also cares for at least one child under 12 (Chari and Valli, 2021). This raises an important question about the impact of the long-term care needs of grandparents on children especially as parents may face a tradeoff between caring for their own parents and investing in their children. Investments in children are an important determinant of intergenerational mobility, and there is meaningful persistence in income across generations in the United States with a correlation of about 0.34 between parent and child income rank (Chetty et al., 2014). Further, nearly 60% of inequality in earnings reflects differences that emerge before children enter the labor market (Huggett et al., 2011). Long-term care needs have the potential to impact investments in children's human capital unequally over the wealth distribution which may influence intergenerational mobility. This paper addresses how long-term care risk facing grandparents impacts the economic mobility of children.

The existing literature on the persistence of economic circumstances across generations[1] has largely focused on how the circumstances of parents determine their ability to invest in their children. I include grandparents in order to capture the effects of long-term care needs on children's intergenerational mobility. There is a separate literature on long-term care and the family that largely focuses on how long-term care needs impact aging individuals' spouses and adult children. However, without addressing the impacts of long-term care needs on children, these studies may misstate the effects of policies that provide insurance against long-term care risk.

There are two main goals of this paper. The first is to quantify the impact of long-term care needs on intergenerational mobility. The second is to compare how different forms of insurance against long-term care risk affect intergenerational mobility and welfare.

I first document how long-term care needs impact both time and monetary investments in children and how these effects vary for families across the wealth distribution. Parents who provide long-term care spend less time with their children than otherwise similar parents. Additionally, expansions in Medicaid Home and Community Based Ser-

[1]These include parental income (Chang et al., 2026) borrowing constraints (Caucutt and Lochner, 2020; Lee and Seshadri, 2019), credit constraints (Braxton et al., 2024), and geographic mobility (Anstreicher, 2023).

vices, a program that allows low-wealth adults to receive long-term care at home, increase the amount of time parents in eligible families spend with their children. Long-term care needs may also affect time investments in children beyond impacts on parental time. Many families rely on grandparents for help with childcare, and, as grandparents develop long-term care needs, they are less able to help with childcare. These effects also vary over the wealth distribution, as less wealthy families are more likely to rely on grandparent-provided childcare (Anstreicher and Venator, 2026).

Long-term care needs also impact families' monetary investments in children. Using the Health and Retirement Study, I show that grandparents' long-term care needs are negatively correlated with investments in the parent's education, controlling for the grandparent's age, wealth, and education, as well as the parent's age. This is consistent with findings in the literature showing that parents who provide intensive eldercare are 20% less likely to have an educational savings account for their children than otherwise similar parents (Bogan, 2015).

Motivated by these facts, I develop an overlapping generations model in which parents and grandparents interact with limited commitment. In canonical models of intergenerational mobility, interactions between parents and their children typically cease when the child becomes an adult.[2] However, because long-term care and childcare decisions require coordination between parents and grandparents over the entire life course, I model interactions between parents and grandparents with limited commitment. In each period, families make joint decisions over childcare, eldercare, labor supply, and savings, as well as time and monetary investments in children. Within this framework, there is risk sharing between family members, but insurance is partial, which is an important empirical feature of family interactions (Hayashi et al., 1996; Attanasio et al., 2019). Further, parents and grandparents each hold their own savings. This is important to capture the effects of Medicaid's asset limits for long-term care coverage on savings behavior and intergenerational transfers.

I estimate the model using data from the Health and Retirement Study and the Panel Study of Income Dynamics. Identification of key parameters is based on savings over time, informal care over the wealth distribution, the fraction of grandparents on Medicaid, and the fraction of children who attend college. The model is able to match key features of the data, including informal eldercare rates, time and monetary investments over the wealth distribution, and key measures of economic mobility, such as the correla-

[2]While there are some models of intergenerational mobility that include interactions between parents and children throughout adulthood, these are largely limited to monetary transfers that result from a dynamic game between parents and children, e.g. Rosenzweig and Wolpin (1993).

tion between parent and child income rank.

I use the parameter estimates to conduct two sets of counterfactuals. First, I shut down the presence of long-term care needs in the model and measure the impact on intergenerational mobility. I find that long-term care needs account for 12.2% of the correlation between parent and child income rank, indicating that the presence of long-term care needs negatively affect intergenerational mobility. This is largely driven by increases in parental time investments for the least wealthy families.

I then use the model to evaluate the impact of two forms of insurance against long-term care needs. First, I implement a policy that provides coverage for all long-term care needs met formally. The cost of implementing the policy is covered by a lump sum tax paid by each family. I compare this with long-term care insurance that provides a payment to all informal care-givers, with the change in cost again covered by a lump-sum tax on each family. I find that both insurance policies are welfare improving. Families are willing to pay an amount of assets equivalent to 1.95% and 2.50% of consumption for formal care coverage and payments for informal care provision respectively. These gains are positive across the wealth distribution with higher gains in the middle of the distribution.

Turning to the effects on intergenerational mobility, I find covering formal care decreases the correlation between parent and child income rank by 5.1%. This implies that the policy increases intergenerational mobility. Coverage for informal care has the opposite effect and increases the correlation between parent and child income rank by 12.0%. Providing coverage against formal care costs leads to parents spending less time on elder-care and more time with their children. However, when informal care-givers are provided with a subsidy, informal caregiving increases the most among low-wealth families, whose parents spend less time with their children. The loss in time is only partially offset by increases in monetary investments, negatively affecting intergenerational mobility. In both cases, welfare increases relative to the baseline environment due to the fact that families value the gains from risk protection more than the welfare costs of the tax.[3]

Finally, if most of the gains from providing insurance against long-term care risk are concentrated at the bottom of the wealth distribution, then it may be more cost-effective to design policies that target these families. To evaluate this, I quantify the impacts of two policy changes that help provide insurance for long-term care. First, I increase Medicaid's asset limits for long-term care eligibility from \$2,000 to \$25,000. Second, I implement a

[3]Welfare gains are positive over the wealth distribution even when intergenerational mobility is lowered in part because grandparents prefer informal care over formal care and because of the increased risk protection.

policy that pays parents who provide informal care to Medicaid-eligible grandparents (under the $2,000 asset limit). Each policy is funded by an income tax[4] and, similar to the more expansive insurance cases, both policies are welfare improving. However, relaxing Medicaid's asset test increases economic mobility, whereas subsidizing informal care decreases economic mobility. These effects are measured by a 3.1% decrease and a 4.8% increase in income rank correlation respectively.

This paper makes several contributions to the literature. The existing literature on long-term care and the family largely focuses on the impact of care needs on the economic outcomes of aging parents and their adult children. The availability of informal care reduces Medicaid utilization (Barczyk and Kredler, 2018) and slows nursing home entry (Barczyk et al., 2023) for grandparents. Long-term care needs also dampen the labor supply of care-givers (Fahle and McGarry, 2022; Maestas et al., 2024; Skira, 2015). Further, informal care suppresses demand for long-term care insurance (Mommaerts, 2025; Pauly, 1990) and exacerbates adverse selection issues in the long-term care insurance market (Ko, 2022). In contrast, this paper investigates the effects of long-term care on children as well as parents and grandparents. Accounting for the impacts on children is important for quantifying the welfare effects of policies that provide insurance against long-term care risk.

Studies on long-term care and the family sit within a broader literature examining the role of health risk and social programs on aging adults' savings behavior. Aging adults draw down their savings slowly due to the possibility of medical expenses (De Nardi et al., 2010). At the same time, means-tested social programs crowd out personal savings that could be used to self-insure individuals against risk over the life-cycle (Hubbard et al., 1995). Regarding Medicaid specifically, De Nardi et al. (2016) find that most single retirees would not value an expansion in the program above its cost. Other aspects of the program also impact transfers from grandparents to parents (Mukherjee, 2022; Mukherjee and Liu, 2021). This paper extends this literature by quantifying the effect of grandparent savings and expansions in Medicaid long-term care coverage over three generations. Beyond the effects of health risks, there are also several studies that document how informal insurance within families shapes economic decisions (Boar, 2021; Kaplan, 2012; Voena, 2015) and how the interaction between public and private transfers impact consumption and savings behavior (McCarthy et al., 2022; Villanueva, 2014). I build on this analysis by investigating how intrafamily insurance against long-term care risk impacts children's intergenerational mobility.

[4]While I use a lump sum tax to measure the impact of providing coverage to all families, here I use an income tax, as changes to Medicaid policies are more likely to be funded via the income tax system.

A separate literature documents several factors that contribute to the persistence of economic outcomes across generations. Family background and parental education positively impact a child's future income (Chang et al., 2026; Bolt et al., 2026). One reason for this is the ability of wealthier families to invest more heavily in their children (Becker and Tomes, 1986; Lee and Seshadri, 2019). Time and monetary investments are both important, though not all time investments are equally productive. Parental time is one of the most productive sources of investment during early childhood (Del Boca et al., 2014a), and the time investments of more educated mothers are more productive than the time investments of less educated mothers (Brilli, 2022).

Families may also rely on market-based childcare or grandparent-provided childcare. The literature finds mixed results on the effectiveness of grandparent-provided childcare and market-based childcare (Del Boca et al., 2014b; Milovanska-Farrington, 2021). However, there is some evidence that market-based childcare is more productive than care provided informally by family members (Brilli, 2022). These time investments are complemented by monetary inputs, and higher levels of monetary investments make time investments more productive (Caucutt et al., 2026). Moreover, investments are most impactful for young children as the skill production function exhibits dynamic complementarity, meaning skills developed early are an input into future skill development (Caucutt and Lochner, 2020; Cunha and Heckman, 2007; Cunha et al., 2010; Heckman and Mosso, 2014). In this paper, I consider time investments from parents, grandparents, and market-based childcare, as well as monetary investments. I quantify the impacts of the long-term care needs of grandparents on these investments and the persistence of inequality across generations.

In addition to the importance of the role of human capital investments made by parents, the literature also documents several other factors that impact intergenerational mobility. These include borrowing constraints faced by parents (Caucutt and Lochner, 2020), parents' ability to access credit (Braxton et al., 2024), early childhood development programs (Daruich, 2026; Galama et al., 2025), neighborhood and migration decisions (Anstreicher, 2023; Chetty et al., 2016). I extend this literature on the persistence of economic outcomes across generations by accounting for the impacts of the grandparent generation on the intergenerational mobility of children in the United States. In order to do so, I develop a model of overlapping generations in which parents and grandparents interact with limited commitment to make choices.

In Section 2 I provide more information on long-term care policy and arrangements in the United States, and in Section 3 I show empirical evidence on the relationship between intergenerational mobility and long-term care. In Section 4 I describe the model, and in

Section 5 I describe the estimation procedure. In Section 6 I report the results from the counterfactuals, and Section 7 concludes.

2 Background: Long-term care in the United States

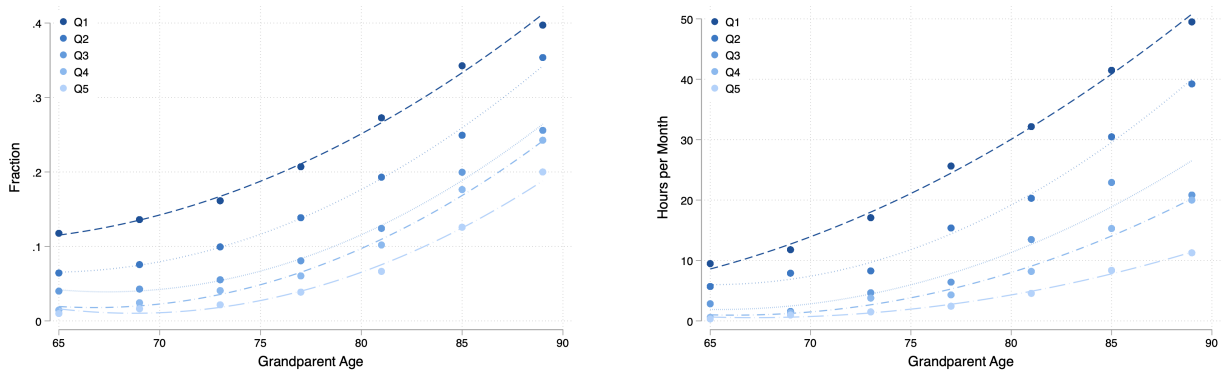
Long-term care needs arise when individuals have difficulty with Activities of Daily Living or Instrumental Activities of Daily Living. These include activities such as bathing, dressing, managing medications, and housekeeping. These needs are not acute medical events but rather long-term difficulties, and 70% of individuals aged 65 will need long-term care at some point (Gruber and McGarry, 2023). However, there is substantial heterogeneity in both the timing and amount of care needed. These care needs may be covered either formally, via out-of-pocket spending or with Medicaid coverage or informally.

2.1 Informal care

In the United States, over half of long-term care needs are met informally, usually by family members (Gruber and McGarry, 2023). Spouses and adult children are the most likely to provide this care, and there are systematic differences over the wealth distribution in care from adult children. Figure 1 shows that poorer grandparents in the Health and Retirement Study receive more care from their adult children on both the extensive (Figure 1a) and intensive (Figure 1b) margins.

Many adult children who provide informal care also have children of their own. Among all informal caregivers, 20% are also caring for at least one child under the age of 18 (Chari and Valli, 2021). For these parents, the opportunity costs of providing long-term care include both lost wages and time they could have spent investing in their children.

Figure 1: Informal care receipt



(a) Fraction receiving informal care

(b) Hours of informal care, conditional

Notes: The sample includes all grandparents in the Health and Retirement study who are at least 65. The left panel reports the fraction who receive informal care from an adult child over age 25, while the right panel reports the average hours of care grandparents receive from adult children as they age, conditional on receiving any hours of care from a parent.

2.2 Formal care

Aging adults may also turn to market-based eldercare when they develop long-term care needs, however, such care is expensive when purchased out-of-pocket. The average price for a home care aide is $20 an hour and a semi-private room in a nursing home costs $111,325 annually (CareScout, 2024). While there is a market for formal long-term care insurance in the United States, it is small, and policies typically do not cover all of a beneficiary's long-term care costs (Brown and Finkelstein, 2007).[5] The private market has difficulty insuring individuals against long-term care risk in part due to supply-side issues including transaction and administrative costs (Braun et al., 2019). There are also demand-side pressures. The availability of informal care depresses demand for long-term care insurance (Mommaerts, 2025) and exacerbates adverse selection (Ko, 2022).

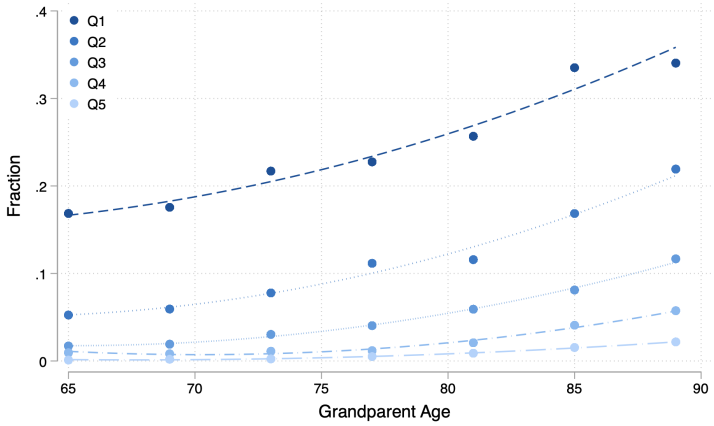
While short-term care needs may be covered under Medicare, the duration of coverage is limited and long-term care needs are not included. Instead, Medicaid covers long-term care for aging adults and is the largest payer of formal long-term care costs. In 2023, Medicaid spent $257 billion dollars on long-term care, making up 46% of all long-term care spending in the United States. Because Medicaid is a means-tested program, recipients must satisfy income and asset limits. In most states, individuals are subject to

[5] About 14% of adults over the age of 65 have a long-term care insurance policy (Hamel and Montero, 2023)

a monthly income limit of $3,000 and an asset limit of $2,000[6] (KFF, 2019).

There are two ways to meet Medicaid's eligibility criteria. First, individuals are categorically eligible if they have very low assets and income prior to incurring long-term care costs. Second, individuals may become eligible by spending down their assets and income on medical expenses until they meet the threshold (termed the "medically needy" pathway to eligibility). While Medicaid's long-term care coverage is most frequently utilized by the least wealthy, it is still relevant for wealthier individuals. Figure 2 plots the rate of Medicaid utilization for long-term care by wealth; while take-up is highest for the least wealthy, there is an uptick for wealthier individuals as they age.

Figure 2: Medicaid rates by wealth



Notes: The sample includes all grandparents aged 65+ in the Health and Retirement Study, 1992-2018. Asset quintiles are computed using all assets (housing and non-housing) at age 65.

Historically, Medicaid has primarily covered institutional long-term care. However, over the past two decades, Medicaid coverage has expanded to include options for care at home through Home and Community Based Services waivers. Medicaid has also recently started to provide informal care coverage in some states. However, this is usually only available for individuals with high care needs and often hard for families to access (Burns et al., 2025).

[6]The asset limit excludes the value of one's primary residence. There is some variation across states in the amount of liquid assets one may hold. Maine has a $10,000 limit, South Carolina's is $9,090, Nebraska, DC, and Rhode Island have a $4,000 limit, North Dakota has a $3,000 limit, New Hampshire and Maryland have a $2,500 limit, and Connecticut has a $1,600 limit (Mutual, 2024).

3 Empirical evidence: Long-term care & intergenerational mobility

Given that formal long-term care is expensive and informal care is common, here I present evidence that the long-term care needs of grandparents impact investments families make in their children. Differences that emerge during childhood reflect variation in inherited skill as well as parental investments in their children. Both time and monetary investments in children are key drivers of the income inequality (Huggett et al., 2011) and thus are heavily intertwined with the persistence of inequality across generations. Long-term care negatively impacts both of these investments, and these effects vary over the wealth distribution. I use this evidence to motivate the need for the structural model of care and investment decisions presented in Section 4.

I first show that parents who provide more eldercare also provide less childcare, suggesting that this tradeoff is relevant. I then investigate the role of long-term care policy using variation in Medicaid spending on long-term care across states and over time. I find that increased access to formal long-term care for grandparents increases parental time spent with children. While parents are the main source of time investments in their children, grandparents are also an important source of childcare for many families. Grandparents with long-term care needs are less able to provide childcare. Turning to the impact of long-term care on monetary investments, I provide suggestive evidence that long-term care needs negatively impact families' ability to make investments in their children's post-secondary education. This is one of the largest financial investments families make in children, and is an important driver of intergenerational mobility (Chetty et al., 2017).

3.1 Parental time investments

3.1.1 Descriptive evidence

Parents who spend more time on eldercare spend less time with children. To document this, I use the American Time Use Survey (ATUS). The ATUS is a nationally representative repeated cross-section that has been conducted annually since 2003. It includes detailed data on how subjects spend their time over the course of the day on which they are surveyed, including time spent on childcare and eldercare. The survey also contains basic demographics, including age, sex, and income, and some information on family members, such as the number and age of one's children.

I use data from the 2003 to 2020 survey waves and I restrict my sample to respondents with children, whose youngest child is less than 18. Summary statistics for the sample are reported in Table 1. Nearly 12% of parents in my sample provide eldercare, and those who do earn less and are slightly less likely to work than parents who do not provide informal care. They also spend less time on childcare and have slightly older children, though these differences are small.

Table 1: Summary statistics by eldercare provision

	No eldercare	Eldercare	p-value
Weekly earnings	581.39	516.70	0.000
Fraction working	0.64	0.62	0.002
Weekly earnings | working	909.52	827.65	0.000
Eldercare minutes	0.00	46.44	0.000
Childcare minutes	71.87	66.90	0.000
Fraction provide childcare	0.59	0.64	0.000
Childcare | childcare provider	121.71	104.27	0.000
Age	37.04	37.32	0.025
Female	0.57	0.60	0.000
Age of youngest household child < 18	7.47	7.83	0.000
Number of children	1.89	1.82	0.000
N	83,477	10,764	.

Notes: The table reports summary statistics for all parents in the American Time Use Survey between 2003 and 2020 with at least one child under 18. Time variables are reported as minutes per day. The p-value is from a two-sample difference of means t-test.

The differences in childcare time by eldercare provision could be due to differences in children's ages or the number of children in the household who need childcare. To get a better sense of the relationship between childcare and eldercare, I regress the number of minutes of childcare cc_i an individual i reported providing on the survey day on a measure of eldercare provision ec_i, including controls X_i for individual i's age, number of children, education, marital status, sex, working hours, and sample day of the week fixed effects. The regression equation is:

$$cc_i = \alpha_0 + \alpha_1 ec_i + \alpha_2 work_i + X_i \upsilon + \epsilon_i \tag{1}$$

α_1 is the coefficient of interest. The estimates are reported in Table 2. Column (1)

uses a continuous measure of eldercare: the number of minutes of eldercare a parent provides on the survey day. Column (2) uses a binary indicator for whether or not a parent provides eldercare. These results indicate that, on average, parents who spend more time on eldercare spend less time with their children.

Table 2: Impacts on parental childcare time

	Childcare minutes	
	(1)	(2)
Eldercare (minutes)	-0.097***	.
	(0.009)	.
Eldercare (indicator)	.	-8.179***
	.	(0.966)
Work (minutes)	-0.101***	-0.101***
	(0.001)	(0.001)
Age of youngest household child < 18	-7.177***	-7.170***
	(0.066)	(0.066)
Number of children	1.061***	1.059***
	(0.338)	(0.338)
Years of education	4.768***	4.792***
	(0.113)	(0.113)
Age	-0.141***	-0.147***
	(0.028)	(0.028)
Female	29.198***	29.388***
	(0.639)	(0.639)
Partnered	18.267***	18.323***
	(0.763)	(0.764)
Constant	36.345***	36.439***
	(1.993)	(1.995)
Mean of dependent variable	71.30	71.30
N	94,241	94,241
Adjusted R^2	0.244	0.244

Notes: The sample includes all respondents in the American Time Use Survey between 2003 and 2020 with at least one child under 18. Time spent on activities is measured in minutes per day. Column (1) uses a continuous eldercare measure, (minutes per day of eldercare). Column (2) uses a binary eldercare measure (an indicator for whether a parent provided any eldercare in the sample day).
Standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Looking at continuous measures of eldercare, for each additional hour of eldercare

a parent provides, he or she provides 6 fewer minutes of childcare. The magnitude is similar in size to the effect of working on childcare hours provided. The results using the binary measure indicate that a parent who provides any eldercare spends about 8 fewer minutes on childcare. These effects are on the same order of magnitude given that parents who provide eldercare spend an average of 45 minutes on eldercare in the sample day. The binary coefficient is larger (11 minutes per hour compared to 6) which is consistent with a nonlinear relationship between eldercare-giving and childcare-giving.

It is important to note that I cannot identify all families in which a grandparent has long-term care needs, only those in which individuals in my sample provide informal eldercare to an aging adult. Therefore there may be additional families in my data that have simultaneous childcare and eldercare needs but rely on formal care. Additionally, there is likely some selection into informal eldercare provision. Here, I do not claim my results are causal, but rather show that providing eldercare is correlated with lower time investments in children after controlling for observable characteristics.

Thus, parents may face tradeoffs between not just work and childcare, but between work, childcare, and eldercare. These tradeoffs are also elucidated in Chari and Valli (2021), who find that increasing childcare availability leads to increases in eldercare provision from parents, rather than increases in labor supply. These results suggest that the long-term care needs of grandparents may negatively impact parental time investments in children.

3.1.2 The role of long-term care policy

Given that providing informal eldercare is correlated with spending less time with children, I investigate how long-term care policy impacts this tradeoff. To do so, I use variation across states and time in Medicaid spending on Home and Community-Based Services (HCBS). These services provide support for low-income, low-wealth individuals with long-term care needs at home, rather than in a nursing home (Mohamed et al., 2025). Therefore expansions in HCBS spending may reduce the barrier to accessing formal care if individuals have a preference for avoiding institutional care.

Table 3 summarizes the distribution of HCBS spending per 65+ adult, as well as total Medicaid spending. HCBS spending makes up about 20% of total Medicaid spending, though there is variation across states and time. More details on this variation can be found in Zai (2024).

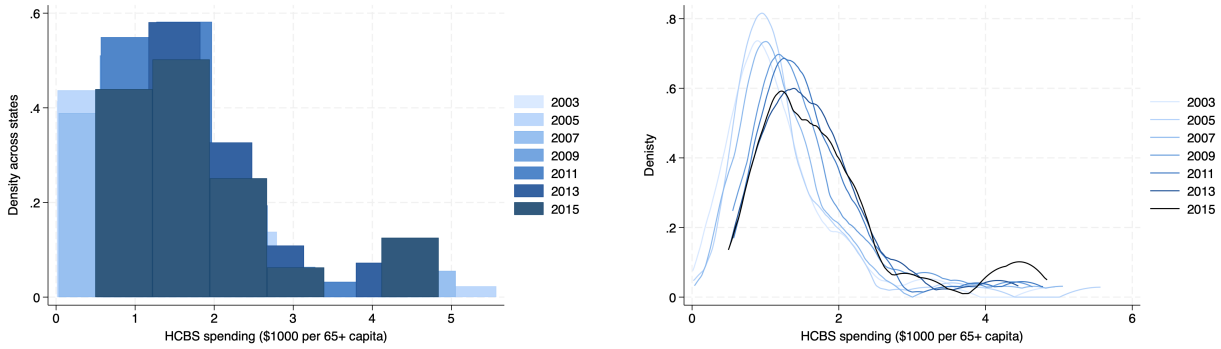
Table 3: Summary statistics: Medicaid spending per 65+ capita

Variable	Mean	Median	P10	P25	P75	P90
HCBS	1,679	1,370	796	1,001	2,022	2,893
Total Medicaid spending	9,819	9,181	6,579	7,447	11,034	13,454

Notes: Data on Medicaid spending was downloaded from Medicaid.gov (Centers for Medicare & Medicaid Services, 2026). The table reports the mean, median and 10th, 25th, 75th, and 90th percentiles of spending between 2003 and 2020 in 2014 dollars.

From Figure 3, it's clear that not only does spending vary across states, but that spending has generally increased over time. Figure 3a plots the distribution of spending each year in 2014 dollars, while Figure 3b shows smoothed density plots of spending over time. Zai (2024) shows that expansions in HCBS spending led to small but positive effects on the self-reported health of aging adults. I use the same variation to investigate the impacts on parents' time spent on childcare and eldercare.[7]

Figure 3: Distribution of Medicaid HCBS expenditures over time



(a) Raw spending by state

(b) Smoothed spending by state

Notes: The left panel reports the distribution of state spending on HCBS over time. The right panel reports the same distribution using a smoothed kernel density. Spending is in 2014 dollars.

To quantify the effects of the policy on how parents allocate their time, I run the following regression:

$$Y_{ist} = \beta_0 + \beta_1 M_{st} + \mu_t + \eta_s + X_{ist}\delta + \epsilon_{ist} \tag{2}$$

[7]Note that this variation may pick up mechanical differences in how sick a state population is if medical needs change over time differently across states.

The dependent variable, Y_{ist}, is minutes of an activity performed on the ATUS diary day of individual i in state s at time t. The outcomes of interest are time spent on childcare and eldercare. The independent variable, M_{st}, is Medicaid spending on HCBS per 65+ capita in state s in year t. I also include year and state fixed effects, μ_t and η_s respectively. Finally, the covariate vector X_{ist} includes age, sex, number of children, years of education, whether an individual is partnered, the age of the youngest child, and day of the week indicators. Standard errors are clustered at the state level. Given that Medicaid primarily provides support to low-income families, in the main results I focus on parents with incomes below $12,500.[8] The results are reported in Table 4.

Table 4: Regression results: Impact of HCBS on parental childcare and eldercare time

	(1) childcare	(2) eldercare
HCBS spending per 65+ capita	0.013**	-0.002
	(0.005)	(0.002)
Age	-0.008	0.107**
	(0.100)	(0.041)
Female	37.412***	-0.739
	(2.834)	(1.345)
Number of children	3.715***	-1.094***
	(1.047)	(0.384)
Years of education	2.136***	-0.003
	(0.394)	(0.214)
Partnered	6.715*	2.407
	(3.447)	(1.597)
Age of youngest household child < 18	-6.646***	0.032
	(0.270)	(0.109)
Mean of dependent variable	78.982	6.656
N	6,464	6,464
Adjusted R^2	0.148	0.004

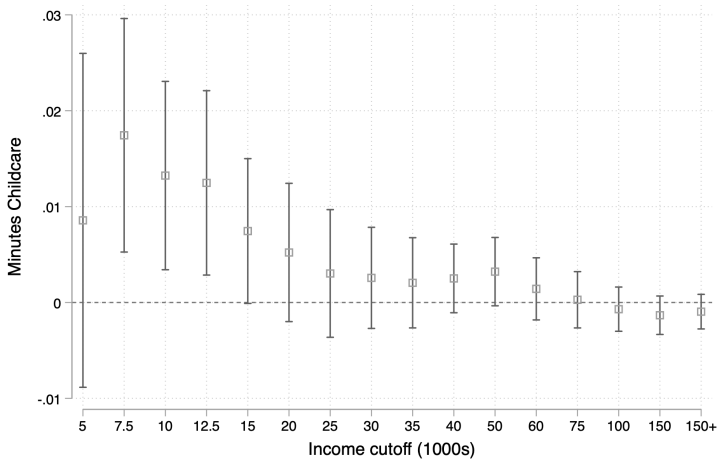
Notes: The sample includes all parents in the American Time Use Survey between 2003 and 2020 with at least one child under 18 and whose annual incomes are below $12,500.
Standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

[8] While eligibility rules for Medicaid long-term care are based on the grandparent's resources, I do not have detailed information on the grandparents in the ATUS, thus I use parent income to capture which families are most likely to be affected.

I find that going from the 25th percentile in HCBS spending to the 75th percentile ($1000 increase in spending per adult over 65) increases childcare by approximately 13 minutes, a 16% increase. The coefficient on eldercare hours is negative, as expected, but insignificant. While these results show that Medicaid HCBS spending increases parental time spent with children, spending on HCBS may also go towards parts of the population that are not over 65. In Appendix A, I show that this result is largely driven by changes in spending on the parts of the policy that target aging adults.

These results indicate that expansions in access to formal long-term care increase parental time spent with children for low-income families. In Figure 4, I plot the coefficient on childcare minutes over income cutoffs. The results are largest for lower-income families, and fade out as higher income families are added to the sample. Parental time is an important source of investments in children, but grandparents may also provide childcare. In the next section I explore how long-term care needs impact grand-parental time investments in children.

Figure 4: Impact of HCBS on parental childcare over income cutoffs



Notes: The sample in the leftmost dot includes only parents in the ATUS who have incomes below $5,000 annually. Moving rightward, each dot adds parents to the sample who are below the given income cutoff.

3.2 Grandparent time investments

Grandparent-provided childcare is important for many families and it is particularly prevalent among low-income and single parent households (Anstreicher and Venator, 2026). Using data from the Health and Retirement Study (HRS), I show that grandparents with long-term care needs are less likely to provide childcare.

The HRS is a longitudinal panel of approximately 20,000 people, with information

collected biennially beginning in 1992. The HRS constains detailed data on aging adults' health status, formal and informal care use, and some information about respondents' children and grandchildren. I define long-term care needs as having difficulty with Activities of Daily Living.[9]

I restrict my sample to individuals in the HRS who have grandchildren. These individuals receive 118 hours of long-term care each month, on average and around 30% of them provide childcare for a grandchild.

To investigate the impact of grandparents' long-term care needs on childcare provision, I run the following regression:

$$CC_i = \beta_0 + \beta_1 ltc_i + \alpha X + \epsilon_i \tag{3}$$

CC_i is an indicator for whether the grandparent provided childcare to grandchildren over the past two years.[10] The estimated coefficient of interest, β_1, is reported in Table 5. In column 1, I report the coefficient from a regression that includes age, age squared, gender, years of education, wealth, and the age of the grandparent's youngest and oldest child. In column 2, I include an individual fixed effect (and omit gender and years of education), using changes within an individual to identify the effect of long-term care needs on childcare provision.

Column (1) shows that grandparents with long-term care needs are 5.1 percentage points less likely to provide childcare than healthy grandparents, a 17.6% decrease. After including a grandparent fixed effect in column (2), the magnitude is smaller but still statistically significant at the 5% level and negative. In Appendix B, I repeat this exercise across different levels of long-term care needs, and the results are similar, with higher-need grandparents less likely to provide childcare.

Given that grandparents with long-term care needs are less likely to provide childcare, parents who rely on such childcare will have to fill this time themselves or with market-based childcare. This effect is compounded for parents who step in to provide informal eldercare and simultaneously lose grandparent-provided childcare. However, this has an ambiguous effect on intergenerational mobility, depending on the quality of care children

[9]While these definitions are based on ADLs, they are highly correlated with Instrumental Activities of Daily Living (IADLs), and the mean number of care hours is roughly consistent across a variety of definitions. ADLs include activities necessary for basic personal care, such as dressing, bathing, and eating. IADLs include a broader set of activities that support general well-being, such as managing ones finances, preparing meals, and shopping.

[10]The HRS asks whether the grandparent provided least 100 hours of childcare in the previous two years. This would imply an average of an hour per week, and the indicator CC_i is based on the binary response to this question.

receive in lieu of care from grandparents.

Table 5: Regression results: Impact of grandparent care needs on grandparent childcare

	Grandparent provides childcare	
	(1)	(2)
Long-term care needs	-0.051***	-0.010**
	(0.004)	(0.005)
Individual fixed effect	No	Yes
Mean of dependent variable	0.29	0.29
N	17,623	17,623
N × year	110,447	110,447

Notes: The sample includes all respondents in the HRS who have grandchildren at some point during the sample period (1992-2022). Coefficients are relative to grandparents who do not have care needs. Controls include a quadratic in age, gender (in the left column), education, wealth, and the ages of a grandparent's youngest and oldest child. Standard errors are clustered at the individual level.
Standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

3.3 Monetary investments

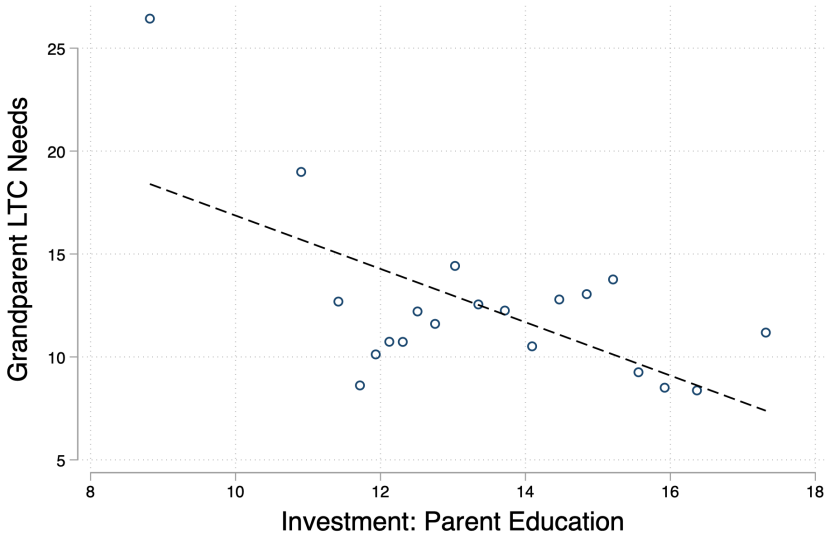
While time investments are a key input into child development, monetary investments are also important. A child's college education is one of the largest monetary investments parents make in their children. Using the Health and Retirement Study, I show that grandparents' long-term care needs are negatively correlated with parents' education. That is, grandparents who develop long-term care needs are more likely to have children with lower levels of education (Figure 5).

While there are several reasons this may be the case, the negative correlation between parent education and long-term care needs may mean families have fewer resources for future generations.[11] This, in turn, may perpetuate inequality across multiple generations. Indeed, Bogan (2015) finds that parents who provide intensive eldercare to their own parents are 20% less likely to have an educational savings account for their children than otherwise similar parents. This suggests that the long-term care needs of grandparents negatively impact parental monetary investments in children's education, which

[11]This correlation may be partially explained by the fact that poorer families tend to need more long-term care and invest less in their children. Nevertheless, the impacts on families' resources may persist across generations.

may strengthen the correlation between parent and child income across generations.

Figure 5: Health Needs



Notes: The sample includes all respondents in the HRS who have grandchildren at some point during the sample period (1992-2022). The plots show the correlation between grandparents' long-term care needs (measured as hours per week of care) and parent education, controlling for the grandparent's age, wealth, and education, and the parent's age

4 Model

In order to quantify the impact of long-term care risk on intergenerational mobility, I develop a model in which families make choices over childcare, eldercare, investments in children, and savings. While the empirical work in the preceding section suggests that long-term care needs may dampen parental time and monetary investments in children, the model allows me account for both channels simultaneously to capture the full effect. I use the model to evaluate a range of counterfactual policies, including both broad and targeted policies that provide families with insurance against long-term care risk. I also compare policies that subsidize formal care with policies that provide payments for informal caregivers.

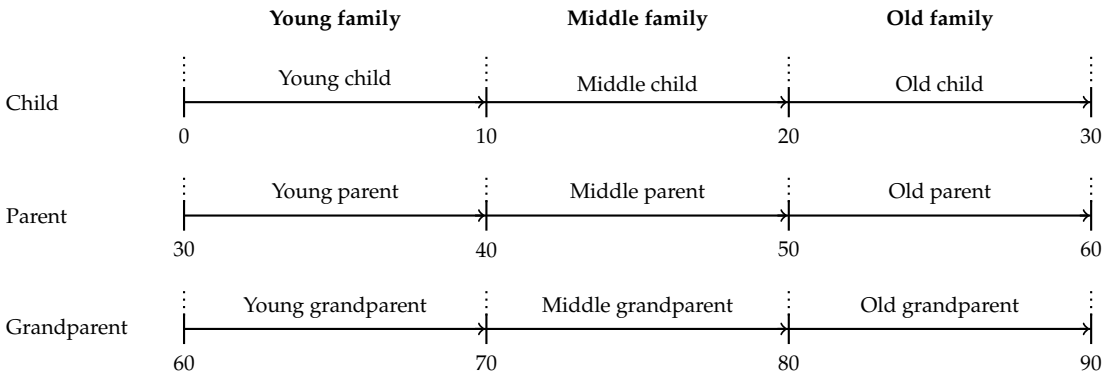
The model is one of overlapping generations in which parents and grandparents interact in each period to make decisions. Dynasties in the model are infinitely lived, while individual agents spend nine periods in the model. There are three generations within a family alive at any given time: a child, a parent, and a grandparent. The child does not make any decisions until she becomes a parent. The parent and grandparent interact with

limited commitment to make consumption, savings, childcare, and eldercare choices as well as monetary and time investments in children. Limited commitment captures the degree of coordination around these choices while maintaining the separation of each agent's assets.

4.1 Timeline

Time is discrete and runs forever. A period in the model is 10 years. Dynasties are infinitely lived and within each dynasty there are three overlapping generations: a child (k), a parent (p) and a grandparent (g). Each agent in the model spends three periods in each generation: three as a child, then three as a parent, and then three as a grandparent. Thus, at any given point in time, a dynasty may be in one of three stages: young ($t = y$), middle-age ($t = m$), or old ($t = o$).

Figure 6: Model timeline



In the model, children receive time and monetary investments and require childcare in the first two periods of their lives. In the third period, they may or may not attend college. These children then become parents where the skills that they developed during their childhood impact their wage offer. Parents split their time between childcare, eldercare, and labor supply and face risk in the form of wage shocks. They also make a savings decision. After three periods as a parent, the parent becomes a grandparent and her child becomes a parent. Grandparents face risk in the form of long-term care shocks, and they may help with childcare if they do not have long-term care needs. Grandparents also make a savings decision. At the end of three periods as a grandparent, an individual dies and leaves any remaining assets as a bequest to the parent, who becomes a grandparent. Therefore, while individuals in the model live for nine periods, a new generation

is born every three periods and the dynasty is infinitely lived. This structure is outlined in Figure 6. Below, I discuss these life stages within each generation in more detail.

4.2 Children

When children are born into the model, their initial skill level s_y^k depends on the skill of the parent s_y^p and a randomly drawn component d. The random component of a child's initial skill, d, is drawn from a normal distribution with mean μ_{sk} and variance σ_{sk}^2. The persistence of ability across generations is governed by ρ_s. The young child's initial skill level is given by

$$s_y^k = \rho_s s_y^p + (1 - \rho_s)d \tag{4}$$

As a young and middle child, the child's skill development depends on the skills she brings into the period s_t^k, as well as monetary and time investments, x_t and T_t respectively. Skills evolve as

$$s_{t+1}^k = (1 - \delta_k)s_t^k + (s_t^k)^{1-\omega_s}(J(T_t, x_t))^{\omega_s} \tag{5}$$

The parameter δ_k controls depreciation of skills from one period to the next, which represents the fact that not all skills carry over into the next period. Following Lee and Seshadri (2019), the child's existing skill increases the productivity of investments, the degree to which is captured by ω_s.[12] Moreover, dynamic complementarity in skill development is an important feature of the child human capital development function (Heckman and Mosso, 2014; Caucutt and Lochner, 2020; Cunha et al., 2010), and emphasizes the importance of early investments. Equation 5 incorporates dynamic complementarity because the child's current skill level impacts her future skills. A high ω_s implies that the development of new skills is largely driven by investments, though the productivity of those investments still scales with the child's existing skill. Time investments (T_t) and monetary investments (x_t) are also complements and enter the child skill development function as

$$J(T_t, x_t) = T_t^{\omega_t} x_t^{1-\omega_t} \tag{6}$$

The complementarity between time and monetary investments is important for families who have dual eldercare and childcare needs. Eldercare responsibilities may impact

[12]Note that their model does not include a depreciation term, but I model it this way to match the rate of skill development over time; without it, skills grow too quickly.

a parent's time or monetary investments in her child, and this form captures the degree to which time can substitute for money, and vice versa. The relative productivity of time and monetary investments varies over the two stages and is captured by ω_t.

The time input T_t in the child's skill development function is a composite of time from parents hp_t^k, grandparents hg_t^k, or market-based childcare hm_t^k. As such, T_t captures a notion of effective time.Young and middle-age children require Hk_t hours of care, and the hours of childcare required vary over stage, with young children requiring more care hours than middle children ($Hk_y > Hk_m$). These childcare hours can be met by any combination of the parent, grandparent, or market. Each of these inputs has a different productivity in the child's skill development, such that the time investment component is given by:

$$T_t = \left[(\frac{s_p}{\hat{s}}) \omega_p (\frac{hp_t^k}{Hk_t})^{\rho_\omega} + \omega_g (\frac{hg_t^k}{Hk_t})^{\rho_\omega} + \omega_m (\frac{hm_t^k}{Hk_t})^{\rho_\omega} \right]^{\frac{1}{\rho_\omega}} \tag{7}$$

where the time inputs from parents hp_t^k, grandparents hg_t^k, and the market hm_t^k, sum to the total number of hours of childcare required Hk_t. The weights on parental time, ω_p, grandparent time ω_g, and market time ω_m sum to 1. The constant elasticity of substitution between time sources is based on the formulation of parent time in Del Boca et al. (2014a). In this formulation, the productivity of parent time scales with parent skill, scaled by median parent skill, $\hat{s}$.

Old children do not require childcare, but they may attend college. In the final period as a child, skill development is a function of the skills they have accumulated thus far and a return to college education ω_X.

$$s_y^p = s_o^k + \omega_X X_o \tag{8}$$

I model college-going as a binary choice, such that $X_o = \{0, 1\}$. The skills that a young parent has in the model are the result of the skills accumulated over her childhood, culminating in a college choice.

4.3 Parents

After the third period as a child, the agent becomes a parent, and her child is born into the model. Parents make a a discrete labor supply choice, where they may choose not to work, to work part-time, or to work full-time such that $L_t^p = \{0, \text{part-time}, \text{full-time}\}$. They receive a wage offer that correspond to their skill level plus a shock. Earnings risk ϵ_t follows a normal distribution with mean of zero and variance σ_ϵ^2.

$$log(w_t) = s_t^p + \epsilon_t \tag{9}$$

Parent's labor earnings are then given by $w_t L_t^p$. The parent's income I_t^p, is made up of her own earnings and an exogenous component that is a function of her skill, $I(s_t^p)$. Total parental income is given by

$$I_t^p = w_t L_t^p + I(s_t^p) \tag{10}$$

The skill level of the parent and her labor supply choices enter her own skill development function, where the return to last period's skills are given by α_{s_p} and the return to experience is given by α_L.

$$s_{t+1}^p = \alpha_{s_p} s_t^p + \alpha_L L_t^p \tag{11}$$

This formulation captures the fact that parents continue to develop skills during their working years.

Parents also have a safety net. In the event the sum of their assets a_t^p, and income I_t^p), falls below a consumption floor c_f^p, they receive $sn_f = \max\{c_f^p - (a_t^p + I_t^p), 0\}$.

4.4 Grandparents

After the third period as a parent, the agent becomes a grandparent. Grandparents do not make labor market choices and spend all their time on leisure or childcare. They receive income I^g in each period, which represents pension and social security income. Grandparents make consumption c_t^g and savings a_t^g decisions each period, and may provide childcare if they do not have long-term care needs.

Grandparents face risk in the number of long-term care hours needed H_t^g. I model these needs as discrete, and I assume that grandparents are either healthy, have light care needs, or have heavy care needs. Grandparents long-term care hours can be met by a combination of informal care from the parent hp_t^g or formal care hm_t^g at an hourly price p^g. In order to capture the social insurance that is available to cover these needs, I model a Medicaid benefit given by:

$$M_t = \max\{0, c_f + p^g hm_t^g - \max\{a_t^g - a_{lim}, 0\} - I^g\} \tag{12}$$

Grandparents are eligible for Medicaid if their net resources, measured as $\max\{a_t^g - a_{lim}, 0\} + I^g$, are less than their care costs, $p^g hm_t^g$, and a consumption floor, c_f. I also

include Medicaid's asset limit for eligibility a_{lim}, which allows grandparents to keep a small amount of their assets and remain eligible for Medicaid coverage. To gain Medicaid coverage, they must spend their asset holdings above the floor on their care costs. The consumption floor captures the basket of social services that is available in addition to Medicaid to individuals with low resources. This is a common way to model Medicaid benefits in the literature (De Nardi et al., 2010; Lockwood, 2018; Mommaerts, 2025), and in the absence of long-term care costs, grandparents may still be eligible to receive this consumption floor if their income and assets are low enough. At the end of the third period as a grandparent, the grandparent exits the model and leaves a bequest to the parent, who becomes a young grandparent.

4.5 Constraints

Families face both time and budget constraints. Children in young and middle-age families require Hk_t hours of childcare. These hours may be met by the parent (hp_t^k), the grandparent (hg_t^k), or market care (hm_t^k) for price p^k. Childcare hours are modeled as

$$H_t^k = hp_t^k + hg_t^k + hm_t^k \tag{13}$$

Each period, the family receives a long-term care shock. Grandparents may need either no care, part-time care, or full-time care. The total hours of eldercare needed in a period is denoted H_t^g. For families that require care, they may meet these informally with parent time, hp_t^g, or by market-based formal eldercare, hm_t^g, at price p^g such that:

$$H_t^g = hm_t^g + hp_t^g \tag{14}$$

In a given period, parents may have childcare and eldercare responsibilities, hp_t^k and hp_t^g respectively. A parent may also spend her time on work, L_t^p, and leisure, ℓ_t^p. The parent's time constraint is given by:

$$\hat{T} = hp_t^k + hp_t^g + L_t^p + \ell_t^p \tag{15}$$

I also assume that parents cannot provide full-time eldercare and work full-time. While it is rare that a parent would want to do so given her preferences over leisure, which I discuss below, this captures the fact that these activities are likely to occupy the same hours of the day, and jobs that are accommodating to such care activities are rare.

Grandparents may spend their time on leisure, ℓ_t^g, and childcare, hg_t^k. The grandparent's time constraint is given by:

$$\hat{T} = hg_t^k + \ell_t^g \tag{16}$$

I model the grandparent's childcare time as subtracting from her leisure. While many grandparents likely enjoy spending time with their grandchildren, the model captures a level of care that is more intensive than occasional visits or time supervised by a parent.

Turning to the family budget constraint, families make consumption and savings choices in each stage.[13] Importantly, parents and grandparents hold their own savings, a_t^p and a_t^g respectively. Care and educational costs vary across the model's stages, and are summarized by B_t. The family budget constraint is given by:

$$c_t^k + c_t^p + c_t^g = w_t L_t^p + I_t^p(s_t^p) + I^g + R(a_t^p + a_t^g) - a_{t+1}^p - a_{t+1}^g + sn_f - B_t \tag{17}$$

The care and education costs B_t include time and monetary investments in children, and eldercare costs. Young and middle-age families make monetary investments in their child, x_t, and may incur childcare costs, $p^k hm_t^k$, if they choose to use formal childcare. If the family incurs eldercare costs and chooses to use formal long-term care, they must cover those as well, $p^g hm_t^g$. Additionally, grandparents may qualify for Medicaid (M_t) to help cover care costs. The Medicaid benefit is described in Equation 12. Thus, care and investment costs for young and middle-age families ($t = \{y, m\}$) are given by:

$$B_t = x_t + p^k hm_t^k + p^g hm_t^g - M_t \tag{18}$$

Old families may also require eldercare and may receive a Medicaid benefit if eligible. However, children in old families no longer require childcare, but may go to college. Families must to pay the monetary cost of college (p^X) if the child attends. The care and educational costs old families incur is then given by:

$$B_o = p^X X_o + p^g hm_o^g - M_o \tag{19}$$

4.6 Per-period preferences

In each stage, parents have preferences over their own consumption, c_t^p, and the consumption of their child, c_t^k, weighted by λ. Because parents make all choices for the child, the child's consumption is a component of the parent's utility function and the child does

[13] While here I describe the budget constraint of the family in each stage, it could equivalently have been written as two individual budget constraints in each period, one for the parent and one for the grandparent, with transfers between them.

not have her own preferences until she becomes a parent. Parents also have preferences over leisure, weighted by α_ℓ. The preferences of the parent are given by:

$$u_t^p(c_t^p, c_t^k, \ell_t^p) = \frac{c_t^{p(1-\gamma_c)} - 1}{1-\gamma_c} + \lambda \frac{c_t^{k(1-\gamma_c)} - 1}{1-\gamma_c} + \alpha_\ell \frac{\ell_t^{p(1-\gamma_\ell)} - 1}{1-\gamma_\ell} \tag{20}$$

where the γ_c and γ_ℓ parameters govern the curvature of consumption and leisure and α_ℓ controls the how much weight individuals place on leisure relative to consumption.

In the third period, parents also receive a preference shock for college-going. This captures the fact that families' preferences over college attendance vary. The shock, ξ is distributed Type I Extreme Value with location μ_ξ and scale σ_ξ and is added to the parent's value function.

Grandparents have preferences over their own consumption, c_t^g, and leisure, ℓ_t^g, as well as the type of eldercare that they receive. The parameter z_F gives the (dis)-utility from receiving formal care ($F_t = 1$). The parameter z_M gives the additional (dis)-utility from receiving Medicaid-funded formal care ($M_t > 0$). This formulation reflects the fact that Medicaid-funded care is often of lower quality than other formal care options and is based on Mommaerts (2025). Grandparent preferences are given by:

$$u_t^g(c_t^g, \ell_t^g) = \frac{c^{g(1-\gamma_c)} - 1}{1-\gamma_c} + \alpha_\ell \frac{\ell^{g(1-\gamma_\ell)} - 1}{1-\gamma_\ell} + z_M \mathbb{1}_{M_t>0} + z_F \mathbb{1}_{F_t=1} \tag{21}$$

4.7 Family Problem

Having outlined the per-period preferences of parents and grandparents, and the time and budget constraints, I now turn to the full dynamic problem the family faces. Each dynasty maximizes the Pareto weighted sum of the parent and grandparent utilities in every period. Agents discount the future at rate β. Grandparents are altruistic and place a weight of η on the parent's utility in each period. Thus, the problem facing a dynasty is given by:

$$V_0 = E_0 \left\{ \sum_{t=0}^{\infty} \beta^t \{\theta_t u_t^p + (1-\theta_t)[u_t^g + \eta u_t^p]\} \right\} \tag{22}$$

subject to the time and budget constraints, as well as their voluntary participation constraints. The voluntary participation constraints arise from the fact that a parent or grandparent could choose to exit the the arrangement at anytime, the value of which is given by their outside option. Given this option to walk away, the interactions between the parents and grandparents are characterized by limited commitment. A model with

full commitment would imply full insurance between the parent and grandparent, and the literature generally rejects full insurance within extended family networks (Hayashi et al., 1996; Attanasio et al., 2019). A model with full commitment would also imply that the family has only a single asset pool shared by the parent and grandparent.[14] However, maintaining separation between the assets of the parent and the grandparent is particularly important in this context because Medicaid covers long-term care, and thus beneficiaries are subject to Medicaid's asset test. In the family's problem the Pareto weights are time varying to ensure that both agent's remain satisfied with the arrangement.

Given that the data reject a fully cooperative model, both non-cooperative and limited commitment models are common when modeling complex family interactions (Kaplan, 2012; Voena, 2015; Mommaerts, 2025). I use limited commitment because the level of coordination between family members in the data suggests a level of cooperation beyond that in a non-cooperative model (Mommaerts, 2025). Further, non-cooperative models require strict timing assumptions that are somewhat unrealistic in this setting. Limited commitment models are also constrained efficient, whereas non-cooperative models need not be.

The state variables are given by z_t and the choice variables are given by j_t. These are summarized in Table C.1. The individual value functions for the parent and the grandparent respectively are given by

$$V_t^p(z_t) = \max_{j_t} u_t^p + \beta E V_{t+1}^p(z_{t+1}) \tag{23}$$

$$V_t^g(z_t) = \max_{j_t} u_t^g + \beta E v_{t+1}^g(z_{t+1}) + \eta V_t^p(z_t) \tag{24}$$

where $v_t^g(z_t) = u_t^g + \beta E v_{t+1}^g(z_{t+1})$ represents the grandparent's own value and V_t^g includes her altruism towards the parent. Since parents become grandparents at the end of the old stage, the parent's continuation value when $t = o$ is given by $V_{o+1}^p(z_{o+1}) = V_y^g(z_y)$. When the grandparent is old, her value from her own utility tomorrow is zero, i.e. $v_{o+1}^g = 0$. However, she is still altruistic and cares about the parent's value tomorrow, when the parent becomes a young grandparent. Therefore, $V_o^g(z_o) = u_t^g + u_t^p + \beta\eta E V_y^g(z_y)$. Appendix D gives more details on grandparent's altruism.

Expectations in each period are taken over the long-term care needs of the grandparent and the wage shock of the parent. Old families also take an expectation over the initial ability of the child born in the next period. Additionally, the value function for

[14] While there could be rules for sharing these assets, they would be unrealistic because they would be entirely determined by Medicaid's rules.

old families includes the expectation over the preference shock for college-going, such that $V_o(z_o) = E_\xi \max_X V_t(z_t, X) + \xi_X$. Details on the preference shock are summarized in Appendix E.

The recursive family problem can be represented as the weighted sum of the parent and grandparent values:

$$V_t(z_t) = \max_{j_t} \theta_t V_t^p(z_t) + (1 - \theta_t) V_t^g(z_t) \tag{25}$$

and is subject to the time constraints (equations 13, 14, 15, and 16) and the budget constraint (equation 17). Because parents and grandparents interact with limited commitment, each is also subject to their own voluntary participation constraint.

The voluntary participation constraints for each stage are given by:

$$\mu_t^p : V_t^p(z_t) \geq W_t^p(z_t) \tag{26}$$

$$\mu_t^g : V_t^g(z_t) \geq W_t^g(z_t) \tag{27}$$

where the outside options W_t^p and W_t^g reflect an inability of parents and grandparents to coordinate on inter vivos transfers and informal care within a dynasty. However, grandparents are still altruistic and may leave a bequest. Appendix F provides more details on the outside options. The Lagrange multipliers on these constraints, μ_t^p and μ_t^g, dictate how the Pareto weights evolve over time in order to maintain cooperation while feasible.

Because grandparents are altruistic towards parents, V_o^g depends on V_y^g. This makes it an infinite horizon problem. The solution is a set of state specific allocations, $j_t(z_t)$, for consumption, savings, labor supply, and care for each stage t: young, middle and old, where $j_t(z_t) = \{c_t^k, c_t^p, c_t^g, a_{t+1}^p, a_{t+1}^g, L_t^p, \ell_t^p, x_t, hm_t^k, hp_t^k, hg_t^k, \ell_t^g, \mu_t^p, \mu_t^g, hm_t^g, hp_t^g\}$. These allocations are obtained by maximizing the weighted sum of parent and grandparent values V_t for each $t = \{y, m, o\}$. Details on the numerical solution method can be found in Appendix G.

4.8 Model discussion

Commitment is limited

Limited commitment has a number of implications for the allocations between parents and grandparents. First, agents are unable to commit to future allocations. In the pres-

ence of risk, parents and grandparents would like to enter into a risk sharing agreement. However, because each agent has the option to walk away from the relationship, they have a limited ability to enforce ex ante promises once shocks are realized.

Limited commitment also implies asset determinacy between the parent and grandparent. When families are making decisions, each agent's individual asset holdings enter the value of their outside option. An individual with more assets has a higher outside option, since she is better able to self-insure against shocks than an individual with fewer assets. This means that her voluntary participation constraint is more likely to bind, and when an agent's voluntary participation constraint binds she receives an allocation that makes her indifferent between staying in the risk sharing arrangement and exiting to her outside option. For this reason, each agent has an incentive to hold on to their own assets, whereas a fully cooperative model would assign all assets to the parent to avoid Medicaid's asset test. Therefore, the model maintains the separation between parent and grandparent savings.

This is achieved by updating the Pareto weight when an agent's voluntary participation constraint binds. Appendix G details how this works in the model solution algorithm. If both agents' voluntary participation constraints were to bind at the same time, the family would move to their outside options. However, because there are always gains from risk-sharing, parents and grandparents will never break up. See Appendix H for a longer discussion about the details. Moreover, in dynamic games between family members, there are often rules about the timing or direction of inter vivos transfers (Kaplan, 2012; Ko, 2022). However, in my setting, there are no restrictions on transfers between parents and grandparents. While this has the advantage of not constraining the behavior of parents and grandparents in the model, it is generally harder for models with limited commitment to match the fraction of families with zero transfers in the data (Mommaerts, 2025).

Limited commitment is not the only way to model family interactions. Fully cooperative interactions between parents and grandparents would imply full insurance between family members, which is not borne out in the data (Hayashi et al., 1996; Attanasio et al., 2019). Dynamic, non-cooperative games are also used to model family interactions, particularly to better understand strategic motivations. While these models can also feature partial insurance, they often result in inefficient allocations as a result of strategic interactions. In contrast, limited commitment does not allow for strategic motives in allocations. While fully cooperative models result in efficient allocations, the solution in limited commitment models is constrained efficient, meaning that, given the commitment frictions, allocations are efficient. If it were possible to remove these frictions, this would result in

full efficiency.[15]

Under full commitment, past and current shocks never matter for intra-household allocations, under no commitment only current shocks matter, and under limited commitment, both current and past shocks matter. Further, Chiappori et al. (2025) and Lise and Yamada (2019) investigate the effects of shocks on household allocations and find empirical support for modeling family interactions with limited commitment.

Model assumptions

The model allows me to capture how parents and grandparents interact to make investments in children and care choices across generations. It also captures how long-term care risk influences these choices and thus impacts intergenerational mobility. However, the model does make a number of abstractions from the real world, including marriage, divorce, and fertility choices. While these mechanisms may be important, I do not consider them here in order to focus on intergenerational interactions while maintaining tractability. The model does incorporate heterogeneity in income and earnings risk, which help to capture the effects of marriage and divorce without introducing another choice variable. While it is possible that large expansions in long-term care policies may have impacts on fertility decisions, many European countries have extensive long-term care insurance programs and persistently low birth rates, so these effects may be secondary.[16]

The model also assumes that all families face the same timing structure in terms of birth, the development of care needs, and death over the wealth distribution. In the data, it is the case that lower wealth families have children at earlier ages than their wealthier counterparts. However, they also develop care needs and die earlier, so that while these events occur at different ages, the relative timing between these events is similar across the wealth distribution (see Appendix I for details).

While the timing assumptions of the model are reflected in the data, differences in the age at which these events occur may matter for wealth accumulation. Families who have children earlier are not able to save as much before they have children and therefore may not be able to invest as much in their children. Similarly, they may have less time to save

[15] An efficient allocation is one in which one agent may not be made better off without making another worse off. A constrained efficient allocation is one under which a planner could improve upon the outcome only if she were not subject to the frictions inherent in the problem (in this case, the commitment frictions). If the planner could force agents to fully commit, they could be made better off (with better risk sharing, in this case).

[16] It is also unclear which direction the impact of long-term care insurance policies would have on fertility. On the one hand, if families are constrained by providing informal eldercare or eldercare costs, these policies may increase fertility by freeing up parental time and resources. On the other hand, if families increase their fertility so that a child will provide eldercare for them in the future, policies that increase formal long-term care may have negative effects on fertility.

before they develop care needs. The model does not account for this directly, as a model period is 10 years. The focus of the model is on long-term care risk, and, to the extent that wealth accumulation prior to the development of care needs is an important mechanism, the model will understate the impact of long-term care risk on intergenerational mobility.

Finally, I abstract from the existence of siblings as well as the fact that families have two sets of grandparents. This is again to focus on interaction across generations, but it is also informed by what is available in the data. Details on the assumptions around family structure can be found in Appendix J.

5 Estimation

I estimate the model using data from the Panel Study of Income Dynamics and the Health and Retirement Study. I first set a number of parameters outside the model and then use the simulated method of moments to structurally estimate the remaining parameters.

5.1 Data

The Panel Study of Income Dynamics (PSID) is a longitudinal survey that has followed a representative sample of descendants from approximately 5,000 families since 1968. The main survey of the PSID contains detailed data on the labor market choices and outcomes of parents, and the Child Development Supplement (PSID-CDS) has information on the investments and educational outcomes of grandchildren. Because the PSID follows entire family lineages, I can link individuals across generations.

I use the PSID for statistics related to savings, earnings, and labor supply choices of parents, and investments in and educational outcomes of children. My sample consists of children in the 1997, 2002 and 2007 waves of the CDS and their parents. While the CDS has also sampled children more recently, I restrict to these years in order to observe sampled children at later ages. A 12-year-old child sampled in 1997 would be 34 in 2019, which allows me to capture some earnings data for these children. Additionally, the CDS includes information on time and monetary investments in children, so I restrict to parents of CDS children to capture their investment decisions in tandem with their labor supply choices. Summary statistics for the sample are presented in Table 6. In total, the sample is made up of 2,378 households, with 2,403 mothers, 1,837 fathers, and 3,561 children. About one-third of the children in my sample eventually attend college.

Table 6: PSID parents & children sample summary statistics

	Mean	Standard Deviation
Mean family income	84,021	89,382
Median family income	65,643	.
Mean family assets	213,118	1,073,779
Median family assets	38,848	.
Fraction in which mothers work full-time	0.38	0.38
Fraction in which fathers work full-time	0.81	0.49
Fraction single-parent households	0.30	0.46
Mean annual investment in children ($)	212	896
Mean letter-word test scores	27.53	16.35
Fraction children attend college	0.35	0.48
Number of families	2,583	

Notes: This table presents summary statistics for the PSID sample. The sample includes households in the 1997, 2002, and 2007 waves of the PSID-CDS, summarized over their entire time in my sample.

While I am able to connect individuals11 across many generations, the PSID does not contain detailed data on formal or informal long-term care. For this, and other information about the grandparent generation, I turn to the Health and Retirement Study (HRS). The HRS is a longitudinal panel of approximately 20,000 people. Surveys have been conducted biennially since 1992, with extensive information about respondents' health and care needs, long-term care arrangements, Medicaid utilization, and assets. The survey also contains some information about the children of the respondents.

In the HRS, I use data from 1992 to 2022 and keep individuals who respond in at least three waves. I also drop respondents who do not have any children or grandchildren throughout the entire sample period. My sample consists of 18,575 households. When mapping grandparent data to the model, I use household level data on care needs, grandparent-provided childcare, income, and savings. Summary statistics for this sample are presented in Table 7. In my sample, 41% of grandparent households provide childcare at some point in their lives, and 41% of households contain at least one individual who will need eldercare beyond what is provided by their spouse.

Table 7: HRS grandparent sample summary statistics

	Mean	Standard Deviation
Age	68.45	10.84
Fraction married	0.54	0.50
Fraction ever provide childcare	0.41	0.50
Fraction ever need LTC	0.41	0.49
Mean family income	53,115	186,927
Median family income	30,250	.
Mean family assets	363,445	1,026,418
Median family assets	119,000	.
Observations	18,575	

Notes: This table presents summary statistics for the HRS sample. The fraction who ever need long-term care includes all households in which at least one spouse needs long-term care beyond what is provided by a spouse. The fraction who ever provide childcare only includes those who provide at least 100 hours of childcare in a two-year period. All other variables are averaged over the entire sample period.

5.2 First-stage parameters

Before estimating parameters inside the model, I set a number of parameters outside the model. These include parameters that do not require the full structure of the model to estimate.

Externally calibrated parameters

I take a number of parameters from the literature and external data sources. These include the amount of time available to parents and grandparents, the discount factor, the interest rate, the hours of childcare required, the cost of childcare, and the cost of college.

I set the number of hours available to an individual in the model to be equal to 16 hours a day $\times$ 7 days a week. Turning to the amount of childcare children require, I take a weighted average over each period in the data. Young children in the model are between the ages of 0 and 10. Between the ages 0 and 4, I assume children need full-time childcare: 8 hours per day 7 days a week. After age 4, children usually enter kindergarten, and some care time is then taken up by school hours. Between the ages of 5 and 10, I assume children need 4 hours of care time 5 days a week and 8 hours two days a week (on the weekends). Averaging these, I assume young children need 2,400 hours annually.

Middle children in the model are middle and high school aged, and even outside of school time need fewer care hours. I assume they need 4 hours per day 5 days a week. This is time that may be filled by parents, grandparents or "childcare", which may include things like after-school extracurriculars or tutoring. These children need 1,040 hours of active care.

Turning to the cost of childcare, a full day of childcare can range from $6,500 to $15,600 annually. Assuming 8 hours a day, this is $3 to $7.5 per hour. Half-day care ranges from $5,900 to $9,200 annually, which works out to $5 to $9 per hour. Hourly caregivers for children range from $15 to $35 per hour (Poyatzis and Livingston, 2024). Given these, I set the cost of childcare to be $10 per hour.

The cost of college is also taken as the sum of an average over four years. Two years of average tuition ($9,750 each) and two years of tuition plus room and board ($35,248 each) gives an annual cost of $22,500, or $90,000 for four years (Hanson, 2026). I also set the discount factor and interest rate to correspond to the annual values of 0.975 and 1.034, respectively. These values are summarized in Table 8.

Table 8: Externally calibrated parameters

Parameter	Description	Value
$\hat{T}$	Total hours	5,824
β	Discount	0.975
R	Interest Rate	1.034
H_y^k	Hours childcare - young	2,400
H_m^k	Hours childcare - middle	1,040
p^k	Price of childcare (hourly)	10.00
P_X	College cost	22,500

Notes: The table provides values for the externally set model parameters. All values with the exception of childcare prices are annual.

Child skill development

The parameters that govern child skill development are reported in Table 9. In the child's initial skill draw (Equation 4), the parameter that determines how much of the child's initial skill is drawn from the parent's initial skill, ρ_s, comes from the value in Lee and Seshadri (2019). The weight on child consumption in the parent's utility function λ is also from Lee and Seshadri (2019). The mean and standard deviation of the component of initial child skills that are drawn randomly come from a normal distribution with mean

μ_d and standard deviation σ_d. The values for μ_d and σ_d come from the distribution of the letter-word tests in the PSID-CDS.

Turning to the function that governs young and middle children's skill development (Equation 5), δ_k is set to 0.15. This is based on the values of cognitive skill-productivity estimated in (Cunha et al., 2010), and implies that a child retains most of her skills over the first two periods of investment. The parameter that governs the degree to which a child's existing skill increases the productivity of new investments, ω_s, is 0.90. This is because the persistence in skill needed to result in appropriate investment values means that the development of new skills is largely driven by investments, rather than past skills.

In Equation 6, which aggregates time and monetary investments, the weights on time investments relative to monetary investments, ω_y and ω_m, are based on the values in Lee and Seshadri (2019). In that paper, a model-period is 6 years, so I rescale their parameters to fit a ten-year period. The weight on time is larger for young children because time is the more important for young children as compared to middle-age children.

Table 9: Child skill parameters

Parameter	Description	Value
ρ_s	Persistence of ability	0.23
μ_d	Mean initial child skill	0.91
σ_d	Std. dev initial child skill	0.30
δ_k	Skill depreciation	0.15
ω_s	Weight on investment	0.90
ω_y	Weight on time (young)	0.81
ω_m	Weight on time (middle)	0.75
ρ_ω	Substitutability of skill inputs	0.60
ω_p	Weight on parent time	0.35
ω_g	Weight on grandparent time	0.32
ω_m	Weight on market time	0.33
$\hat{s}$	Parent skill scaler	3.00
ω_X	Return to college	0.48
σ_ξ	Scale of TIEV shock (10^{-5})	5.00
μ_ξ	Location of TIEV shock	0.00
λ	Weight on child consumption	0.30

Notes: The table reports the values for the model parameters related to the child skill development process. Parameter values are based on the PSID-CDS data and values from the literature as described in the text.

In the time aggregation function (Equation 7), the substitutability of skill inputs, ρ_ω, is set to be 0.60, implying that market care, parental care and grandparent care are imperfect substitutes in the child skill production function. The weights on time from parents ω_p, grandparents ω_g, and the market ω_m, reflect the notion that all else equal, parent time is, on average, more productive than grandparent or market time. These numbers are based on findings in Del Boca et al. (2014b) that parent, grandparent, and market-based childcare are imperfect substitutes.

The productivity of parent time also scales with the skills of the parent, so that more time from higher-skilled parents is more productive in the child's skill development. This reflects finding from the literature that the productivity of parents' time is increasing in her years of education (Brilli, 2022). In contrast, Caucutt et al. (2026) find little difference in productivity of parental investments across the education distribution. They do find, however, that more highly educated parents invest more time in their children. In the context of my skill development function, there is no distinction between "active time," time spent on activities that enhance the child's skills, and "passive time," or time spent watching the child. These have different implications for skill development (Del Boca et al., 2014a). The scaling of parental time by skill in my context also helps capture that the fraction of childcare time spent on "active time" may be higher in more educated families. In Equation 7 parent skill is scaled by $\hat{s}$, the median level of parent skill in the model so that changes are scale invariant.

Turning to skill development for old children, the return to college is based on the earnings difference between children in the CDS who attend college and those who do not, accounting for initial skill differences. The shocks to families' preferences for college-going are distributed Type I Extreme Value. The location μ_ξ of the college-going preference shock distribution is set to 0 and the scale, σ_μ, is set to 0.00005. This is based on value in Lee and Seshadri (2019).[17]

To give a sense of the impact of the preference shock, I compute the size and probability needed to push an average family[18] at the median of the wealth distribution to choose college over no college. I find that the preference shock that would result in the family choosing to send their child to college is equivalent to receiving an additional $26,671 in consumption in the period in which they make the college-going choice. This is 30% of

[17]Note that Lee and Seshadri (2019) have a preference for college attendance, whereas I have a taste-shock. However, their preference parameter implies a consumption equivalence of about 25% of one-period consumption. This is roughly in line with the size of the preference shock needed to push a family from non-college going to college-going in my model. I model this as a preference shock rather than absolute preference to capture heterogeneity in both taste for college and the impact of things not explicitly modeled.

[18]While college-going probabilities vary over the entire state space, by average family I mean that I use the average state, based on the simulations, for families of median wealth in the old stage.

the price of college attendance. Given the scale of the distribution, the likelihood of a shock of that magnitude is approximately 20%. This implies that, for a family at the median of the wealth distribution, the college-going choice is in line with what they would choose to do in the absence of a preference shock 80% of the time.

Parent skill development & earnings

The parameters in the parent's skill development function (Equation 11) are determined by the returns to parental skills and labor market experience. These values are come from a regression of hourly earnings on lagged earnings, experience, and age for working mothers in my sample of PSID parents. The standard deviation of income shocks in the parent's wage offer (Equation 9) is based on the value in Meghir and Pistaferri (2004). These parameters are summarized in Table 10.

Table 10: Parent skills & earnings parameters

Parameter	Description	Value
α_{sp}	Return to parental skill	1.10
α_L	Return to parental experience	0.16
σ_ϵ	Std. deviation of wage shocks	0.20
c_f^p	Parent's consumption floor (annual)	1000
$I(s_t^p)$	Exogenous income (annual)	[0, 20,000, 40,000, 60,000]

Note: The table reports the parameter values related to parental skills and earnings in the model. The values are based on the PSID data and spousal income levels are a function of parent skill as described in the text.

Parental income in the model is made up of two components. First, there is a component that is constant for a given level of skill of the parent. I model this component as a step function based on the parent's skill, with annual income given by:

$$I(s_t^p) = \begin{cases} 0 & s_t^p < 1.25 \\ 20,000 & s_t^p \geq 1.25 \text{ and } s_t^p \leq 2.55 \\ 40,000 & s_t^p \geq 2.55 \text{ and } s_t^p < 3.85 \\ 60,000 & s_t^p \geq 3.85 \end{cases} \tag{28}$$

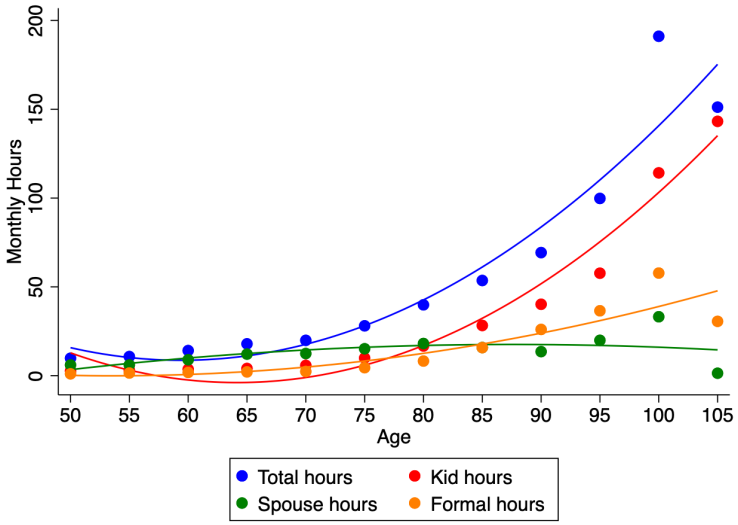
The other component of parental skill is her labor earnings. The combination of these two represents the total income of the parent. The functional form of the parent's exogenous income is based the fact that there is positive assortative matching in the marriage

market. The cutoffs are based on the the hourly spousal earnings by mother's level of education for PSID parents.[19] See Figure L.2 for more details.

Long-term care & grandparent income

For information on long-term care risk, I turn to the HRS sample. The HRS reports hours of eldercare that respondents and their spouses receive across many different sources. I aggregate long-term care needs of grandparents to the household level, meaning that I use the total hours of care needed by both grandparents in a household if two are present. The number of hours of care across each source is summarized in Figure 7. The parameters related to grandparent income and long-term care are summarized in Table 11.

Figure 7: Eldercare hours by source



Notes: The figure summarizes the main sources of eldercare over grandparent age, using the HRS grandparent analytical sample. Eldercare hours are aggregated to the household level.

When measuring the long-term care needs of respondents, the HRS asks about the hours of care an individual received over the past month. To computing the needs that enter the model, H_t^g, I first remove the long-term care hours that are covered by spouses. This implicitly assumes that spouses provide care before any other source when they do not have care needs of their own. I then convert the monthly hours to the total number of hours received in the sample period in the HRS (two years).[20] Finally, I aggregate the

[19] Because there is no notion of spousal time in the model, a spousal income of zero could imply single parenthood or that ones partner does not work. Additionally, because parent skills grow over time, spousal income is not fixed across stages.

[20] I assume that these hours are representative of care hours over the two-year period between waves in the HRS.

number of care hours in each two-year period up to the total number of hours of care a grandparent household needs in each corresponding ten-year model period.

In the model, I assume care needs are discrete. Families either have no care needs, light care needs, or heavy care needs. To get the probability of care needs from the data, I assign families who have fewer than 1,000 total hours of care needs over a ten-year period to the no care group. Grandparent households with between 1,000 hours and 15,000 hours are assigned to light care needs, and households with above 15,000 hours are assigned to heavy care needs. These cutoffs are chosen to align the mean values in the light care needs and heavy care needs groups with 1,000 hours annually, representing part-time care and 2,000 hours annually, representing heavy care. I empirically calculate the probabilities using these discretized care needs. Because the probabilities are very small for young grandparents, I assume that young grandparents do not need long-term care, and they know this in advance.

Table 11: Grandparent income and long-term care parameters

Parameter	Description	Value
I^g	Grandparent income (annual)	20,000
p^g	Price of eldercare (hourly)	20.0
P_y^{Hg}	Young grandparent long-term care risk	[1.0, 0.0, 0.0]
P_m^{Hg}	Middle-age grandparent long-term care risk	[0.85, 0.09, 0.06]
P_o^{Hg}	Old grandparent long-term care risk	[0.69, 0.14, 0.17]
H^g	Hours of eldercare (annual)	[0, 1000, 2000]

Note: The table reports the parameter values related to grandparent income and long-term care in the model. The values are based on the HRS sample as described in the text.

Taking values from Brown and Finkelstein (2007), part-time care costs $20,000 annually which is $20/hour and full-time care is $61,700 annually, approximately $30/hour. Additionally, a semi-private room in a nursing home ranges from $112,420-186,000 ($25/hour assuming 12 hours of care a day). Home care is around $51,000 annually or $33 per hour and assisted living is $66,132 annually ($15/hour assuming 12 hours of care a day) (OPM, Federal Long Term Care Insurance Program, 2026). Averaging these, I set the hourly cost of care at $20 per hour in the model. Grandparent income is set to $20,000 annually to approximate social security and pension income.

5.3 Estimated parameters

Taking the first stage parameters as given, I estimate the remaining parameters using the simulated method of moments. I estimate the curvature on consumption and leisure, γ_c and γ_ℓ; the weight on leisure, α_ℓ; the formal care and Medicaid utility parameters, z_M and z_F; the consumption floor for Medicaid eligibility, c_f; and the degree to which grandparents are altruistic towards parents, η. These parameters are summarized in Table 12.

Table 12: Estimated parameters

Parameter	Description	Estimate	Standard error	Cons. units
z_M	Medicaid dis-utility (10^{-5})	-33.35	0.0981	\$8,943
z_F	Formal care dis-utility (10^{-5})	-8.30	0.0447	\$1,411
c_f	Consumption floor	8,436	95.94	
γ_c	Consumption curvature	1.59	0.0020	
γ_l	Leisure curvature	1.55	0.0019	
α_ℓ	Leisure weight	0.56	0.0010	
η	Altruism	0.12	0.0003	

Notes: This table reports the parameter estimates of the model. The estimates are obtained using the simulated method of moments with a diagonal weighting matrix. Standard errors are calculated using the sandwich formula.

I target parents' and grandparents' savings choices over time, as well as rates of college-going, full-time work, Medicaid, and informal care over the wealth distribution. In order to match the data moments, I use the subplex algorithm to minimize Equation 29. The subplex algorithm improves upon the standard Nelder-Mead algorithm by applying Nelder-Mead in a series of subspaces. This is particularly well suited to problems in which the objective function may be discontinuous near the solution or feature multiple minima (Soritz et al., 2022). I minimize

$$M(\Theta) = (m_d - m_M(\Theta))' W (m_d - m_M(\Theta)) \tag{29}$$

with respect to the parameter vector Θ. I use a diagonal weighting matrix, W, which puts equal weight on each of the moments, m_d is a vector of moments from the HRS and PSID data, and $m_m(\Theta)$ is a vector of moments calculated from simulated data. To get standard errors I use the standard sandwich formula, with the first-stage parameters fixed.

To interpret the parameters that govern Medicaid and formal care utility, I convert the values into consumption units. I calculate the additional consumption that a grandparent

receiving formal or Medicaid care would need to be indifferent between receiving formal care and median consumption or informal care and median consumption in a given period, all else equal. I find that grandparents are willing to pay $1,411 annually to avoid formal care and $8,943 annually to avoid Medicaid-funded long-term care. The estimated value for the consumption floor is in line with the average value of Supplemental Security Income (SSI) for individuals over 65, which is $7,320 annually (Congressional Research Service, 2026).

Agents in the model weight leisure by 0.56 relative to consumption, and the curvature on consumption and leisure is around 1.5 for both. This is slightly lower than what is typically found in the literature using dynamic games between family members. Barczyk et al. (2023), Barczyk and Kredler (2018), and Boar (2021) fix the coefficient on consumption to 2.0 and (Mommaerts, 2025) estimates a value of 2.1. On the other hand, many models of overlapping generations assume log utility over consumption (implying a CRRA coefficient of 1) (Anstreicher, 2023; Lee and Seshadri, 2019). This puts my estimate of the curvature on consumption in between these two values.

I find a value of 0.12 for grandparent altruism, which is slightly higher than what is typically found in finite horizon models between parents and children. Kaplan (2012) finds a value of 0.04 for parents of young adults and Mommaerts (2025) finds a value of 0.08 for aging parents of adult children. The fact that the value in my model is higher than those in finite horizon models is consistent with the fact that altruism captures the weight placed not only on the subsequent generation, but all future generations.[21]

5.4 Model fit

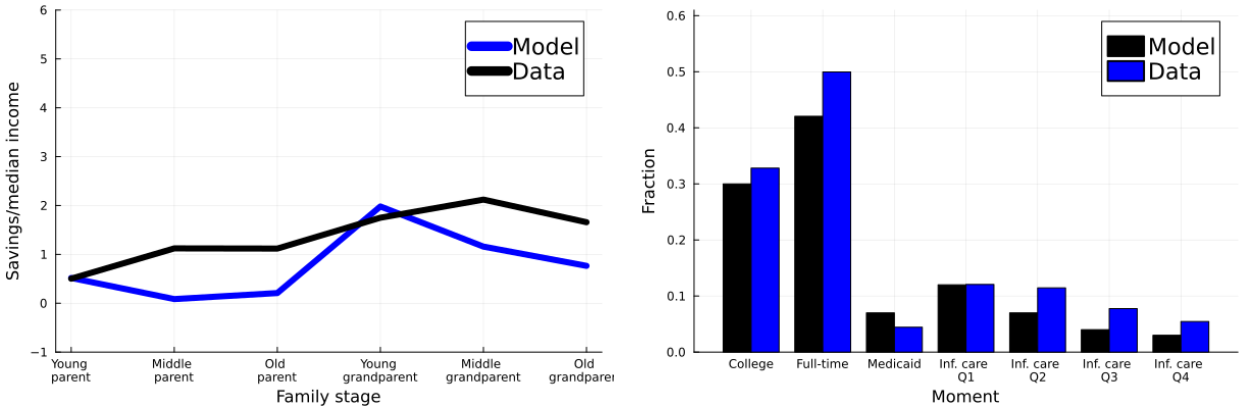
The model is able to fit the moments targeted in the estimation procedure, as well as moments not targeted by the estimation well.

Targeted moments

The model fit is summarized in Figure 8. These moments are chosen to identify the key parameters, and identification is discussed in subsection 5.5. The model matches the savings rate of grandparents and parents in young families very well, but savings in middle and old families are slightly too low, shown in Figure 8a.

[21] While the altruism parameter enters the grandparent's value each period as a weight on the parent's utility function, it is also therefore in the discounted value function for each grandparent in the future, giving weight to these future generations.

Figure 8: Targeted moments



(a) Median savings

(b) College, work, and LTC care moments

Notes: The figure reports how the moments targeted in the estimation procedure compare to the corresponding data moments. The left panel reports median savings, scaled by the median income in the model and the PSID in blue and black, respectively. In the data, parent savings are based on values in the PSID and grandparent savings are based on values in the HRS. The right panel reports rates of college-going, full-time work, Medicaid, and informal care over four quartiles of grandparent wealth. The model moments are in blue and the data moments are in black.

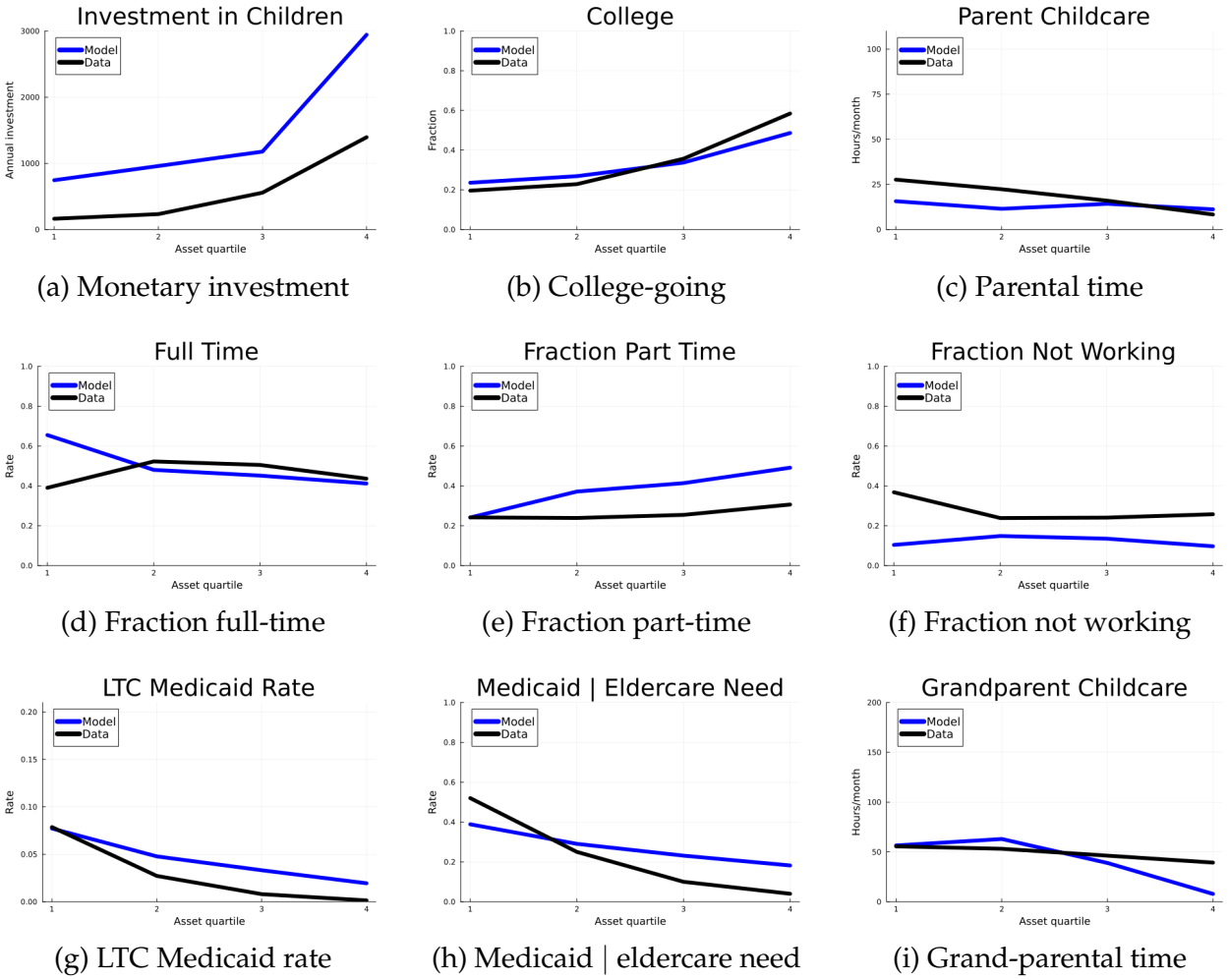
In Figure 8b, the model matches the rates of college attendance quite well. Full-time work is slightly higher in the model than in the data and Medicaid is slightly lower in the model than in the data. The model also matches the gradient of informal care over the wealth distribution, with less wealthy families providing more informal eldercare. Overall, these moments match the data well.

Non-targeted moments by wealth

The model is also able to fit key moments that are not targeted by the estimation procedure. Figure 9 shows moments related to time and monetary investments in children, parental labor supply, and grandparent long-term care over the wealth distribution. Broadly matching trends over the wealth distribution is important for correctly capturing the impact of long-term care on intergenerational mobility. The fact that these moments, which are not targeted in the estimation procedure, fit fairly well suggests that the externally set parameters are not causing issues in the model fit.

I use the PSID for moments related to monetary investments in children, parental time investments, and parental labor supply. For moments on grandparental time investments in children and moments related to long-term care, I turn to the HRS. I use the corresponding asset distribution in the model (i.e. moments related to parents use the PSID data and the wealth distribution of the parents in the model).

Figure 9: Non-targeted moments over the wealth distribution



(a) Monetary investment (b) College-going (c) Parental time

(d) Fraction full-time (e) Fraction part-time (f) Fraction not working

(g) LTC Medicaid rate (h) Medicaid | eldercare need (i) Grand-parental time

Notes: The figure reports how non-targeted moments vary over the wealth distribution in the model (in blue) and the data (in black). Moments on monetary investments in children, college-going, parental time, and the fraction of parents working part-time and not working are computed from the PSID sample. I use the parent asset distribution in both the data and the model when calculating these moments in both the model and the data. Moments on grand-parental time, and long-term care are computed using the HRS sample, and the grandparent wealth distribution in both the data and the model.

Turning first to monetary investments in children, investments during the young and middle-age period (Figure 9a) match the gradient in the data well, albeit at different levels. The model also matches college-going rates across the wealth distribution (Figure A.2b). Time investments from parents and grandparents (Figure 9c and Figure 9i) are largely consistent with the patterns in the data, but parental time investments are flatter in the model relative to the data while grandparental time investments are slightly steeper. Looking at parental labor supply, the model matches the rate of full-time work well over the highest three asset quartiles, but overstates the fraction of the least wealthy parents

who work full-time (Figure 9d). The model also slightly overstates the fraction of parents working part-time (Figure 9e) and understates the fraction not working (Figure 9f).

The model also broadly matches moments related to the long-term care needs of grandparents. In addition to the gradient in informal care over wealth targeted in the estimation, the model matches patterns in the rates of Medicaid long-term care overall and among those with eldercare needs (Figure 9g and Figure 9h).

Non-targeted moment: intergenerational mobility

In addition to matching moments over the wealth distribution, the model is also able to match the correlation between parent and child income, a key measure of intergenerational mobility. The rank-rank correlation between parent and child income is measured by regressing parent earnings rank on child earnings rank

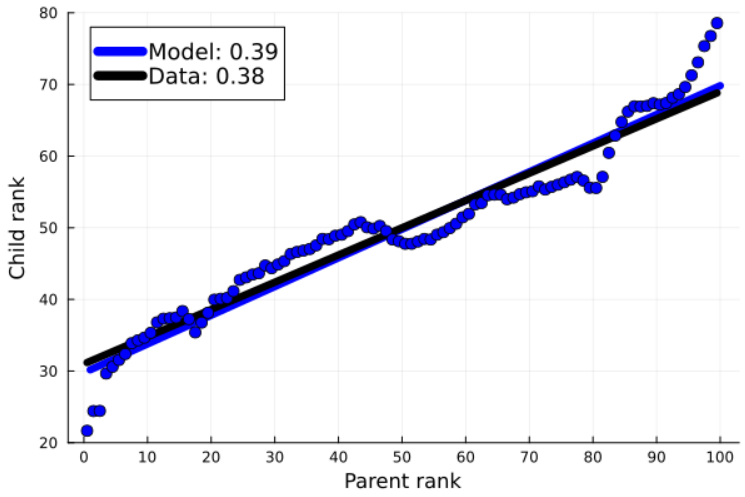
$$y_c = \alpha_1 + \alpha_2 y_p + \epsilon \tag{30}$$

Decreases in α_2 imply less correlation across generations and thus more intergenerational mobility. In my PSID sample, I use parent income and child income between the ages of 30 and 35. This is because I cannot observe the life-cycle earnings of the children in my sample, but I do observe many of them at this stage. To map this to the model, I use the parental income of young parents and their children when they become parents. This corresponds approximately to parents aged 30-40.

Figure 10 shows that the model is able to match the rank-rank correlation between parent and child income. In the model, the correlation is 0.39, compared to 0.38 in the PSID data.[22] In Figure 10, I plot the model-generated correlation between parent and child income rank (in blue) as well as the trend from the data (in black). The dots show the average child rank for a parent in the given income rank. In addition to matching the trend well, the model also matches the distribution over parent income rank. Chetty et al. (2014) find that the distribution is linear throughout the majority of parental income ranks with nonlinearities in the tails of the distribution. In the model, the middle is largely linear (albiet with some noise), and the nonlinearities in the tails are present.

[22]The difference is slightly higher than in Chetty et al. (2014), who finds a value of 0.34. This is likely in part due to sample differences. Chetty et al. (2014) measures parent income between ages 35–40 and child income between ages 29–32, which may lead to lower correlation than using the same age range for both groups.

Figure 10: Rank-rank income correlation



Notes: The figure the rank-rank correlation between parent and child income in the PSID data (in black) and the model (in blue). The lines show the trend, while the dots report the distribution in the model. Mirroring Chetty et al. (2014), parent and child income are measured in the data when individuals are aged 30-40. The rank-rank correlation is based on 783 CDS children and their parents. The standard error is 0.032. In the model I use young parent income (which corresponds to the age of 30-40).

The model is able to match the overall distribution by incorporating the persistence of skills across generations, the time and monetary investments families make in children, and the labor supply choices of parents.

5.5 Identification

Identification of the parameters is based on the moments that are most heavily influenced by these parameters. While all the parameters influence each of the moments chosen, here I outline which moments are most influential for each parameter.

The altruism parameter, η, governs how much families care about the future of the dynasty, and, as a result, how much they invest in their children. More weight on the future of the dynasty results in higher investments in children which translates into higher future earnings. Therefore, the rate at which children attend college is most closely related to the degree of altruism.

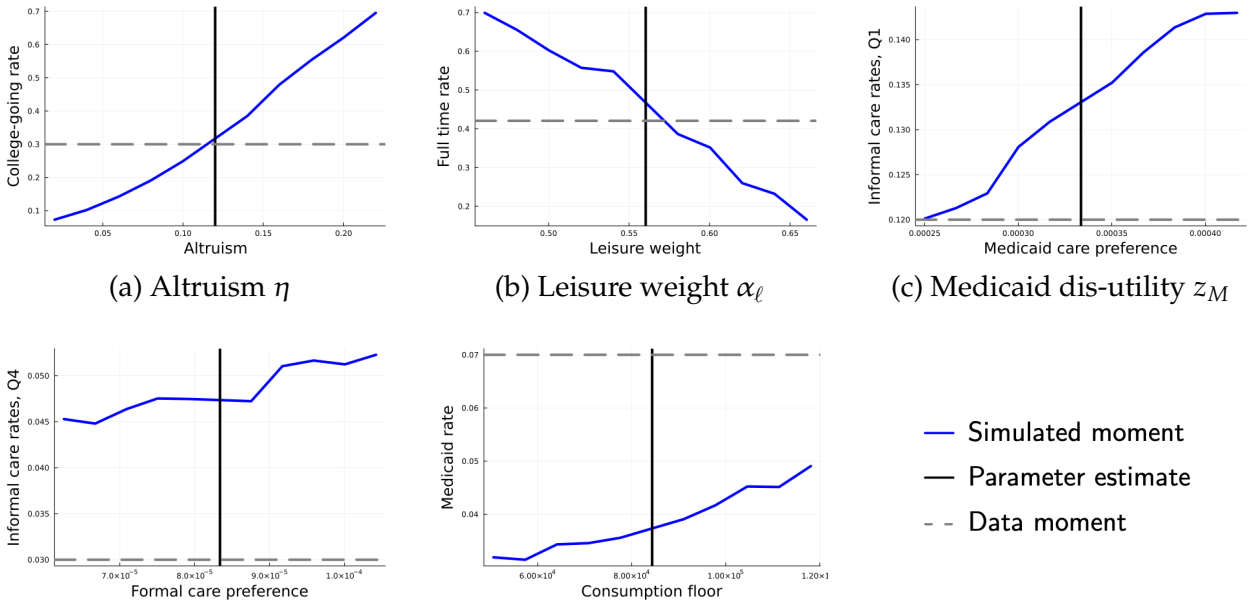
Turning to the grandparent's preferences over formal and Medicaid-funded long-term care, the rates of informal care at the top of the wealth distribution help identify the degree to which grandparents wish to avoid formal care z_F. Additionally, given Medicaid-funded formal care is of a lower quality than other sources of formal care, the informal care rate of the lowest wealth quartile also helps identify grandparent's dis-utility from

Medicaid funded care, z_M. The Medicaid consumption floor c_f is identified by the overall Medicaid rate.

Among the parameters that govern how agents in the model value leisure, the overall rate of full-time work also helps to identify how much weight leisure receives in the utility function, α_ℓ. The curvature on leisure, γ_ℓ, is identified by rates of informal care in the middle of the wealth distribution. The curvature on consumption, γ_c, governs risk aversion, and how families are willing to substitute consumption over time. A family's savings over each stage in the model help identify γ_c. For higher γ_c, families save more when young and spend down less as they age.

In addition to an argument about which moments are most influential for each parameter, for a subset of parameters I show how the most closely related moment varies as the parameter changes. The results for the altruism, leisure weight, formal and Medicaid eldercare preferences, and consumption floor parameters are reported in Figure 11.

Figure 11: Identification of key parameters



(a) Altruism η (b) Leisure weight α_ℓ (c) Medicaid dis-utility z_M

(d) Formal care dis-utility z_F (e) Consumption floor c_f

Notes: The figure shows how key model moments vary as parameters change. The blue lines plot the model moment, the grey dashed line plots the data moment, and the black line plots the parameter estimate.

From Figure 11a, it is clear that as altruism rises, so does the rate of college-going. In Figure 11b, the rate of full-time work is decreasing in the weight on utility from leisure. In Panels (c) and (d), informal care is increasing in dis-utility from Medicaid and formal care. In Figure 11e, the Medicaid rate is increasing in the generosity of the program. It

is also clear from panels (d) and (e) that the model under-predicts the Medicaid rate and over-predicts the rate of informal care in the top asset quartile. This is likely driven by the model trading off increasing the savings rate by dampening the amount of formal insurance available to grandparents.

6 Counterfactuals

In this section I first measure the impact of long-term care needs on intergenerational mobility. I then evaluate the impacts of two types of insurance against long-term care risk: insurance that covers only formal care costs and insurance that provides compensation for informal caregivers. I evaluate the effects of these coverage schemes for all families, funded by a lump-sum payment. Because these policies are hard to implement in practice, I also evaluate the impact of more targeted versions, funded by income taxes.

6.1 The impact of long-term care on intergenerational mobility

To capture the impact of long-term care needs on intergenerational mobility, I shut down all long-term care needs in the model. That is, all grandparents are healthy and have no expectations of developing long-term care needs. This reduces the correlation between parent and child income rank from 0.39 to 0.34.

To put this effect size in context, I equalize the impact of time and monetary investments in children in the model and find that this leads to a 35% decrease in the correlation between parent and child income. This is similar to Bolt et al. (2026), who find that skill differences at 16 explain 30% of intergenerational mobility. The impact of long-term care needs is smaller than the effect of parental borrowing constraints, which, when eliminated, lead to a 29% decrease in the correlation between parent and child income (Lee and Seshadri, 2019).

While many families face long-term care needs, not all families realize this shock. Here, I evaluate the extent to which the *prospect* of long-term care needs impacts intergenerational mobility. I use the baseline policy functions and simulate the model without realizations of long-term care needs, but while maintaining the possibility of long-term care in expectation. In this case, the correlation between parent and child income is 0.37. This indicates that while realized needs are important, families do adjust their behavior in the presence of long-term care risk, even when that risk is never realized.

Table 13: Long-term care & intergenerational mobility

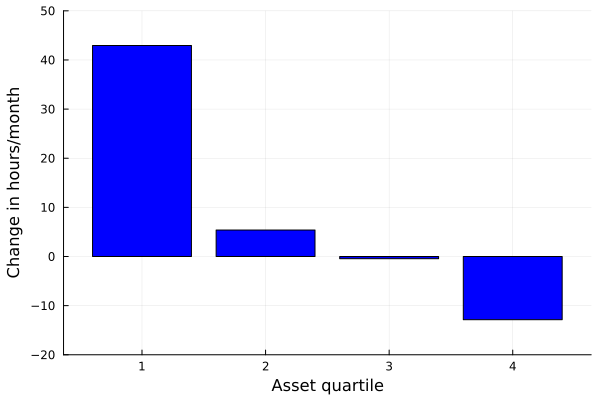
	Rank-rank correlation
Baseline	0.39
	[0.386, 0.396]
No long-term care needs	0.34
	[0.333, 0.348]
Prospect of needs, no realizations	0.37
	[0.366, 0.373]

Notes: The table reports the average correlation between parent and child income rank across many generations in the model. The range reports the 10th and 90th percentiles of the rank-rank correlation over the period.

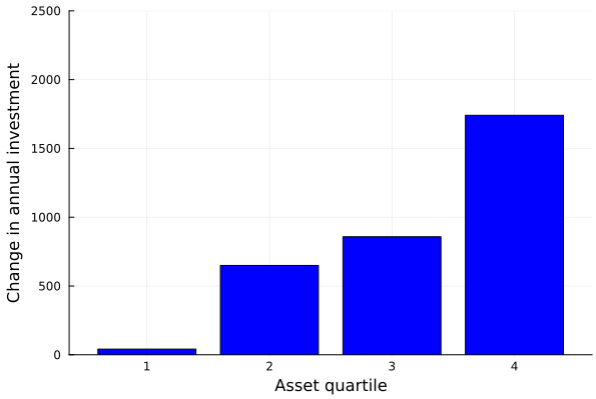
To explain what drives the change in intergenerational mobility when long-term care needs are absent, I show how investments in children change when families know with certainty they will not need long-term care. In Figure 12a and Figure 12b, I plot the difference between parental time and monetary investments in children over the wealth distribution in the baseline model and in the model in which families know they will not develop long-term care needs.

Figure 12: Changes in the absence of long-term care needs

(a) Parental time investments



(b) Monetary investments



Notes: The left panel plots the difference between parental time in the counterfactual in which no families need long-term care (known in advance) and the baseline model over the wealth distribution. The right panel plots the analogous difference in monetary investments in children over the wealth distribution.

In the absence of long-term care needs, parental time investments rise the most for the least wealthy families. Monetary investments increase over the wealth distribution, but

they increase the most for the wealthiest families. Additionally, for the highest wealth quartile, parental time decreases. This is driven by families who shift resources towards market-based childcare and monetary investments in the absence of long-term care shocks. In Figure L.3, I show that college-going increases the most for families in the middle of the wealth distribution. Taken together, this indicates that the gains in parental time are a key determinant of the increase in intergenerational mobility. In subsection K.1, I provide more detailed information on how a broad range of families' outcomes change after a long-term care shock, and how these effects persist across generations.

6.2 Willingness-to-pay for insurance against long-term care risk

The results above show that long-term care shocks negatively impact the investments families make in their children and their children's earnings later on. Here I use the model to quantify how much families are willing to pay to live in a world in which there is coverage for formal long-term care costs and a world in which long-term care insurance provides payments for informal care-givers.

Coverage for formal care

First, I implement coverage for formal care costs for all families.[23] Formal care costs ($p^g \times hm_m^g$) are fully covered for all families whenever they are incurred. To fund this policy, I assume that each family pays the expected cost of long-term care, split evenly across the three stages. The lump-sum tax each family pays each period is given by τ_f.

For $\hat{t}$ generations, I sum formal care costs over N families, and the three stages, such that expected cost of all formal long-term care is given by

$$\tau_f = \sum_{\hat{t}} \sum_{i=\{1,\dots,N\}} \sum_{t=\{y,m,o\}} hm^g_{\hat{t},t,i} * p^g \tag{31}$$

where each family faces the same expected cost.[24] To get the cost a family pays, I divide the total cost by $\hat{t} * t * N$. I assume that parents and grandparents split this cost evenly. Because families still have the option to provide informal care, this is not ex-ante equivalent to the expected cost of all long-term care being covered formally.

To capture how much families value the policy, I compute willingness-to-pay as the

[23] To model the provision of full coverage for formal long-term care costs in the model, I remove coverage for long-term care from Medicaid but maintain the presence of a social safety net. So, the Medicaid benefit becomes $M_t = \max\{0, c_f - max\{a_t^g - a_{lim}, 0\} - I^g\}$.

[24] Note that this is true because the probability of developing long-term care needs is the same for everyone.

amount of assets that would be necessary to give to a family in the baseline environment to make them indifferent between that environment and the counterfactual policy environment.

Coverage for informal care

Rather than covering the cost of formal long-term care, one could also provide families with insurance against long-term care risk by providing a subsidy for informal caregivers. I introduce a subsidy, S, to measure the effects of subsidizing informal care in the model. The amount of the subsidy is equal to 75% of the mean hourly wage of parents. Parents who provide informal care receive $S \times hp_t^g$ meaning that the subsidy amount scales with the amount of eldercare a parent provides. As with the formal care subsidy, I assume that each family pays the expected cost of the policy as a lump-sum tax, τ_s split evenly across the three stages.[25]

Results

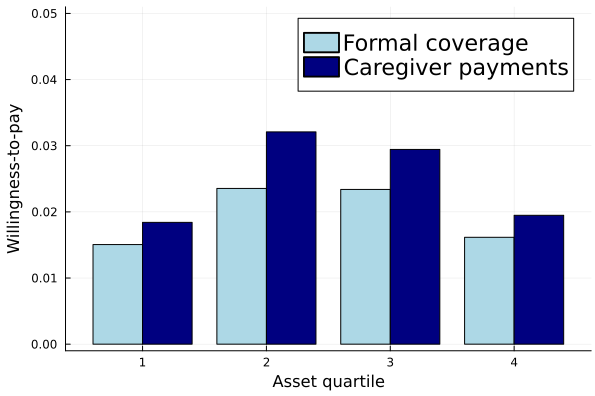
I find that families in the middle of the wealth distribution benefit the most from coverage for both formal and informal care, though families in the lowest and highest wealth quartiles families also benefit. In Figure 13a, I report the willingness-to-pay for full insurance across the wealth distribution. Across the wealth distribution, families are willing to pay an amount of assets equivalent to 1.95% of family consumption for coverage for all formal care costs. Families are willing to pay the equivalent of 2.50% of their consumption for coverage for informal care costs.

However, these policies differentially impact intergenerational mobility. In Figure 13b I report the impacts on the rank-rank correlation between parent and child income. Under the formal care subsidy, the rank-rank correlation in parent and child income decreases by 5.1%, from 0.39 to 0.37. While fully insuring families against long-term care costs blunts the effects of a long-term care shock, families' still lose access to grandparent-provided child care, and therefore insuring the cost does not fully negate the effects of the shock. On the other hand, providing a subsidy for informal caregivers *increases* the rank-rank correlation between parent and child income by 12%.

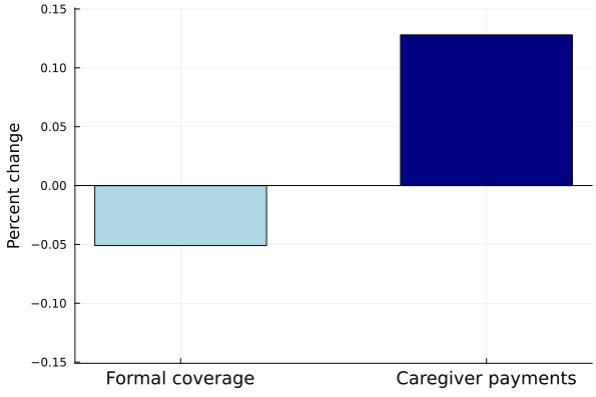
[25]Here, the cost of the policy is the difference between the cost to provide Medicaid under the baseline plus the revenue from the lump sum tax and the cost of the subsidy plus the cost of Medicaid under the counterfactual. The cost per family, τ_s is split evenly between parents and grandparents in all generations.

Figure 13: Impacts of insurance against long-term care risk

(a) Willingness-to-pay by wealth



(b) Intergenerational mobility

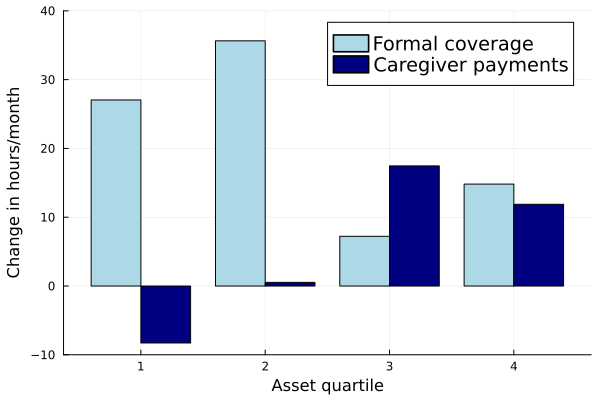


Notes: Willingness-to-pay is measured as the amount of assets a family in the baseline model would need to be indifferent between the baseline model and the counterfactual model. WTP is reported as a fraction of family (child, parent, and grandparent) consumption.

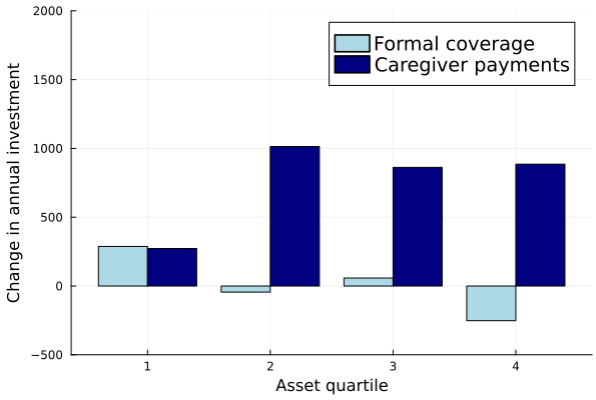
Why do formal care subsidies increase economic mobility whereas informal care subsidies decrease economic mobility? Under the latter, families across the wealth distribution provide more informal care, but the increases in informal care provision are largest for the least wealthy families. In contrast, under the formal care subsidy, all families choose to use formal care. Both policies result in changes to time and monetary investments made in children. In Figure 14a and Figure 14b I show how time and monetary investments change under each counterfactual policy. Under the informal care subsidy, time investments from parents decrease for the least wealthy. At the same time, monetary investments made by all families increase, though the gradient over the wealth distribution steepens (the dark blue bars in Figure 14b). Low wealth parents provide more informal eldercare and spend less time on childcare. While some of the decrease in parental time is made up for by increases in monetary investments, the effects of decreased parent time are not fully offset.

Figure 14: Impacts on time and monetary investments by coverage

(a) Parent childcare time



(b) Monetary investments in children



Notes: The figures report level changes from the baseline model to the corresponding counterfactual. The left panel reports changes in parental time investments and the right panel reports changes in monetary investments. The dark blue bars represent coverage for all formal care costs and the light blue bars represent payments for informal care-givers.

In contrast, under the formal care subsidy, time investments from parents increase the most at the low end of the wealth distribution, and the gradient in monetary investments flattens (the light blue bars in Figure 14b). The gradient in college-going over wealth follows a similar pattern across the counterfactuals, flattening under the formal care subsidy and steepening under the informal care subsidy (see Figure L.5). Access to formal care allows parents to spend more time with children, with the effects being particularly concentrated among low wealth families.

This mirrors the empirical results in subsubsection 3.1.2 showing that when families gain access to formal long-term care, parents spend more time with their children. Using the model, I show that the gains in parental time investment are enough to result in changes to intergenerational mobility, accounting for how families re-optimize across the counterfactuals. For more detailed information on how families' decisions change in the wake of a long-term care shock under each of the counterfactual insurance policies, see subsection K.2. In the next section, I consider smaller policy changes to the Medicaid program, and find similar patterns with regard to subsidizing informal versus formal eldercare.

6.3 Changes to Medicaid's long-term care policies

In this section, I evaluate the impacts of changes in Medicaid coverage for long-term care policies. I first consider the impact of raising Medicaid's asset limits for long-term care eligibility. This expands access to formal care for aging grandparents while allowing them to hold on to more of their wealth. I then use Medicaid's baseline means-testing to provide a subsidy for informal caregivers. This allows Medicaid-eligible grandparents to receive informal care, and informal caregivers to be compensated for their time. I fund these policy changes with income taxes, in contrast to the lump-sum payments for full insurance. This captures the fact that policy changes are funded through the tax system, whereas the counterfactuals in subsection 6.2 operate as insurance coverage funded through premiums (albeit without giving families the option to opt out of coverage).

This evaluation is important because implementing long-term care coverage for all families is difficult in practice (Brown and Finkelstein, 2007). Further, given that grandparents may have an incentive to overstate their long-term care needs so their child can receive payment, targeting concerns arise when providing payments for informal care, in particular.[26]

Asset tests

To evaluate changes to Medicaid's asset limit, I increase the amount of assets families are able to hold to gain access to Medicaid, a_{lim} in the Medicaid benefit:

$$M_t = \max\{0, c_f + p^g hm_t^g - max\{a_t^g - a_{lim}, 0\} - I^g\} \tag{32}$$

I increase Medicaid's asset limit from \$2,000 to \$25,000, implementing an income tax to cover the costs of the program.

Medicaid payments to informal care-givers

In subsection 6.2 I show that informal care insurance increases the rank-rank correlation between parent and child income. Here, I evaluate the effects of a means-tested subsidy for informal caregivers. I introduce a subsidy, $\hat{S}$, equal to 50% of the mean hourly wage of parents, for families that are eligible for Medicaid under the \$2,000 asset limit.[27] Parents who provide informal care receive $\hat{S} \times hp_t^g$ so that the subsidy amount scales with

[26] Providing payments to low-income informal caregivers still brings up targeting concerns, but because eligibility rules are fairly strict, they are less rampant than when all families are eligible.

[27] Note that the subsidy amount is less than in the case for coverage for all families. This is both to keep the costs of the policy low and because the population targeted by the policy is lower-income than the overall population.

the amount of eldercare a parent provides. The policy is funded by an income tax.

Results

The results are summarized in Table 14. The impacts of more targeted changes mirror the effects of the broad policies above. Both increase welfare, but subsidizing formal care decreases the correlation between parent and child income rank and subsidizing informal care raises the correlation. The impacts of changes to Medicaid policies on the rank-rank correlation are smaller than in the case where everyone receives the benefit. This is partially due to the fact that the cut-offs for eligibility are still fairly low. [28]

Table 14: Medicaid policy changes

	Increased asset limit	Payments for informal care
Change in rank-rank correlation	-3.1%	4.8%
Willingness-to-pay	0.04%	2.1%
Tax (% of income)	0.48%	1.67%

Notes: The table reports changes from the baseline model to each policy counterfactual. Willingness-to-pay is measured in assets and reported as a fraction of consumption.

7 Conclusion

This paper quantifies the impact of long-term care risk facing grandparents on the economic mobility of grandchildren. To do so, I construct a model that captures the tradeoffs between care choices, savings, and investments in children. The model features overlapping generations to capture the impact of long-term care on the persistence of inequality across generations. Parents and grandparents interact with limited commitment in order to capture the coordination needed to make care choices while maintaining separate asset holdings.

I find that the presence of long-term care needs increases the correlation between parent and child income by 12%. In the absence of these long-term care needs, parental time investments increase the most for the least wealthy parents, while monetary investments increase the most for the *most* wealthy parents. This suggests that changes in time investments are more important than changes in monetary investments for the increase in the economic mobility of children. Moreover, the presence of long-term care needs more

[28] These policies are also funded differently, and thus not directly comparable.

negatively impacts investments in children in low-wealth families compared to children in wealthier ones.

These results suggest that the design of long-term care insurance, particularly whether policies incentivize informal care, has important implications for intergenerational mobility. Indeed, I find that while both broad and targeted policies that provide insurance are welfare improving, coverage for formal care costs increases intergenerational mobility, while payments for informal caregivers decrease intergenerational mobility. The increase under formal care coverage is driven by larger increases in time and monetary investments in children for the least wealthy families relative to the wealthiest families. In contrast, subsidies for informal care decrease parental time investments among the least wealthy families because they rely more on informal care. These decreases are not fully offset by increases in monetary investments families are able to make due to the caregiver payment. These mechanisms are also present under changes to Medicaid policy: increasing Medicaid's asset limit for formal care coverage increases intergenerational mobility, whereas providing payments for informal caregivers in Medicaid-eligible families decreases intergenerational mobility.

An important caveat to these results is that, in order to focus on intergenerational interactions, I make a number of simplifying assumptions about the family structure. While I capture some of the variation in family structure when taking the model to the data, the model is largely focused on interactions across, rather than within, generations. The results of the model mirror impacts of expansions in formal long-term care coverage in the data and allow me to comment of broader policies and changes over the entire wealth distribution. Nevertheless, the assumptions related to family structure are an important limitation, and I leave complications related to family structure for future work.

Understanding the impact of long-term care policies is particularly important as the US population ages, life expectancies rise, and families have fewer children, all of which will likely increase the burden of long-term care on families. The results of this paper show that long-term care risk has important implications across generations and that the design of insurance against this risk should account for the effects on future generations.

References

Anstreicher, Garrett, "Spatial influences in upward mobility," *Journal of Political Economy*, 2023, *132* (1), 149–199.

_ and Joanna Venator, "To grandmother's house we go: Informal childcare and female labor mobility," *International Economic Review*, 2026, *67* (3).

Attanasio, Orazio, Costas Meghir, and Corina Mommaerts, "Insurance in extended family networks," *NBER Working Paper*, 2019.

Barczyk, Daniel and Matthias Kredler, "Evaluating long-term-care policy options, taking the family seriously," *The Review of Economic Studies*, 2018, *85* (2), 766–809.

_ , Sean Fahle, and Matthias Kredler, "Save, spend or give? A model of housing, family insurance, and savings in old age," *The Review of Economic Studies*, 2023, *90* (5).

Becker, Gary and Nigel Tomes, "Human capital and the rise and fall of families," *Journal of Labor Economics*, 1986, *4* (3), S1–S39.

Bhaumik, Deepon, Jacob Wallace, David C Grabowski, and Mark J Schlesinger, "The Impact of Introducing Managed Care Intermediaries for Long-Term Services and Supports," *Health Services Research*, 2025, *60* (4).

Boar, Corina, "Dynastic precautionary savings," *The Review of Economic Studies*, 2021, *81* (6).

Bogan, Vicki, "Household asset allocation, offspring education, and the sandwich generation," *American Economic Review: Papers and Proceedings*, 2015, *105* (5), 611—-615.

Bolt, Uta, Eric French, Jamie Hentall-MacCuish, and Cormac O'Dea, "The Intergenerational Elasticity of Earnings: Exploring the Mechanisms," *Journal of Political Economy*, 2026. Forthcoming.

Borusyak, K, X Jaravel, and J Spiess, "Revisiting Event Study Designs: Robust and Efficient Estimation," *Review of Economic Studies*, 2024, *91* (6), 3253–3285.

Braun, R, K Kopecky, and T Koreshkova, "Old, frail, and uninsured: accounting for features of the US long-term care insurance market," *Econometrica*, 2019, *87* (3), 981–1019.

Braxton, J. Carter, Nisha Chikhale, Kyle Herkenhoff, and Gordon Phillips, "Intergenerational mobility and credit," *NBER Working Paper*, 2024.

Brilli, Ylenia, "Mother's time allocation, childcare, and child cognitive development," *Journal of Human Capital*, 2022, *16* (2), 233–272.

Brown, Jeffrey and Amy Finkelstein, "Why is the market for long-term care insurance so small?," *Journal of Public Economics*, 2007, *91* (10).

Burns, Alice, Abby Wolk, Molly O'Malley Watts, and Maiss Mohamed, "How Do Medicaid Home Care Programs Support Family Caregivers?," Technical Report, KFF 2025. Issue Brief.

CareScout, "Cost of care survey 2024," 2024.

Caucutt, Elizabeth, Lance Lochner, Joseph Mullins, and Youngmin Park, "Child skill production: accounting for parental and market-based time and goods investments," *Journal of Political Economy*, 2026, *134* (1), 150–209.

Caucutt, Elizabeth M. and Lance Lochner, "Early and late human capital investments, borrowing constraints, and the family," *The Journal of Political Economy*, 2020, *128* (3), 1065–1147.

Centers for Medicare & Medicaid Services, "Reports and evaluations: Long term services and supports," 2026.

Chang, Yoosoon, Steven Durlauf, Bo Hu, and Joon Park, "The effects of parental income and family structure on intergenerational mobility: A trajectories-based approach," *Journal of Applied Econometrics*, 2026, *41* (5), 655–668.

Chari, Amalavoyal and Elsa Valli, "The effect of subsidized childcare on the supply of informal care: Evidence from public kindergarten provision in the US," *Journal of Health Economics*, 2021, *77* (102458).

Chetty, Raj, John N. Friedman, Emmanuel Saez, Nicholas Turner, and Danny Yagan, "Mobility Report Cards: The Role of Colleges in Intergenerational Mobility," *NBER Working Paper*, 2017, (23618).

_ , Nathaniel Hendren, and Lawrence Katz, "The effects of exposure to better neighborhoods on children: New evidence from the moving to opportunity experiment," *American Economic Review*, 2016, *106* (4), 855–902.

_ , _ , Patrick Kline, and Emmanuel Saez, "Where is the land of opportunity? The geography of intergenerational mobility in the United States," *The Quarterly Journal of Economics*, 2014, *129* (4), 1553–1623.

Chiappori, Pierre-Andre, Alexandros Theloudis, Jorge Velilla, J. Ignacio Gimenez-Nadal, and Jose Alberto Molina, "Commitment and the dynamics of household labor supply," *The Economic Journal*, 2025, *135* (665), 354–386.

Congressional Research Service, "Supplemental Security Income (SSI)," CRS In Focus 2026.

Corak, Miles, *Do poor children become poor adults? Lessons from a cross-country comparison of generational earnings mobility*, Vol. 13,

Cunha, Flavio and James Heckman, "The technology of skill formation," *The Economics of Human Development*, 2007, *97* (2), 31–47.

_ , _ , **and Susanne Schennach**, "Estimating the technology of cognitive and noncognitive skill formation," *Econometrica*, 2010, *78* (3), 883–931.

Daruich, Diego, "The macroeconomic consequences of early childhood development policies," *The Journal of Political Economy*, 2026, *134* (7), 2023–2074.

De Nardi, Mariacristina, Eric French, and John B. Jones, "Why do the elderly save? The role of medical expenses," *Journal of Political Economy*, 2010, *118* (1), 39–75.

_ , _ , **and John Bailey Jones**, "Medicaid insurance in old age," *The Americn Economic Review*, 2016, *106* (11), 3480–3520.

Del Boca, Daniela, Christopher Flinn, and Matthew Wiswall, "Household choices and child development," *The Review of Economic Studies*, 2014, *81* (1), 137–185.

_ **, Daniela Piazzalunga, and Chiara Pronzato**, "Early Child Care and Child Outcomes: The Role of Grandparents.," *IZA Discussion Paper*, 2014, (8565).

Fahle, Sean and Kathleen McGarry, "How Caregiving for Parents Reduces Women's Employment: Patterns across Sociodemographic Groups," *Overtime: America's Aging Workforce and the Future of Working Longer*, 2022.

Galama, Titus, Andrei Munteanu, and Kevin Thom, "Intergenerational Persistence in the Effects of Compulsory Schooling in the U.S.," *Working paper*, 2025.

Gruber, Jonathan and Kathleen M. McGarry, "Long-term care in the United States," *NBER Working Paper*, 2023.

_ , _ , **and Charles Hanzel**, "Long-term care around the world," *NBER Working Paper*, 2023.

Hamel, Liz and Alex Montero, "The affordability of long-term care and support services: Findings from a KFF survey," 2023.

Hanson, Melanie, "Average cost of college & tuition," https://educationdata.org/average-cost-of-college 2026.

Hayashi, Fumio, Joseph Altonji, and J. Laurence Kotlikoff, "Risk-Sharing between and within families," *Econometrica*, 1996, *64* (2), 261–294.

Heckman, James and Stefano Mosso, "The economics of human development and social mobility," *Annual Review of Economics*, 2014, *6*, 689–733.

Hubbard, R. Glenn, Jonathan Skinner, and Stephen Zeldes, "Precautionary saving and social insurance," *Journal of Political Economy*, 1995, *103* (2), 360–399.

Huggett, Mark, Gustavo Ventura, and Amir Yaron, "Sources of lifetime inequality," *American Economic Review*, 2011, *101* (7), 2923–2954.

Kaplan, Greg, "Moving back home: insurance against labor market risk," *Journal of Political Economy*, 2012, *120* (3).

KFF, "Medicaid financial eligibility for seniors and people with disabilities: Findings from a 50-state survey.," Technical Report, Kaiser Commission on Medicaid & the Uninsured 2019.

Ko, Ami, "An equilibrium analysis of the long-term care insurance market," *The Review of Economic Studies*, 2022, *89* (4).

Lee, Tim and Ananth Seshadri, "On the intergenerational transmission of economic status," *Journal of Political Economy*, 2019, *127* (2), 855–921.

Ligon, Ethan, Jonathan Thomas, and Tim Worrall, "Mutual insurance, individual savings, and limited commitment," *The Review of Economic Dynamics*, 2000, *3* (2), 216–246.

Lise, Jeremy and Ken Yamada, "Household sharing and commitment: Evidence from panel data on individual expenditures and time use," *Review of Economic Studies*, 2019, *86* (5), 2184–2219.

Lockwood, Lee, "Incidental bequests and the choice to self-insure late-life risks," *American Economic Review*, 2018, *108* (5), 2513–2550.

Maestas, Nicole, Matt Messel, and Yulya Truskinovsky, "Caregiving and Labor Supply: New Evidence from Administrative Data," *Journal of Labor Economics*, 2024, *42* (S1).

Marcet, Albert and Ramon Marimon, "Recursive contracts," *Econometrica*, 2019, *87* (5), 1589–1631.

McCarthy, David, James Sefton, Ronald Lee, and Joze Sambt, "Generational Wealth Accounts: Did Public and Private Inter-Generational Transfers Offset Each Other over the Financial Crisis?," *The Economic Journal*, 2022, *132* (647), 2412–2437.

Meghir, Costas and Luigi Pistaferri, "Income Variance Dynamics and Heterogeneity," *Econometrica*, 2004, *72* (1), 1–32.

Milovanska-Farrington, Stefani, "The effect of parental and grandparental supervision time investment on children's early-age development," *Research in Economics*, 2021, *75* (3), 286–304.

Mohamed, Maiss, Alice Burns, and Molly O'Malley Watts, "What is Medicaid home care (HCBS)?," 2025.

Mommaerts, Corina, "Long-term care insurance and the family," *Journal of Political Economy*, 2025, *133* (1).

Mukherjee, Anita, "Intergenerational Altruism and Retirement Transfers: Evidence from the Social Security Notch," *Journal of Human Resources*, 2022, *57* (5), 1466–1497.

_ **and Junhao Liu**, "Medicaid and long-term care: The effects of penalizing strategic asset transfers," *Journal of Risk and Insurance*, 2021, *88*, 53–77.

Mutual, Choice, "Medicaid asset limits by state: Eligibility guidelines," https://choicemutual.com/blog/medicaid-asset-limits-by-state/ 2024.

OPM, Federal Long Term Care Insurance Program, "Long term care costs," https://www.ltcfeds.gov/long-term-care/costs 2026.

Pauly, M. V., "The Rational Nonpurchase of Long-Term-Care Insurance," *Journal of Political Economy*, 1990, *98* (1).

Poyatzis, Georgia and Gretchen Livingston, "New data: Childcare costs remain an almost prohibitive expense," https://blog.dol.gov/2024/11/19/new-data-childcare-costs-remain-an-almost-prohibitive-expense November 2024.

Rosenzweig, Mark and Kenneth Wolpin, "Intergenerational support and the life-cycle incomes of young men and their parents: Human capital investments, coresidence, and intergenerational financial transfers," *Journal of Labor Economics*, 1993, *11* (1).

Skira, Meghan, "Dynamic wage and employment effects of elder patient care," *International Economic Review*, 2015, *56* (1).

Soritz, Sebastian, Daniel Moser, and Heidrun Gruber-Wölfler, "Comparison of derivative-free algorithms for their applicability in self-optimization of chemical processes," *Chemistry - Methods*, 2022, *2* (5).

Villanueva, Ernesto, "Inter vivos transfers and bequests in three OECD countries," *Economic Policy*, 2014, *20* (43), 506–565.

Voena, Alessandra, "Yours, mine, and ours: Do divorce laws affect the intertemporal behavior of married couples?," *American Economic Review*, 2015, *105* (8), 2295–2332.

Zai, Xianhua, "Evaluating the health outcomes of aging in place: the role of medicaid aging waiver program on U.S. older adults," *BMC Public Health*, 2024, *24* (1).

Appendix

A Medicaid long-term care policy and parental time investments

In the main specification, I use all HCBS spending, which includes coverage for mentally ill and developmentally disabled individuals in addition to aging adults. Here, I use variation in Medicaid spending on managed long-term services and supports for aging adults. I use the American Time Use Survey and I run the following specification:

$$Y_{ist} = \beta_0 + \beta_1 M_{st} + \mu_t + \eta_s + X_{ist}\delta + \epsilon_{ist} \tag{A.1}$$

The dependent variable, Y_{ist}, is minutes of each outcome of interest on the ATUS sample day. The independent variable, M_{st}, is Medicaid spending on managed long-term services and supports per 65+ capita in state s in year t. I include year and state fixed effects, μ_t and η_s, and the covariate vector X_{ist} includes age, sex, number of children, years of education, whether an individual is partnered, the age of the youngest child, total Medicaid spending in state s at time t, and day of the week indicators. Standard errors are clustered at the state level. In the main results, I focus on parents with incomes below $12,500. The results are reported in Table A.1.

Appendix Table A.1: Regression results: Impact of managed HCBS on parental childcare and eldercare time

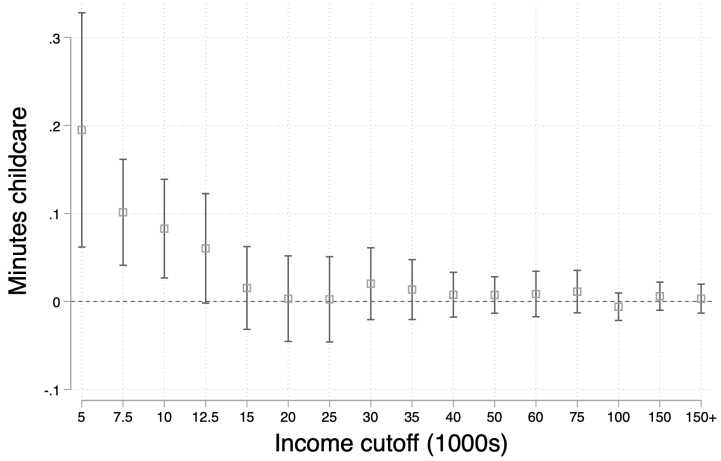
	(1) childcare	(2) eldercare
HCBS spending per 65+ capita	0.060*	-0.055*
	(0.032)	(0.029)
Mean of dependent variable	80.300	6.646
N	3,781	3,781
Adjusted R^2	0.141	0.005

Notes: The sample includes all parents in the American Time Use Survey between 2006 and 2014 with at least one child under 18 and whose annual incomes are below $12,500.
Standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

I find an increase of 6 minutes of childcare time for each $100 of spending on managed HCBS for aging adults. The magnitude of this increase is matched by a decrease in eldercare by about 5.5 minutes. To put these effect sizes in context, average spending on nursing facilities is 1,398 per aged 65+ adult, and this declined from about 1,600 to 1,200 over my sample period. This indicates that increasing families' access to Home and Community Based Care increases parental time spent with children. These results indicate that shifting these resources towards care that more easily substitutes for informal care leads to parents spending more time with their children.

In Figure A.1, I plot the coefficient on childcare minutes over income cutoffs. The results are largest for lower-income families, and fade out as higher income families are added to the sample.

Appendix Figure A.1: Impact of HCBS on parental childcare over income cutoffs



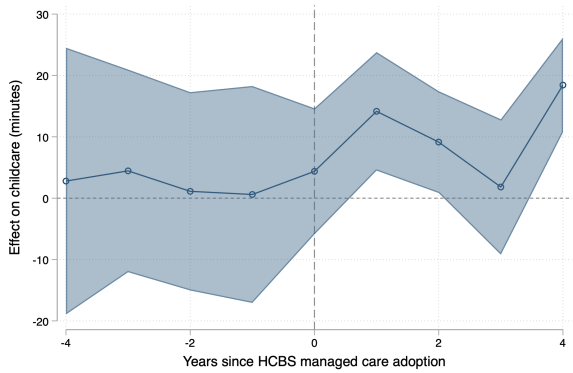
Notes: The sample in the leftmost dot includes only parents in the ATUS who have incomes below $5,000 annually. Moving rightward, each dot adds parents to the sample who are below the given income cutoff.

Above I use a continuous treatment, but Bhaumik et al. (2025) investigate the effect of the roll-out of managed long-term services and supports on formal home care use and informal care use. They use a staggered difference-in-differences design that utilizes the variation in the roll-out between 2004 and 2018. Their sample includes adults 65 and older in the HRS with at least one ADL or IADL limitation. They find that the adoption of managed care increased formal home care utilization by 35% (from a pretreatment mean of 7.5%) and decreased informal care utilization by 8% (from a pretreatment mean of 34.66%). I am interested in the effects on time parents spend with their children and on eldercare.

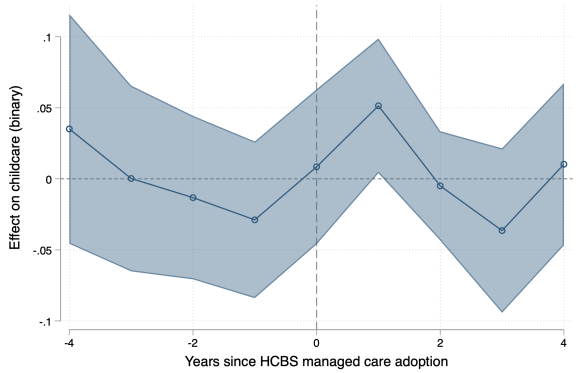
While the continuous treatment offers meaningful variation in treatment intensity, I also investigate the effects of the roll-out of these services. In Figure A.2 I show the event studies using the adoption of managed care for long-term care services and supports for the aged, blind, and disabled population. This is the variation used in Bhaumik et al. (2025). I include the same covariates as in Equation A.1 and find no evidence of pre-trends. I include specifications for continuous and binary measures of both childcare and eldercare, and the results are largely in line with my main specification.

Appendix Figure A.2: Effects of managed care adoption on caregiving

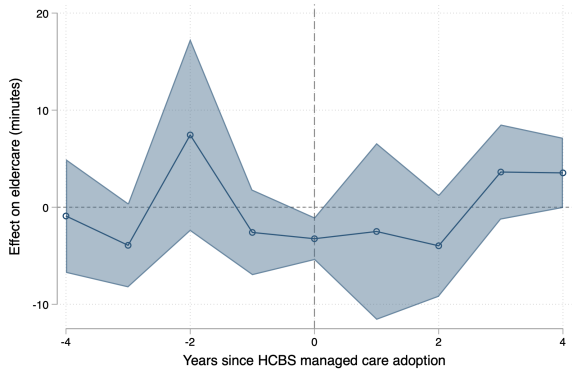
(a) Childcare (minutes)



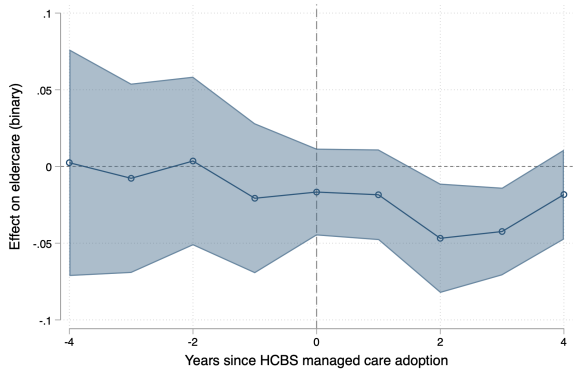
(b) Childcare (binary)



(c) Eldercare (minutes)



(d) Eldercare (binary)



Notes:

I use the difference-in-differences method described in Borusyak et al. (2024) to complement my continuous treatment effect above. The results are reported in Table A.2. This method accommodates staggered adoption and heterogeneous treatment effects better than the standard two-way fixed effects model. Here, I find a significant and positive effect of the roll-out of managed HCBS long-term care on minutes of childcare, and a negative and significant effect on a binary measure of eldercare. I find a 2.5 percentage point decrease in the provision of eldercare, which is similar to the 3 percentage point decrease found in Bhaumik et al. (2025). The effects on a binary measure of childcare and a continuous measure of eldercare go in the expected directions, but the coefficients are insignificant.

Appendix Table A.2: Managed Care HCBS Adoption

	Childcare		Eldercare	
	Minutes	Binary	Minutes	Binary
Managed care adoption (ATT)	8.682**	0.010	-1.105	-0.025**
	(3.712)	(0.014)	(1.591)	(0.011)
Mean of dependent variable	79.017	0.604	6.641	0.105
N	6485	6485	6485	6485

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

B Grandparent-provided childcare

Here, I define four levels of long-term care need: no care, light care, full-time care, and round-the-clock care. Light care is defined as having slight difficulty with ADLs, and these individuals receive, on average, 50 hours of care a month. Full-time care is defined as having moderate difficulty with ADLs, and these individuals receive an average of 132 hours of care per month. Finally, I define round-the-clock care as having significant difficulty with ADLs, and these respondents receive about 310 hours per month of care. To investigate the impact of grandparents' long-term care needs on childcare provision, I run the following regression:

$$CC_i = \beta_0 + \beta_1 light_i + \beta_2 heavy_i + \beta_3 rtc_i + \alpha X + \epsilon_i \tag{B.1}$$

CC_i An indicator for whether the grandparent provided at least 100 hours of childcare to grandchildren over the past two years. The coefficients of interest are β_1, β_2, and β_3. The results in both specifications indicate that grandparents with long-term care needs are less likely to provide childcare for parents, with the magnitude increasing as grandparents move from no care needs to full-time care needs.

C Model details

Appendix Table C.1: State and Choice Variables

Type	**Variable**	**Elements**
State	z_y	$\{\theta_y, a^p_y, a^g_y, s^p_y, s^k_y, \epsilon_y, H^g_y\}$
State	z_m	$\{\theta_m, a^p_m, a^g_m, s^p_m, s^k_m, \epsilon_m, H^g_m\}$
State	z_o	$\{\theta_o, a^p_o, a^g_o, s^p_o, s^k_o, \epsilon_o, H^g_o\}$
Choice	j_y	$\{c^k_y, c^p_y, c^g_y, a^p_m, a^g_m, L^p_y, \ell^p_y, x_y, hm^k_y, hp^k_y, hg^k_y, \ell^g_y, \mu^p_y, \mu^g_y\}$
Choice	j_m	$\{c^k_m, c^p_m, c^g_m, a^p_o, a^g_o, L^p_m, \ell^p_m, x_m, hm^k_m, hp^k_m, hg^k_m, hm^g_m, hp^g_m, \ell^g_m, \mu^p_m, \mu^g_m\}$
Choice	j_o	$\{c^k_o, c^p_o, c^g_o, a^p_y, a^g_y, L^p_o, \ell^p_o, X_o, hm^g_o, hp^g_o, \ell^g_o, \mu^p_o, \mu^g_o\}$

Appendix Table B.1: Regression results: Impact of grandparent care needs on grandparent childcare

	Grandparent provides childcare	
	(1)	(2)
Light care needs	-0.036***	-0.006
	(0.005)	(0.005)
Full time care needs	-0.062***	-0.016**
	(0.006)	(0.007)
Round-the-clock care needs	-0.070***	-0.011
	(0.007)	(0.008)
Individual fixed effect	No	Yes
Mean of dependent variable	0.29	0.29
N	17,623	17,623
N × year	110,447	110,447

Notes: The sample includes all respondents in the HRS who have grandchildren. Coefficients are relative to grandparents who do not have care needs. Controls include a quadratic in age, gender (in the left column), education, wealth, and the ages of a grandparent's youngest and oldest child.
Standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

D Altruism

Grandparents are altruistic towards parents to degree η. let v_t^g be the grandparent's value without altruism for $t = \{y, m, o\}$ such that the grandparent's value is her utility from consumption plus her discounted value tomorrow.

$$v_t^g = u_t^g + \beta v_{t+1}^g \tag{D.1}$$

When the grandparent is old, her value from her own utility tomorrow is zero, that is $v_{o+1}^g = 0$. Without altruism, the model collapses to a finite horizon life-cycle model that can be solved with backward induction.

Now consider the altruism term. The grandparent weights the parent's value by η, such that she cares about the parent's utility today u_t^p and her value tomorrow V_{t+1}^p. Denote the grandparent's total value V_t^g.

$$V_t^g = v_t^g + \eta u_t^p + \beta \eta V_{t+1}^p \tag{D.2}$$

Then, we can re-write V_t^g as:

$$\begin{aligned} V_t^g &= u_t^g + \beta v_{t+1}^g + \eta u_t^p + \beta \eta V_{t+1}^p \\ &= u_t^g + \eta u_t^p + \beta V_{t+1}^g \end{aligned}$$

Then, for each stage:

$$V_y^g = u_y^g + \eta u_y^p + \beta V_m^g \tag{D.3}$$

$$V_m^g = u_m^g + \eta u_m^p + \beta V_o^g \tag{D.4}$$

$$V_o^g = u_o^g + \eta u_o^p + \beta V_{o+1}^g = u_o^g + \eta u_o^p + \beta\eta V_y^g \tag{D.5}$$

In the last period, grandparents care about their discounted future value βV_{o+1}^g, which includes their own value $v_{o+1}^g = 0$ and their altruism toward the parent's future value when she becomes the young grandparent V_y^g.

E T1EV shock details

In the third stage, the family value function is the expectation over the preference shock for college-going. The shock is a Type I Extreme Value shock. A household sees ξ_X before making the college choice, thus the value function for the old family is given by

$$V_t(z_t) = E_\xi \max_X V_t(z_t, X) + \xi_X \tag{E.1}$$

Taking the expectation over the shocks, the value function can be written as

$$V_t(z_t) = \sigma_\xi \log \sum_X \exp\left(\frac{V_t(z_t, X)}{\sigma_\xi}\right) \tag{E.2}$$

and the probability of college-going is given by

$$\Pr(X|z_t) = \frac{\exp(V_t(z_t, X)/\sigma_\xi)}{\sum_{\hat{X}} \exp(V_t(z_t, \hat{X})/\sigma_\xi)} \tag{E.3}$$

F Outside options

I model the outside options of parents and grandparents as a non-cooperative game. I assume that cross-generation time and monetary transfers are not possible for the rest of the dynasty, with the exception of a bequest at the end of the grandparent's life. Because it is a non-cooperative game, I assume a timing structure: the grandparent makes her choices first, anticipating parent's choices, and the parent follows.

F.1 Parents

Parents maximize

$$W_t^p(z_t) = \max_{j_t^p} \frac{c^{p(1-\gamma_c)}}{1-\gamma_c} + \lambda \frac{c^{k(1-\gamma_c)}}{1-\gamma_c} + \alpha_\ell \frac{\ell^{p(1-\gamma_\ell)}}{1-\gamma_\ell} + \beta E W_{t+1}^p(z_{t+1}) \tag{F.1}$$

subject to their own budget constraint

$$c_t^p + c_t^k = I_t^p(s_t^p) + w_t L_t + R a_t^p - a_{t+1}^p - p^k h m_t^k - x_t - p^X X_t \tag{F.2}$$

and time constraint

$$\hat{T} = h p_t^k + L_t^p + \ell_t^p \tag{F.3}$$

Additionally, childcare hours must be met by the market or parent such that

$$H_t^k = h p_t^k + h m_t^k \tag{F.4}$$

The parent's continuation value when $t = o$ is given by $W_{o+1}^p(z_{o+1}) = W_y^g(z_y)$. The parent's choice variables are $j_t^p = \{c_t^p, c_t^k, hk_t^p, hk_t^m, X_t, a_t^p\}$. In the third period, the parent receives a Type I Extreme Value shock over college-going preferences.

F.2 Grandparents

Grandparents maximize their outside value W_t^g. This value includes the grandparent's utility from consumption and leisure, and she is still altruistic toward the parent.

$$W_t^g(z_t) \max_{j_t^g} \frac{c^{g(1-\gamma_c)}}{1-\gamma_c} + \alpha_\ell \frac{\ell^{g(1-\gamma_\ell)}}{1-\gamma_\ell} + z_M \mathbb{1}_{m_t=1} + z_F \mathbb{1}_{F_t=1} + \beta E W_{t+1}^g(z_{t+1}) + \eta u_t^p(c_t^p, c_t^k, \ell_t^p) \tag{F.5}$$

She maximizes her value subject to her own budget constraint, given by:

$$c_t^g = I^g + R a_t^g - a_{t+!}^g + M_t - p^g h m_t^g \tag{F.6}$$

and time constraint, given by:

$$\hat{T} = \ell_t^g \tag{F.7}$$

Any eldercare hours must be met formally, such that

$$H_t^g = h m_t^g \tag{F.8}$$

The grandparent's continuation value when $t = o$ is given by $W_{o+1}^g(z_{o+1}) = \eta W_y^g(z_y)$. Where she is still altruistic towards the parent and may leave a bequest. The grandparent's choice variables are given by $j_t^g = \{c_t^g, a_t^g, h m_t^g\}$.

G Model solution

To solve the model, I use value function iteration. The young grandparent's value function appears in the old parent's value function and the grandparent is altruistic, thus the parent's value function appears in the grandparent's value function, which makes it an infinite horizon model. Further, because families make decisions jointly, I solve the family problem in each family stage by maximizing the Pareto-weighted value functions of the parent and grandparent. The solution algorithm is given by the following:

1. Solve the non-cooperative problem.

2. Use the solution to the non-cooperative model as the outside option value in the limited commitment model. Update the Pareto weights and asset distribution to ensure both parties remain in the arrangement. The solution proceeds as follows:

   (a) For each combination of state variables, solve the problem at each θ.

   (b) For a given set of state variables, check the commitment constraints at each θ. There are three possible scenarios (because there are always gains from cooperation, both constraints will never bind at the same time):

      i. Neither constraint binds.

      ii. The parent's binds. In this case, find μ_t^p such that $V_t^p(z_t, \mu_t^p) - V_t^{po}(z_t) = 0$. This gives the solution to the problem:

      $$\max_{j_t}(\theta_t + \mu_t^p)V_t^p(z_t) + (1 - \theta_t)V_t^g(z_t)$$

      I then update and normalize the Pareto weight to reflect the commitment constraints, such that $\hat{\theta}_t = \frac{\theta_t + \mu_t^p}{1 + \mu_t^p}$.

      iii. The grandparent's binds. In this case, find μ_t^g such that $V_t^g(z_t, \mu_t^g) - V_t^{go}(z_t) = 0$. This gives the solution to the problem:

      $$\max_{j_t}(\theta_t)V_t^p(z_t) + (1 - \theta_t + \mu_t^g)V_t^g(z_t)$$

      I then update and normalize the Pareto weight to reflect the commitment constraint, such that $\hat{\theta}_t = \frac{\theta_t}{1 + \mu_t^g}$.

   (c) Iterate until convergence of the value functions.

This solution method follows the method described in Marcet and Marimon (2019) given the optimization problem has includes forward looking constraints. When these constraints are present, the problem does not satisfy the standard Bellman equation because feasible choices depend on future decisions (i.e. allocations are restricted by resources and whether decisions will keep agents in the contract).

To solve such a problem recursively Marcet and Marimon (2019) show that one may solve a recursive saddle point problem which includes a co-state variable. The co-state variable is necessary because the problem is generally time-inconsistent due to the presence of forward looking constraints. However, solving the planner's problem in the future with the current state and costate variables gives the same continuation value that was obtained from the original optimal allocation – the co-state summarizes previous commitments reflected in past Lagrange multipliers. The continuation problem is then formulated with the costate variable as a weight in the objective function. Consider the Lagrangian that incorporates the commitment constraints:

$$\mathcal{L} = \max_{j_t} \theta_t V_t^p(z_t) + (1 - \theta_t)V_t^g(z_t) + \mu_t^p(V_t^p(z_t) - V_t^{po}(z_t)) + \mu_t^g(V_t^g(z_t) - V_t^{go}(z_t)) \quad \text{(G.1)}$$

Then, by complementary slackness either the multiplier must be zero or the constraint must be slack, such that

$$\mu_t^p = 0$$

or

$$V_t^p(z_t) - V_t^{po}(z_t) \leq 0$$

So, if $V_t^p(z_t) < V_t^{po}(z_t)$ then we must find μ_t^p such that $(\theta_t + \mu_t^p)V_t^p(z_t) = V_t^{po}(z_t)$. Then, we evaluate the objective function at the new optimum j_t^* implied by the updated Pareto weight $\hat{\theta}_t$. However since $\mu_t^p(V_t^p(z_t) - V_t^{po}(z_t)) = 0$ after the adjustment, we evaluate the objective at θ_t rather than $\hat{\theta}_t$.

Prior to this formulation, the problem was often solved by adding a state variable for the promised utility of one agent and constraining the allocation to result in a value above that promised utility (see Ligon et al. (2000) for an example). This gives the same result but is more computationally burdensome than the approach in Marcet and Marimon (2019).

H Limited commitment details

Limited cooperation

In finite horizon models with limited commitment, when the last period is known with certainty, commitment tends to unravel. Without the value of future risk-sharing in the agreement, the agent with the more favorable position almost always has an incentive to default to their outside option (i.e. the agent with more assets or a good shock). Knowing this is the case, in the period prior to that, the agents are incentivized to default, and thus cooperation unravels. In other words, without the value of future risk sharing, it becomes impossible to sustain cooperation. Thus, when the parameters that govern how much families care about the future of the dynasty are sufficiently low, break-up may occur.

In my model, given that agents value the future, they will never break up because they want to maintain the value from the possibility of cooperation in the future. That is, break-up can only occur if the value agents place on the future is sufficiently low, as governed by the degree of grandparent's altruism η and the discount factor β.

Even without break-up, agents can receive the allocations in their outside options. This would happen if all surplus in the arrangement is given to one agent. However, because there are gains to cooperation above what would be possible in the outside options, the allocations in the outside option are not replicated in all states of the world. This surplus comes from gains from cooperating relative to defaulting. Parents don't want to default because they would not have access to informal care when they become grandparents. Grandparents don't want to default because receiving informal care is preferable to formal care and they are altruistic. These mechanisms would break down if agents did not care enough about the future. Further, families may prefer to provide informal eldercare rather than use formal care to avoid Medicaid income and asset tests. Providing

care generally may raise the total surplus in the arrangement if families can allocate their resources in a way that is more productive than the outside option would allow.

The Pareto weight

Because of the overlapping generations structure of my model, there are three ways to model what happens to the Pareto weight when the parent becomes a grandparent. The Pareto weight may either follow the person, it may stay with the generation, or a new Pareto weight could be drawn at the start of each young family stage.

I model the Pareto weight as following the generation. So, when an old parent becomes a young grandparent, she inherits the Pareto weight. That is, at $t = o$, the parent's weight is θ_o and when she becomes a young grandparent in the next period $t = y$, her Pareto weight is $(1 - \theta_y)$ and the old child becoming the young parent keeps the weight associated with her, θ_y.

Modeling the Pareto weight as following the individual would mean that the parent keeps her weight when she becomes a grandparent, but would also imply that the child becoming a parent would inherit the weight of the grandparent, which seems less realistic. Drawing a new Pareto weight for young parents fails to capture the persistence in the effect of shocks for the family, since, in effect it would draw a new Pareto weight for the grandparent.

I Timing

In the model, all families face the same timing structure. That is, regardless of wealth, all families face childcare and eldercare concerns at the same time. In the data, the *ages* at which families face these concerns are not the same, but the *timing* is very similar. Table I.2 gives the average ages at which women first give birth in the PSID and aging households first develop care needs and die in the HRS over the wealth distribution. From the data, it is clear that less wealthy families have children and develop care needs earlier.

Appendix Table I.1: Age at event

Asset quartile	Age at first birth	Age at first care need	Age at death
Q1	19.9	67.5	82.0
Q2	21.4	70.3	83.9
Q3	22.1	72.5	85.4
Q4	24.1	74.0	86.0
Q5	26.9	75.8	87.0
Observations	25,236	56,484	56,484

The gap between the lowest quartile and the highest quartile is 7 years for fertility timing, 8.3 years for developing care needs, and 5 years for death. Thus, while less wealthy families develop care needs earlier and have children earlier, the timing of childcare and

eldercare needs is very similar across the wealth distribution. These differences are summarized in Table I.2. This is not to say that wealth causes earlier first births and earlier care needs. It very well could be the case that earlier care needs impede families' ability to save and accumulate wealth. Indeed, the model captures the fact that less wealthy families require more care without imposing different care timing across the wealth distribution.

Appendix Table I.2: Timing

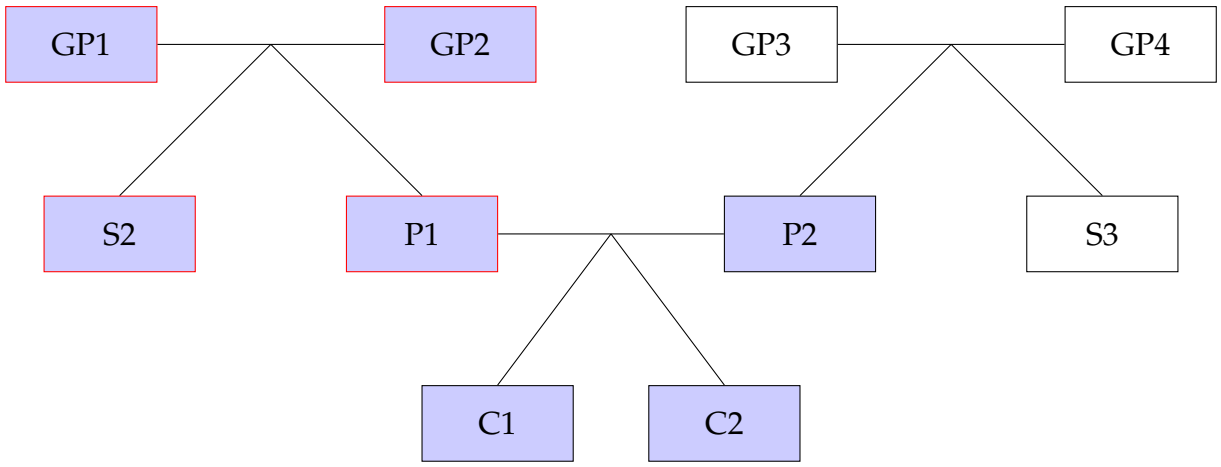
Asset quartile	First care need - first birth	Death - first care need	Death - first birth
Q1	47.6	14.5	62.1
Q2	48.9	13.6	62.5
Q3	50.4	12.9	63.3
Q4	49.9	12.0	61.9
Q5	48.9	11.2	60.1
Observations	25,236	56,484	56,484

The fact that less wealthy families have children, develop care needs, and die at earlier ages means that the timing of the model fits the timing of these concerns in the data, though not the exact ages.

J Family structure

In the model I also make assumptions about family structure. Namely, I abstract from the existence of siblings and a second set of grandparents. This is again to maintain tractability and focus on intergenerational interactions, but it is also informed by what is available in the data. Figure J.1 outlines an example of a family tree across three generations. In this family, there are four grandparents, each parent has a sibling, and there are two children. However, in the data, I am at most able to observe half of this family tree (shaded in blue).

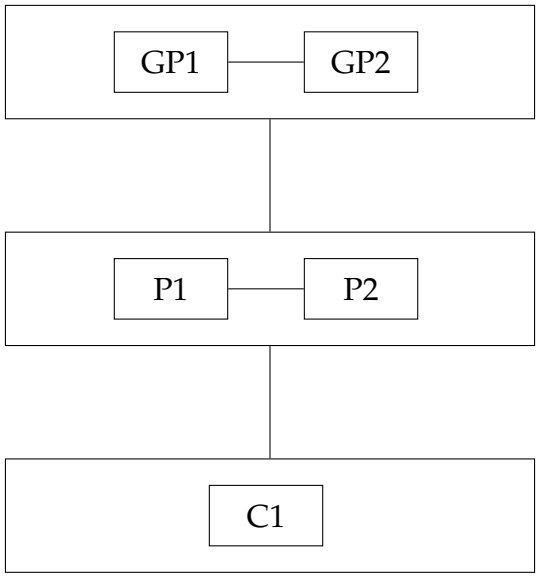
Appendix Figure J.1: Family Tree: Data



Notes: Red boxes indicate data available in the HRS. Blue shading indicates data available in the PSID.

Given this, along with a focus on intergenerational interactions, the structure of them model collapses this family tree into a grandparent generation, made up of two grandparents, a parent generation, made up of two parents, and a child generation, currently made up of one child. This is described in Figure J.2.

Appendix Figure J.2: Family Tree: Model



K The impact of a long-term care shock

K.1 Baseline model

To understand the impact of a long-term care shock on families, I use the baseline policy functions and simulate two groups of families. First, a group that never receives a long-term care shock though they maintain their expectations of the possibility of a long-term care shock. Second, a group that draws a light care needs shock as a middle-age family and a heavy care need shock as an old family. These shocks are drawn for one generation of the dynasty. Figure K.1 shows how outcomes diverge after the realization of a long-term care shock across generations.

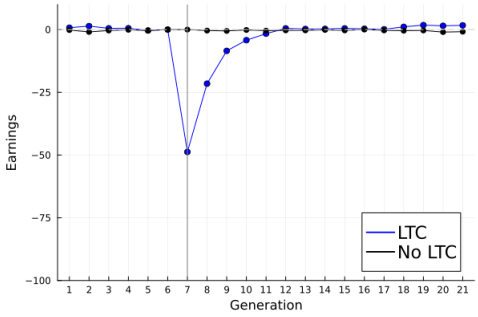
As expected, earnings and labor supply fall in the period in which the shock is realized (Figure K.1a and Figure K.1b). Labor supply rebounds the fastest, returning to the pre-shock level the following generation. However, earnings do not rebound fully in the following generation. This is because the long-term care shocks impact investments in children, and these effects persist across multiple generations.

Figure K.1c shows that parent skills in the period of the shock decrease as they work less and accrue less human capital from labor supply. The children born in the period of the shock are most severely affected in terms of skill loss (period 8 in Figure K.1c). This happens as a result of a large dip in monetary investments in children (Figure K.1e) and the fact that they're 12.8% less likely to attend college than children in families that do not receive a long-term care shock (Figure K.1f).

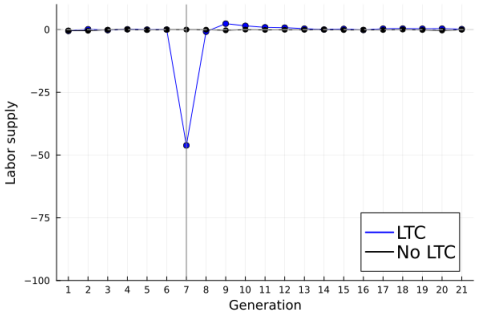
Time investments in children are also affected. Because grandparents with care needs are unable to provide childcare, care from parents increases in the period of the shock and rebounds in the following period (Figure K.1g). Care from grandparents decreases in the period of the shock as expected (Figure K.1h). However, in the following periods, grandparent care actually increases. This is because families are poorer in the aftermath of the shock, and rely more on grandparent care. This is outline in Figure K.1d, which shows that savings are the slowest to rebound in the aftermath of the long-term care shock.

Appendix Figure K.1: Impact of a long-term care shock

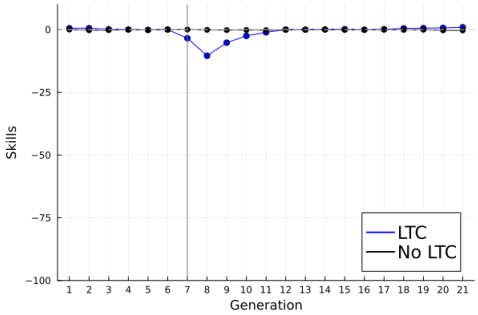
(a) Earnings



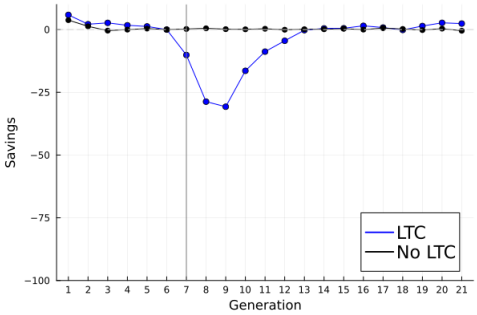
(b) Labor supply



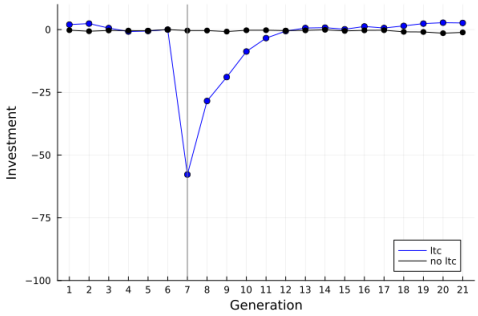
(c) Parent skill



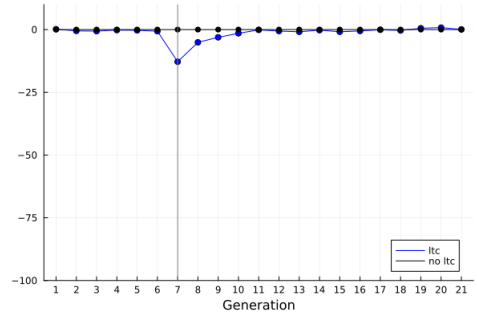
(d) Family savings



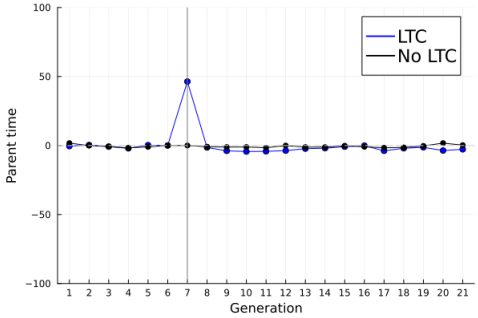
(e) Monetary investment in children



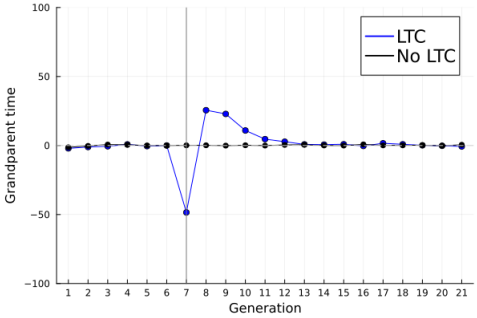
(f) College-going



(g) Time investment: parents



(h) Time investment: grandparents



Notes: The gray line indicates the generation in which the shock is realized. Outcomes are averaged over each stage in the generation. The y-axis represents percentage changes from the pre-shock mean of all families. Family savings are measured as the sum of parent and grandparent assets.

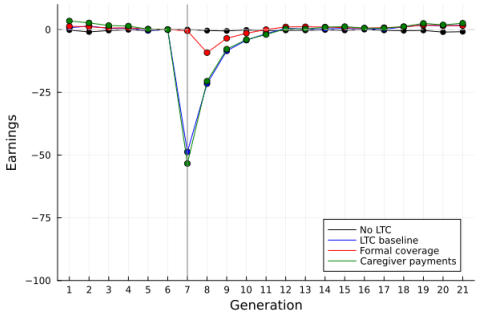
K.2 Policy changes

Here, I plot the impact of long-term care shocks on families under each counterfactual insurance policy. I again simulate a group of families that never receive a long-term care shock. I then simulate three groups of families. One that receives a long-term care shock in the baseline model, one that receives a long-term care shock when all formal care costs are covered, and one that receives a long-term care shock when all informal care is eligible for a subsidy.

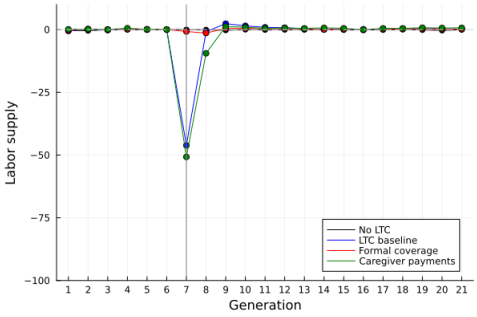
These figures show how the insurance policies blunt the impacts of the long-term care shock. These results indicates the importance of accounting for the impact on children when thinking about long-term care insurance policies. Under full insurance, the earnings and labor supply of the parent in the period of the shock do not change, and family savings see only slight decreases. However, investments in children are still impacted, and there are still impacts on future generations.

Appendix Figure K.2: Impact of a long-term care shock by policy

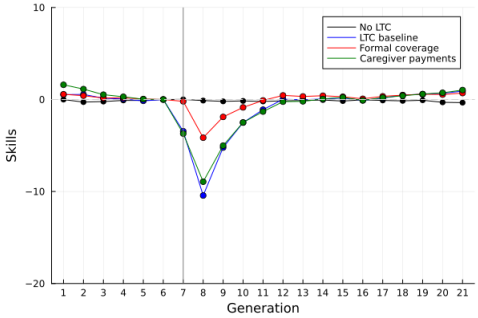
(a) Earnings



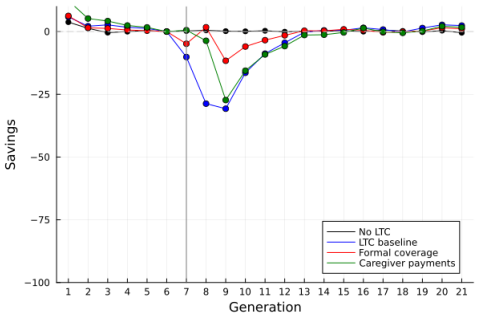
(b) Labor supply



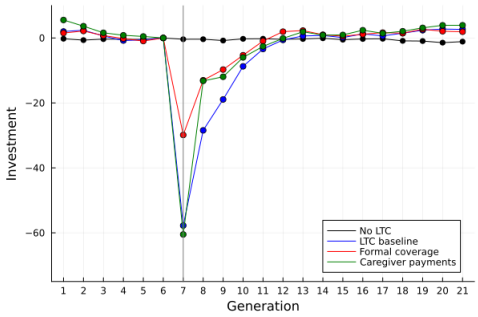
(c) Parent skill



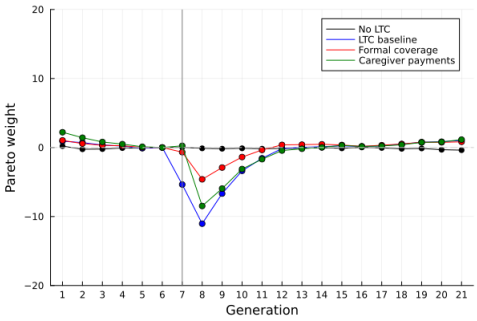
(d) Family savings



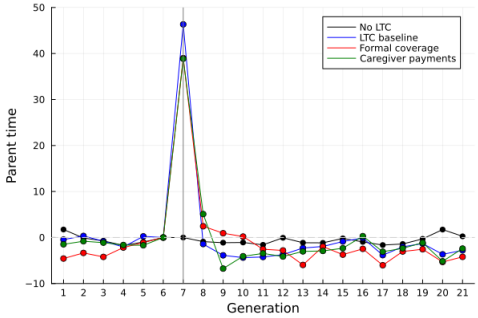
(e) Monetary investment in children



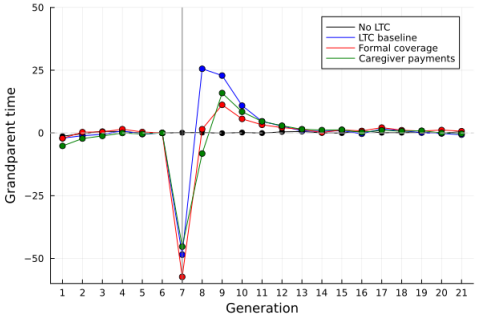
(f) College-going



(g) Time investment: parents



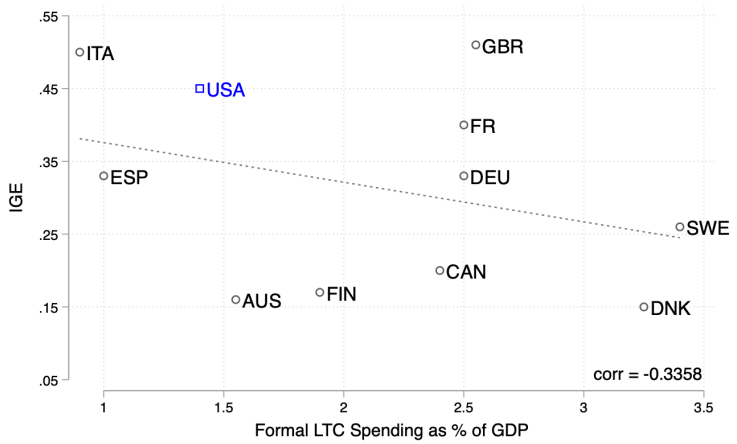
(h) Time investment: grandparents



Notes: The gray line indicates the generation in which the shock is realized. Outcomes are averaged over each stage in the generation. The y-axis represents percentage changes from the pre-shock mean of all families. Family savings are measured as the sum of parent and grandparent assets. The red lines indicate the outcomes under full insurance and the blue lines give the outcomes with the shock without any insurance.

L Additional figures

Appendix Figure L.1: Intergenerational earnings elasticity and formal long-term care spending



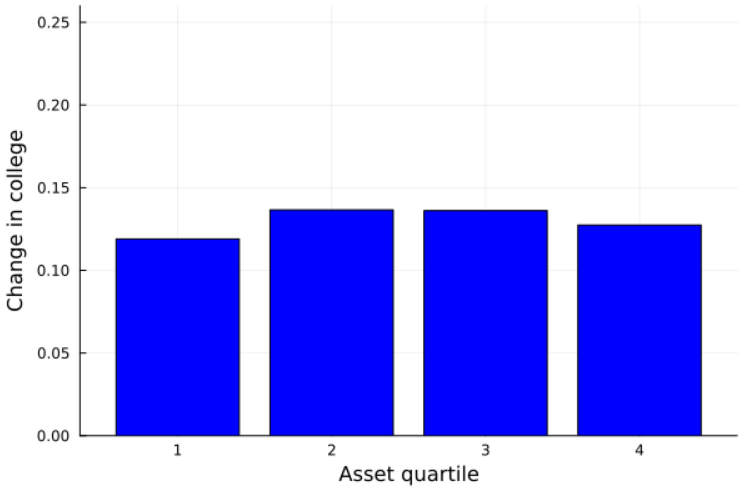
Notes: For formal long-term care spending, I use values from Gruber et al. (2023) and for intergenerational income elasticities, I use Corak (2006)

Appendix Figure L.2: Mother education and spousal earnings



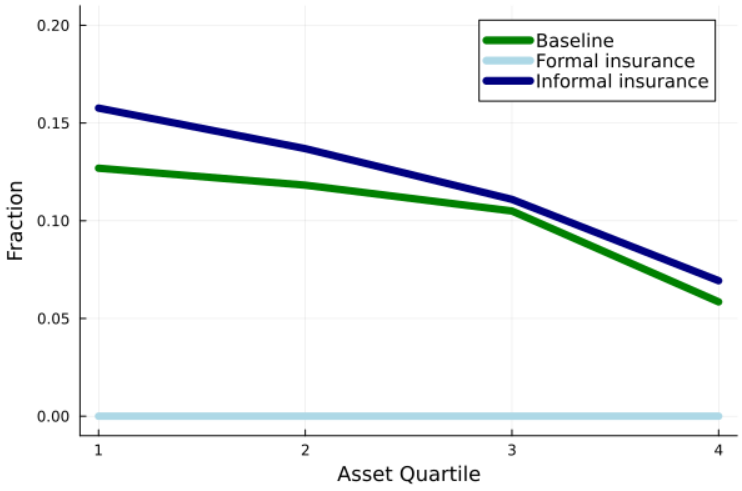
Notes: The dots plot average log spousal hourly earnings by the mother's level of education. Single parents have zero spousal income. In practice I replace the zeros with ones so they are handled by the log. The vertical lines represent the cut-offs for spousal income level in the model.

Appendix Figure L.3: Change in college-going



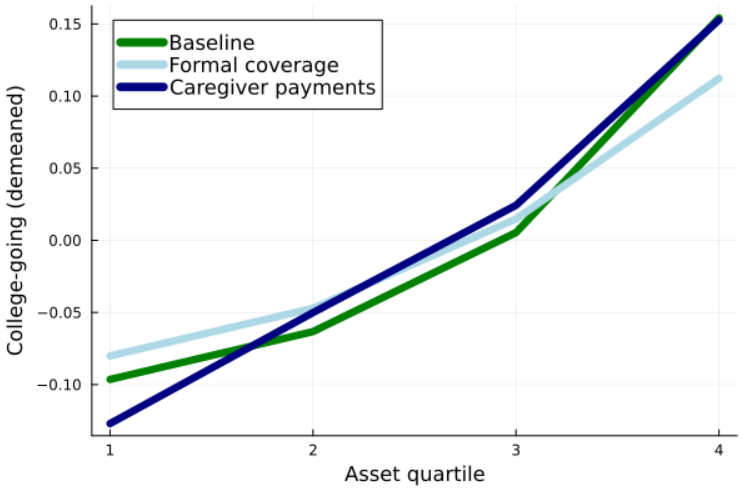
Notes: The figure plots the change in college-going rates over the wealth distribution between the model in which grandparents know with certainty that they will never develop long-term care needs and the baseline model.

Appendix Figure L.4: Informal Care Rates



Notes: The figure plots informal care rates by wealth across the baseline model and counterfactuals in which formal care costs are covered (light blue) and informal care-givers receive payments (dark blue).

Appendix Figure L.5: College-Going Gradient



Notes: The figure plots the gradient in college-going over the wealth distribution across the baseline model and counterfactuals in which formal care costs are covered (light blue) and informal care-givers receive payments (dark blue).