Intergenerational Mobility and Long-Term Care*

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Abstract

This paper investigates how long-term care risk facing grandparents impacts the economic mobility of children in the United States. Empirically, 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 a dynamic model in which families make long-term care and childcare choices, as well as investments in children. In order to capture impacts across multiple generations and risk-sharing within the family, I build limited commitment between parents and grandparents into a model of overlapping generations. Limited commitment is important to capture interactions between parents and grandparents over the entire life-course while maintaining individual savings, which are important for Medicaid eligibility. Long-term care needs explain 12.2% of the intergenerational correlation in earnings. Policies that provide insurance against long-term care risk are welfare improving, but policy design matters for intergenerational mobility. Subsidizing formal eldercare increases the intergenerational mobility of children whereas subsidizing informal eldercare-givers decreases intergenerational mobility.

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1 Introduction

Long-term care risk is one of the largest risks facing aging adults. Nearly 70% of adults who reach age 65 will need long-term care at some point, and 69% of this care is provided informally by family members, including adult children with children of their own (Gruber et al., 2023). Currently, 1 in 5 elder caregivers also cares for at least one child under 12 (Chari and Valli, 2021), and as the US undergoes demographic changes, more and more families are likely to encounter these dual care needs. This raises an important question about the impact of long-term care needs on children. The existing literature on long-term care and the family has largely focused on how long-term care needs impact spouses and adult children. However, long-term care needs have the potential to impact investments in children's human capital development unequally over the wealth distribution, which may influence intergenerational mobility.

There is meaningful persistence in income across generations in the United States, with a correlation of about 0.34 between parent and child income (Chetty et al., 2014). Nearly 60% of this correlation reflects differences that emerge before children enter the labor market (Huggett et al., 2011). The existing literature on the determinants of intergenerational mobility has largely focused on how the circumstances of parents determine their ability to invest in their children[1]. However, for families facing simultaneous childcare and eldercare needs, parents may face a tradeoff between caring for aging grandparents and young children. Further, the presence of long-term care risk may change families' behavior, even if the risk is never realized. This paper addresses how long-term care facing grandparents impacts the economic mobility of children.

There are two main goals of this paper. The first is to quantify the impact of long-term care needs on intergenerational mobility. Long-term care needs may affect parents' time and monetary investments in their children. Because these impacts are not uniform over the wealth distribution, there may be impacts on intergenerational mobility. The second is to compare how different forms insurance against long-term care risk affect intergenerational mobility and welfare. In the US, most insurance coverage for long-term care only includes formal care, such as a home health aide or nursing home[2]. However, 30%

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

[2]Medicaid, which covers long-term care for aging adults, largely covers formal care, though some states have recently implemented programs to provide some compensation for informal caregivers. There is also a small, private insurance market for formal long-term care, but policies typically do not cover all of one's long-term care expenditures and policies are priced above total expected benefits (Brown and Finkelstein, 2007). For these reasons, in this paper I focus on long-term care insurance provided by Medicaid.

of all long-term care is provided informally by adult children, and providing coverage that helps offset the costs of family care may be welfare improving relative to subsidizing formal care (Mommaerts, 2024). I compare the effects of providing coverage for formal long-term care to subsidizing informal caregivers in terms of overall welfare and impacts on intergenerational mobility.

First, I document empirically how long-term care impacts both time and monetary investments in children and how these effects vary for families across the wealth distribution. I show that parents who provide long-term care spend less time with their children than otherwise similar parents. Additionally, using exogenous variation across states and time, I show that a policy that expands access to formal long-term care services for low-wealth aging adults increases the amount of time parents in eligible families spend with their children. Further, parental time is not the only type of time investment that may be affected by long-term care needs. Many families rely on grandparents for help with childcare, and grandparents in poor health are limited in the amount of childcare they can provide. Thus for families relying on grandparent childcare, a long-term care shock may reduce time investments from both grandparents and parents if parents choose to provide eldercare. Because less wealthy families are more likely to rely on informal eldercare and childcare, these results suggest that long-term care needs have the potential to impact the persistence of economic outcomes across generations.

In addition to impacts on time investments, long-term care also impacts families' monetary investments in children. Using the Health and Retirement Study, I show that parents' realizations and expectations of long-term care needs are negatively correlated with investments in their children's education. This is consistent with findings in the literature that show parents who provide intensive eldercare are 20% less likely to have an educational savings account than otherwise similar parents (Bogan, 2015). Further, as grandparents develop long-term care needs, they are less able to help with childcare, and parents with young children may face changes in childcare costs. These effects also vary over the wealth distribution, as less wealthy families are more likely to rely on grandparent-provided childcare (Anstreicher and Venator, 2022).

Motivated by these facts, I develop an overlapping generations model in which parents and grandparents interact with limited commitment. Families make joint decisions over childcare, eldercare, labor supply, and savings, as well as time and monetary investments in children. I use an overlapping generations framework to capture how long-term care risk affects the persistence of inequality across generations. However, in canonical models of intergenerational mobility, interactions between parents and their children typ-

ically cease when the child becomes an adult[3]. 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. Limited commitment also allows for partial risk sharing between family members, which is an important empirical feature of family interactions (Hayashi et al., 1996; Attanasio et al., 2019). Within this framework, parents and grandparents each hold their own savings, which is critical for capturing 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 rates over time, informal care over the wealth distribution, Medicaid take-up, 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 including the correlation 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 correlation between parent and child income rank. Further, while many families do eventually need long-term care, there is significant heterogeneity in the timing and amount of care needed. The expectation of possible care needs may shape families' behavior. To measure the impact of these expectations, I shut down realizations of care needs, but maintain families' expectations around the possibility of developing long-term care needs. I find that expectations of long-term care account for 5.1% of the correlation between parent and child income, even when these needs are never realized. While these effects are sizable, they are are smaller than things that directly constrain parents. For example, the borrowing constraints parents face account for 29% of the correlation between parent and child income (Lee and Seshadri, 2019).

Next, I evaluate the impact of two forms of insurance against long-term care needs. First, I implement full insurance against long-term care in which any formal care costs are fully covered. The cost of implementing the policy is covered by a lump sum tax that all families pay. I compare this with long-term care insurance that provides a subsidy to all informal care-givers, with the change in cost again covered by a lump-sum tax. I find

[3]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, Rosenzweig and Wolpin (1993) for example.

that both insurance schemes are welfare improving, but covering formal care increases the economic mobility of children while covering informal care has the opposite effect. Providing coverage against formal care costs leads parents to spend less time on elder-care, and increases the amount of time parents spend with their children. However, when informal care-givers are provided with a subsidy, informal care increases the most among low-wealth families, and these parents spend less time with their children. The loss in time is only partially offset by increases in monetary investments, and thus intergenerational mobility is negatively affected. In both cases, welfare increases due to the fact that families value the gains from risk protection more than the welfare costs imposed by the tax.

Finally, while providing full insurance for long-term care is informative about the mechanisms through which insurance against long-term care risk impacts intergenerational mobility, such large changes are unlikely to be feasible in practice. Thus, I evaluate 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 subsidy for informal care-givers in families who are eligible for Medicaid. Each policy is funded by an income tax and, similar to full insurance example, both policies are welfare improving but increasing Medicaid's asset test increases economic mobility whereas subsidizing informal care decreases economic mobility.

While the model allows me to compute the effects of insurance against long-term care risk on intergenerational mobility and welfare, I make a number of simplifying assumptions. In the real world, family structure is complicated: families may have between zero and four grandparents, siblings may help with long-term care, and families may break up and reform. All of these facts complicate long-term care decisions. In order to focus on interactions across generations, I simplify the family structure within a generation. While I capture some of these dynamics when taking the model to the data, the model is largely focused on interactions across, rather than within, generations.

This paper makes several contributions to the literature. First, the existing literature on long-term care and the family has largely focused 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., 2022). Further, informal care suppresses demand for long-term care insurance (Mommaerts, 2024) and exacerbates adverse selection issues in the long-term care insurance market (Ko, 2022). This paper, in contrast, investigates the effects of long-term care on not only grandparents and parents, but on children as well. Accounting for the impacts on children is important for quantifying the impact of policies that provide

families with insurance against long-term care risk.

The literature on long-term care and the family sits within a broader literature examining the role of health risk and social programs on aging adults' savings behavior. Aging adults dis-save slowly due to the possibility of medical expenses (Nardi et al., 2010). At the same time, means-tested social programs crowd out personal savings that would be used to self-insure individuals against risk over the life-cycle (Hubbard et al., 1995). Turning to Medicaid specifically, Nardi et al. (2016) find that most single retirees would not value an expansion in the program above it's cost. This paper expands upon this literature to think about the effect of grandparent savings and effects of expansions in Medicaid over three generations, and how the effects of these programs on grandparents impacts the economic mobility of children.

Beyond the effects of health risks, there are also several studies that document how informal insurance within families shapes economic decisions. Parents save to insure their children against income risk, with the amount varying by the riskiness of the child's occupation (Boar, 2021). For young men, the option for coresidence with one's parents provides labor market insurance and helps explain why that group has a low elasticity of labor supply (Kaplan, 2012). Thus family-provided insurance plays an important role in determining outcomes across generations. I build on this literature by investigating how long-term care risk facing grandparents may impact not only parents but their children as well, and how changes in long-term care insurance policy impact the persistence of inequality across generations.

A largely separate literature documents several factors that contribute to the persistence of economic outcomes across generations. These include the role of human capital investments made by parents (Becker and Tomes, 1986; Lee and Seshadri, 2019), borrowing constraints facing parents (Caucutt and Lochner, 2020), parents' ability to access credit (Braxton et al., 2023), early childhood development programs (Daruich, 2026), and neighborhood and migration decisions (Anstreicher, 2024; Chetty et al., 2016). Further, the structure of the immediate family, namely the presence of two parents, positively impacts a child's future income (Chang et al., 2024). I extend this literature by accounting for the impacts of a third generation, 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 over the entire life-cycle–a novel contribution to this literature.

In Section 2 I provide more information on long-term care policy and arrangements in the United States and in Section 3 I provide 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 Long-term care in the United States

Long-term care (LTC) needs arise when individuals have difficulty with Activities of Daily Living (ADLs) or Instrumental Activities of Daily Living (IADLs). 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. However, there is substantial heterogeneity in both the timing and amount of care needed.

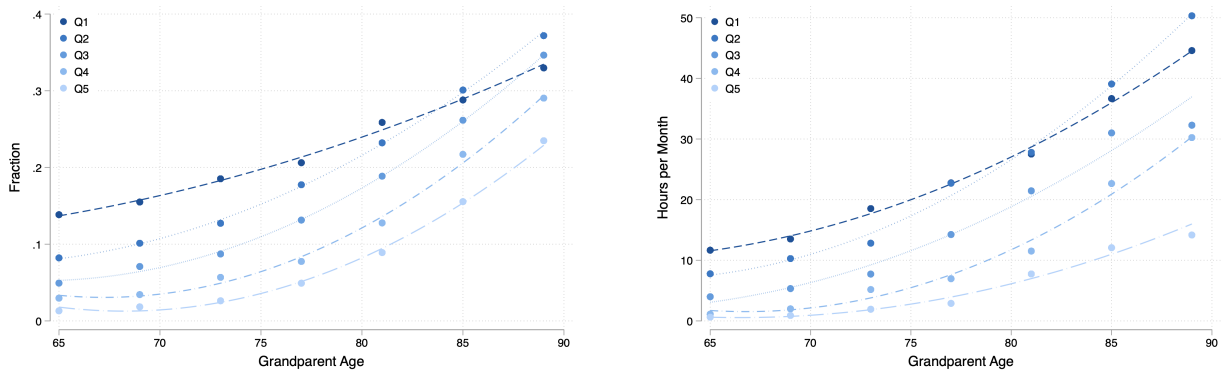
In the United States, over half of long-term care needs are met informally, usually by family members. In addition to informal care, formal long-term care is available but expensive. The average price for a home health aide is $20 an hour and a semi-private room in a nursing home costs $111,325 (CareScout, 2024). These costs are not covered under Medicare, which provides coverage for short-term medical needs, but does not cover long-term care. Instead, Medicaid covers long-term care for aging adults, and recipients are therefore subject to strict income and asset requirements. While there is a market for formal long-term care in the United States, it is small[4] and policies typically do not cover all of a beneficiary's long-term care costs (Brown and Finkelstein, 2007).

2.1 Informal care

Informal care is the largest source of long-term care in the US (Gruber and McGarry, 2023) with most care provided by spouses and adult children. 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 not only lost wages, but time they could have spent investing in their children.

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

Figure 1: Informal care receipt



(a) Fraction receiving informal care

(b) Hours of informal care

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, while the right panel reports the average hours of care grandparents receive from adult children as they age. Grandparent asset quintile is defined based on total assets at age 65.

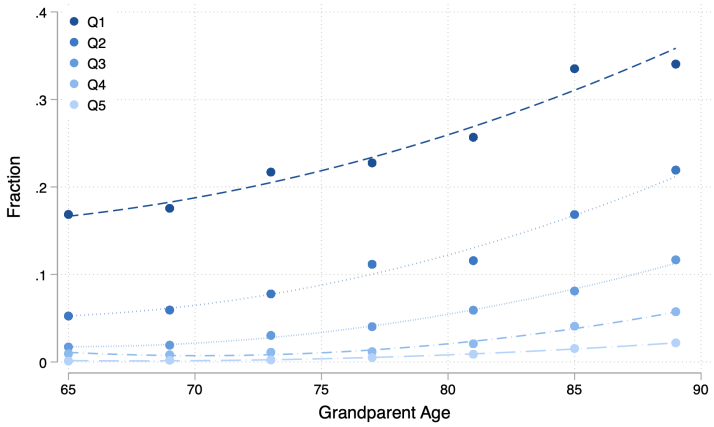
Further, the provision of informal care by parents is not evenly distributed across the wealth distribution. Using data from the Health and Retirement Study, Figure 1a shows that poorer grandparents are more likely to receive informal care from parents, and Figure 1b shows that, conditional on receiving informal care from parents, less wealthy grandparents receive more informal care than wealthier grandparents.

2.2 Medicaid

Medicaid, rather than Medicare, covers long-term care for aging adults, meaning that coverage is means-tested. 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 the income and asset requirements. In most states, individuals are subject to an income limit of $3,000 in monthly income and an asset limit of $2,000[5] (KFF, 2019).

[5]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 (Choice Mutual, 2024).

Figure 2: Medicaid long-term care rates by wealth



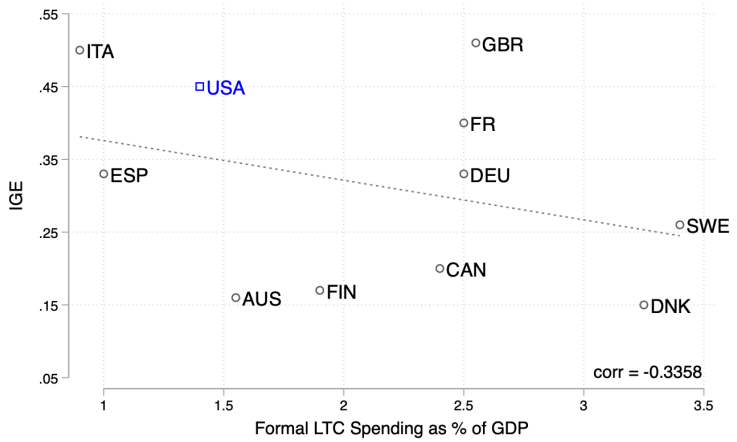
Notes: The sample includes all grandparents aged 65+ in the Health and Retirement Study, 1992-2018. Asset quintiles are computed using all assets (housing and non-housing) at age 65.

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 prevalent among the least wealthy, it is still relevant for wealthier individuals. Figure 2 plots the rate of Medicaid utilization for long-term care by wealth, and while take-up is highest for the least wealthy, there is an uptick for wealthier individuals as they age.

2.3 Long-term care across countries

The US spends less on formal care per capita than many other high income countries and has a higher intergenerational earnings elasticity (Figure 3). Given that long-term care spending is correlated with general spending on social insurance, this is not meant to establish a causal relationship, but suggests that social insurance may help explain why poverty is more persistent across generations in the United States than in many of these countries.

Figure 3: 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)

3 Empirical evidence

Here, I present evidence that the long-term care needs of grandparents impact investments families make in their children. Variation in investments in children is one of the main drivers of the persistence of income across generations. Nearly 60% of the correlation between parent and child income is explained by differences that emerge during childhood (Huggett et al., 2011). These differences reflect differences in inherited skill as well as parental investments in their children. Both time and monetary investments are important for children's skill development (Cunha et al., 2010b), and here I show that long-term care impacts both. Further, 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. Additionally, while parents are the main source of time investments in their children, I show that grandparents with long-term care needs are less able to provide childcare to their grandchildren. After describing the effects of long-term care on time investments, I turn to monetary investments. Education is one of the largest monetary investments parents make in children, and I provide suggestive evidence that

parents' education levels are related to not only grandparents' long-term care needs, but also their expectations of these needs. Finally, as discussed above, informal care from parents is more prevalent among less wealthy families (subsection 2.1) and Medicaid utilization for long-term care varies over the wealth distribution (subsection 2.2), suggesting that the effects of long-term care on investments in children may dampen intergenerational mobility.

3.1 Parental time investments

3.1.1 Descriptive evidence

Parents who spend more time on eldercare spend less time with children. To document the impact of eldercare on parental time investments in their children, 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 some demographic information, such as age, sex, and income, and some information on family members, such as the number and age of one's children.

I restrict my sample to respondents with children, whose youngest child is less than 18. I use data from the 2003 to 2020 survey waves. 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. Summary statistics for the sample are reported in Table 1. Nearly 12% of parents in my sample provide eldercare, and parents who provide eldercare earn less and are slightly less likely to be working than parents who do not provide informal care. They also provide less 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. ATUS time variables are reported as minutes per day.

From Table 1, it's clear that parents who provide eldercare spend less time providing childcare. However, from the summary statistics, it is unclear if this is because their children are older or that they are slightly less likely to have a child under 18. To get a better sense of the relationship between childcare and eldercare, I regress the number of minutes of childcare an individual i provides cc_i, 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 whether their partner works. The regression is given by:

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

α_1 is the coefficient of interest. The results 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. For each additional hour of eldercare a parent provides, she provides 10 fewer minutes of childcare, on average. The magnitude is similar in size to the effect of working on childcare hours provided.

Table 2: Impacts on parental childcare time

	(1) Continuous eldercare	(2) Binary eldercare
Eldercare	-0.096***	-8.218***
	(0.009)	(0.965)
Work (minutes)	-0.100***	-0.100***
	(0.001)	(0.001)
Age of youngest household child < 18	-7.242***	-7.234***
	(0.066)	(0.066)
Number of children	1.170***	1.168***
	(0.337)	(0.338)
Years of education	4.627***	4.650***
	(0.113)	(0.113)
Age	-0.103***	-0.108***
	(0.028)	(0.028)
Female	27.132***	27.304***
	(0.656)	(0.656)
Partnered (indicator)	7.663***	7.634***
	(1.090)	(1.090)
Partner works (indicator)	12.806***	12.910***
	(0.941)	(0.941)
Constant	38.653***	38.776***
	(1.998)	(2.000)
N	94,241	94,241
Adjusted R^2	0.246	0.245

Notes: The sample includes all respondents in the American Time Use Survey between 2003 and 2020 with at least one child under 18. Variables on time spent on activities are measured in minutes per day. Continuous eldercare refers to minutes per day of eldercare. Binary eldercare is an indicator for whether a parent provided any eldercare in the sample day.

Standard errors in parentheses.

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

These results reflect the fact that parents make tradeoffs between not just work and childcare, but between work, childcare, and eldercare. This tradeoff is 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. Further, the results presented here suggests that parents who provide more eldercare spend less time with their children, suggesting that the long-term care needs of grandparents impact parental time investments in children.

3.1.2 The role of long-term care policy

Parents spend more time with children when their access to formal long-term care increases. Given that providing informal eldercare is correlated with spending less time with children, I investigate how long-term care policy impacts this tradeoff for parents. To do so, I use variation across state and time in Medicaid's Home and Community-Based Spending (HCBS), which provides support for low-income, low-wealth individuals with long-term care needs at home, rather than in a nursing home (Mohamed et al., 2025).

Historically, Medicaid has primarily covered institutional long-term care, and individuals typically wait to enter a nursing home until their care needs are fairly severe. However, given that long-term care needs develop over time, individuals entering a nursing home likely needed support while they were still at home. Prior to expansions in HCBS, this support could come in the form of a home health aide, paid out of pocket, or informal care. Over the past two decades, Medicaid coverage has expanded to include options for care at home through HCBS. This reduces the barrier to accessing formal care, particularly for low-income families, given that individuals who meet Medicaid's eligibility requirements do not have to pay out of pocket for care and can receive care from a home health aide at home. Table 3 summarizes the distribution of HCBS spending per aging adult, as well as total Medicaid spending.

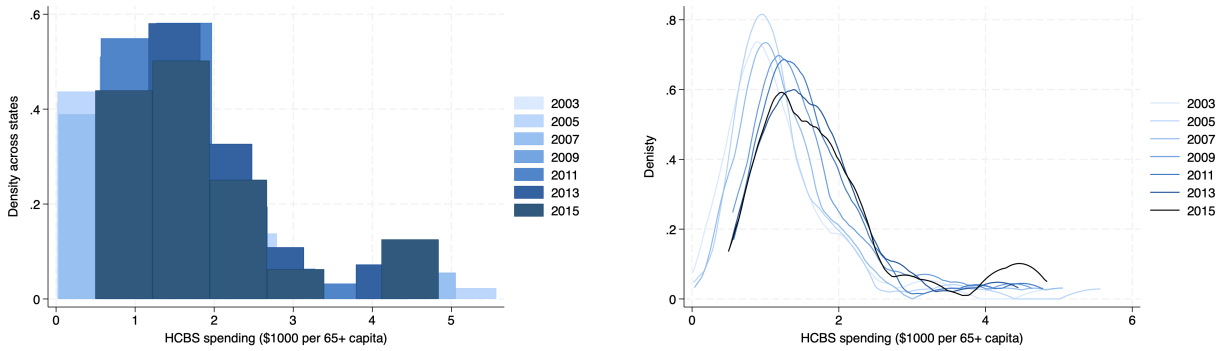
Table 3: Summary statistics: Medicaid spending per 65+ capita

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). In addition to the mean and median, the table reports the 10th, 25th, 75th, and 90th percentiles of spending between 2003 and 2020 in 2014 dollars.

Expansions in HCBS vary across states and time, which can be seen in Figure 6. Figure 4a plots the distribution of spending each year in 2014 dollars, while Figure 4b shows smoothed density plots of spending over time. These plots show the trend in increased spending on HCBS 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 of expansions in access to Medicaid care at home for grandparents on parents' time spent on childcare and eldercare.

Figure 4: 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 specification:

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

The outcome, 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 Home and Community Based Services 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, whether an individual's partner works, the age of the youngest child, and day of the week indicators. Standard errors are clustered at the state level.

The results are reported Table 4. Given that Medicaid primarily provides support to low-income families, in the main results I focus on parents with incomes below $12,500. In

Figure 5, I plot the coefficient of interest β_1 for other income cutoffs. 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 12.5 minutes. The coefficient on eldercare hours is negative, as expected, but insignificant.

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

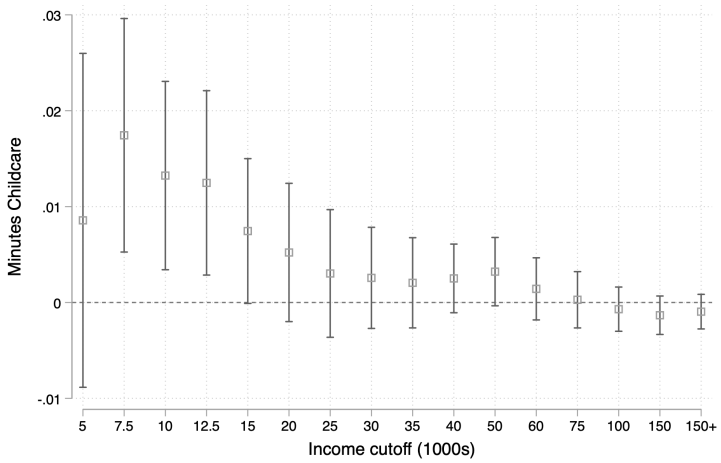
	(1) childcare	(2) eldercare
HCBS spending per 65+ capita	0.012**	-0.002
	(0.005)	(0.002)
Age	0.011	0.106**
	(0.099)	(0.042)
Female	36.086***	-0.689
	(2.885)	(1.416)
Number of children	3.740***	-1.095***
	(1.049)	(0.385)
Years of education	2.118***	-0.002
	(0.401)	(0.213)
Partnered	1.250	2.611
	(3.967)	(1.683)
Partner works	10.140*	-0.380
	(5.763)	(2.560)
Age of youngest household child < 18	-6.663***	0.033
	(0.271)	(0.108)
N	6,464	6,464
Adjusted R^2	0.149	0.003

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

These results indicate that expansions in Medicaid HCBS do increase parents' time spent with children, particularly for low income families. In Figure 5, I plot the coeffi-

cient on childcare minutes across income cutoffs. The results are largest for lower-income families, and fade out as more higher income families are added to the sample.

Figure 5: 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.

Medicaid funding is likely to have the largest effects for the lowest income groups, and these results suggest that long-term care policy can impact the investments parents make in their children. This, in turn, might increase parental time investments in children of lower income families, which may help those children develop the skills needed to rise in the income distribution later in life. Another important source of time investments in children is grandparent time, and I explore how long-term care needs impact grandparental time investments in children in the next section.

3.2 Grandparent time investments

Grandparents with long-term care needs spend less time providing childcare than healthy grandparents. While parents are the main source of time investments in children, grandparents may also help provide childcare. Grandparent-provided childcare is particularly prevalent among low-income and single parent households (Anstreicher and Venator, 2022). However, grandparents with long-term care needs are less likely to provide childcare.

To show this, I use data from the Health and Retirement Study (HRS). The HRS is a longitudinal panel of approximately 20,000 people, with information collected biennially beginning in 1992. I restrict my sample to individuals who are at some point in the sample

grandparents (i.e. they have at least one child and that child has at least one child, though that need not be true throughout the entire sample period). 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, round-the-clock care is defined as having significant difficulty with ADLs, and these respondents receive about 310 hours per month of care. The HRS also asks respondents whether they provide childcare to their grandchildren and around 50% of grandparents provide such care.

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

$$CC_i = \beta_0 + \beta_1 light_i + \beta_2 heavy_i + \beta_3 rtc_i + \alpha X + \epsilon_i \tag{3}$$

CC_i is an indicator for whether a grandparent provides childcare. The coefficients of interest are β_1, β_2, and β_3. These coefficients are reported in Table 5. In column 1, I report the coefficients from a regression that includes a quadratic in age, 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. The results in both specifications are similar, and indicate that grandparents with long-term care needs are less likely to provide childcare for parents, with the magnitude increasing as care needs increase.

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

	Grandparent provides childcare	
	(1)	(2)
Light care needs	-0.065***	-0.061***
	(0.005)	(0.005)
Full time care needs	-0.097***	-0.096***
	(0.006)	(0.007)
Round-the-clock care needs	-0.115***	-0.121***
	(0.007)	(0.008)
Individual fixed effect	No	Yes
N	18,404	18,404
N × year	153,326	153,326

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. Standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

As grandparents develop long-term care needs, they're less able to provide childcare. Parents who rely on grandparent-provided 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 lose grandparent-provided childcare. However, this has an ambiguous effect on intergenerational mobility, depending on the quality of care children receive in lieu of care from grandparents.

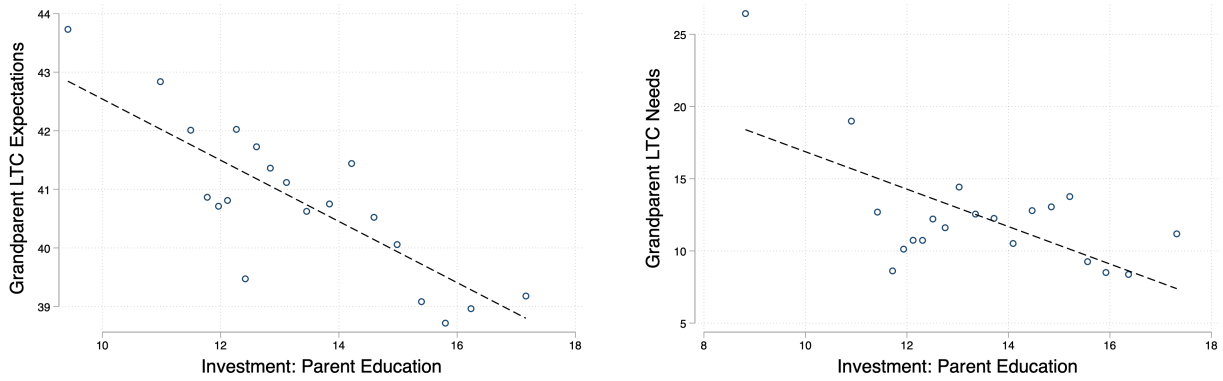
3.3 Monetary investments

Parents' long-term care expectations and realized needs are correlated with investments in child's education. One of the largest monetary investments families make in their children is their education. Using the Health and Retirement Study, I investigate the relationship between grandparents' long-term care expectations and parents' education. I show that grandparents' expectations of health, as well as their realizations, are correlated with the parent's education.

The HRS asks healthy respondents how likely they are to have a work-limiting health limitation within the next 10 years. Grandparents who say they are more likely to have

such a limitation are also more likely to have children with lower levels of education. This correlation is summarized in Figure 6a. Further, this relationship does not only exist in expectation. Grandparents who develop long-term care needs are more likely to have children with lower levels of education.

Figure 6: Parental investments by grandparent long-term care status



(a) Health Expectations

(b) 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 grandparent long-term care expectations (Panel (a)) and needs (Panel (b)), controlling for the grandparent's age, wealth, and education, and the parent's age

These results show that grandparents' health expectations and long-term care needs are related to parents' education. While there are several reasons this may be the case, Bogan (2015) finds that parents who provide intensive eldercare are 20% less likely to have an educational savings account than otherwise similar parents. This suggests that long-term care concerns impact investments in education, and that these impacts can be seen before care needs are realized.

4 Model

In order to quantify the impact of long-term care risk on intergenerational mobility, I develop a model in which families make childcare and eldercare choices, save, and invest in children. 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 also use the model to evaluate a range of counterfactual policies, including full insurance against

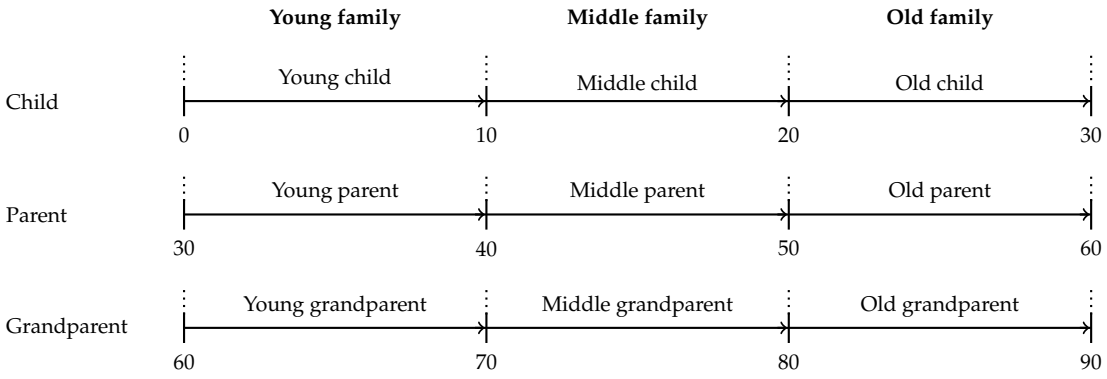
long-term care risk, and changes to Medicaid eligibility rules and coverage for informal elder caregivers.

Thus, I develop a model 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 is cared for by her parent, and parents and grandparents interact with limited commitment to make consumption, savings, childcare, and eldercare choices as well as monetary and time investments in children. Limited commitment is important to capture 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. I model infinitely lived dynasties, 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, a family within a dynasty may be in one of three stages: young ($t = y$), middle-age ($t = m$), or old ($t = o$).

Figure 7: Model timeline



In the model, children receive time and monetary investments from parents 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, and enter the labor market where they make childcare, eldercare, and labor supply choices and face earnings risk. Parents

also make a savings decision. After three periods as a parent, the parent becomes a grandparent and the child becomes a parent. Grandparents face eldercare risk, may help with childcare, and make a savings decision. At the end of three periods as a grandparent, the grandparent exits the model, and may leave a bequest to the parent, who becomes a grandparent. Thus, 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 7. Below, I outline 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 persistence of ability across generations is governed by ρ_s. The young child's skill level is given by

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

where 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.

In the first two stages of life, 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. The child's existing skill increases the productivity of investments, the degree to which is captured by ω_s. Time investments and monetary investments are also complements, and enter the child skill development function as

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

Because the child's skills in the next period depend on the skills the child has today, this formulation incorporates dynamic complementarity. This is an important feature of child skill development (Heckman and Mosso, 2014; Caucutt and Lochner, 2020; Cunha et al., 2010a), and emphasizes the importance of early investments. This functional form also captures the complementarity of monetary and time investments. This is important for families who have dual eldercare and childcare needs. Eldercare responsibilities may impact a parent's invest time or monetary investments in her child, and this form captures

degree to which time can compensate 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. In sum, T_t captures a notion of effective time. I assume that young and middle-age children require Hk_t hours of care, and that these childcare hours can be met by the parent, grandparent, or market (or any combination therein). However, each of these inputs has a different productivity in the child's skill development, such that the time investment component is given by:

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

where $\omega_p + \omega_g + \omega_m = 1$. 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. Thus, 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 $X_o = \{0, 1\}$. Thus, 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. There is also a preference shock for college-going, to capture 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.

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 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, $I(s_t^p)$.

This exogenous component is meant to represent those of a spouse or partner. $I(s_t^p)$ is increasing in the parent's skill to match the fact that spouses tend to have similar levels of education in the data. Total parental income I_t^p is made up of the parent's labor earnings and the spousal income component.

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

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.

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, meant to represent pension and social security income. Grandparents make consumption and savings 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. 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 Medicaid gain 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 to individuals with low resources in addition to Medicaid. 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. Thus childcare hours are modeled as

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

Similarly, grandparents may face eldercare needs. The total number hours of eldercare a grandparent requires, H_t^g may be 0, part-time, or full-time care needs. Each period the family receives a long-term care shock. For families that require care, they may meet these by time from the the parent, hp_t^g, or by market-based formal eldercare, hm_t^g, at price p^g such that:

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

Thus, in a given period, parents may have childcare and eldercare responsibilities. A parent may also work and enjoy leisure, and her time constraint is given by:

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

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 is to capture the fact that these activities are likely to occupy the same hours of the day, and jobs that are highly accommodating to such care activities are rare.

Turning to grandparents, they may spend their time on leisure and childcare. The grandparents time constraint is given by:

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

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, in all stages, families make consumption and

savings choices. Importantly, parents and grandparents hold their own savings, , a_t^p and a_t^g respectively. The parent's income is made up of her labor earnings, $w_t L_t^p$, and spousal income, $I_t^p(s_t^p)$. Grandparents receive income I^g each period, meant to approximate pension income. Finally, care and educational costs vary across the model's stages, and are summarized by B_t. Thus, the family budget constraint is given by:

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

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, 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 ($t = \{y, m\}$) is 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, and thus families must to pay the monetary cost of college (p^X) if the child attends. So, the care and educational costs old families incur is given by:

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

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.

4.6 Per-period preferences

In each stage, parents have preferences over their own consumption, c_t^p, and the consumption over 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. Parents also have preferences over leisure, weighted by α_ℓ. Thus, the preferences of the parent are given by:

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

Grandparents have preferences over their own consumption, c^g, and leisure, ℓ^g, as well as the type of eldercare that they receive. Grandparents may rely on informal care from parents or formal care, which may be covered by Medicaid. 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 reflects the fact that Medicaid-funded care is often of lower quality than other formal care options. The Medicaid benefit is described in Equation 12. Grandparent preferences are given by:

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

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.

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:

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

Families are 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 unitary model 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 cooperative model would also imply that the family has only a single asset pool shared by the parent and grandparent. However, maintaining separation between the assets of the parent and the grandparent is particularly important

in this context given that 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 rejects a fully cooperative model, both non-cooperative and limited commitment models are common when modeling complex family interactions (Kaplan, 2012; Voena, 2015; Mommaerts, 2024). I have chosen limited commitment because the level of coordination between families suggests a level of cooperation beyond that in a non-cooperative model (Mommaerts, 2024). Further, non-cooperative models require strict timing assumptions. Limited commitment models are also constrained efficient, whereas non-cooperative models need not be.

The individual value functions for the parent and the grandparent respectively are give 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 $v(z_t) = u_t^g + \beta E v_{t+1}^g(z_{t+1})$ Appendix B gives more details on grandparent's altruism. Then, since parents become grandparents at the end of the old stage, the parent's continuation value when $t = o$ is given by $V_{o+1}^p(z_{o+1}) = V_y^g(z_y)$. Since grandparents pass away at the end of the old family stage, their continuation value at $t = o$ is given by $v_{o+1}^g(z_{o+1}) = 0$.

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

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

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 state variables are given by z_t and the choice variables are given by j_t. These are summarized in Table A.1. In the third stage, the family value function is the expectation over the preference shock for college-going. Details on the preference shock are summarized in Appendix C.

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 transfers or care within a dynasty. However, grandparent are still altruistic and may leave a bequest. 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. Appendix D provides more details on the outside options.

Because grandparents are altruistic towards parents, V_o^g depends on V_y^g. This makes the problem an infinite horizon problem. The solution to this problem is a set of state specific allocations $Z(z_t)$, for consumption, savings, labor supply, and care for each stage t: young, middle and old, where $Z(z_t) = \{c_t^k, c_t^p, c_t^g, a_t^p, a_t^g, L_t^p, \ell_t^p, x_t, hm_t^k, hp_t^k, hg_t^k, \ell_t^g, \mu_t^p, \mu_t^g, hm_t^g, hp_t^g\}$. 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 E.

4.8 Model discussion

Commitment is limited

Limited commitment has a number of implications for the allocations between parents and grandparents. First, limited commitment is so called because agents are unable to commit to future allocations. In the presence of risk, parents and grandparents would like to enter into a risk sharing agreement. However, because each agent has the ability 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. Thus, the model maintains the separation between parent and grandparent savings. Further, unlike some dynamic games which impose rules about the timing or direction of inter vivos transfers, there are no restrictions on transfers between parents and grandparents in my setting.

The solution in limited commitment models is also efficient, though the point on the Pareto frontier is constrained by the voluntary participation constraints (the solution is sometimes referred to as constrained efficient).

Mathematically, this is achieved by updating the Pareto weight when an agent's voluntary participation constraint binds. When one agent's voluntary participation constraint binds, the Pareto weight updates such that the household moves to a new allo-

cation that keeps both parties satisfied. Appendix E 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 F for a longer discussion about the details.

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 bourne 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. In contrast, limited commitment does not allow for the strategic motives in allocations, but allocations are efficient.

In sum, 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 spousal income, earnings risk, and single parent households, which help to capture the effects of marriage and divorce without introducing another choice variable. Further, while 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.

The model also assumes all families face the same timing structure in terms of birth, the development of care needs, and death over the wealth distribution. While in the data, lower wealth families have children at earlier ages and develop care needs and die earlier than their wealthier counterparts, the timing between these three events is similar across the wealth distribution (see Appendix G 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 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 assume all families are made up of two grandparents, two parents, and one child. In doing so, I abstract from the existence of siblings as well as a second set 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 H.

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 children sampled 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 investments made 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 is presented in Table 6. In total, the sample is made up of 6,185 children in 4,444 households. About 35% of these households are headed by single parents. One-third of the children in my sample eventually attend college.

Table 6: PSID parent & child sample summary statistics

	Mothers		**Fathers**		**Children**	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Age	35.99	8.36	38.45	8.75	7.20	3.50
Fraction attend college	0.29	0.45	0.30	0.46	0.33	0.47
Fraction married	0.69	0.46	0.96	0.20	-	-
Fraction working full-time	0.38	0.49	0.82	0.38	-	-
Mean family income	42,412	44,534	51,530	48,555	-	-
Mean family assets	312,859	1,116,205	418,322	1,313,276	-	-
Mean investment	-	-	-	-	217.16	1,024.87
Mean letter-word test score	-	-	-	-	33.64	14.79
Observations	4,401		3,147		6,185	

Notes: This table presents summary statistics for the PSID sample. The sample includes children in the 1997, 2002, and 2007 waves of the PSID-CDS (in column 3) and their parents (in columns 1 and 2).

While I am able to connect individuals in the PSID 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 31,789 individuals in 18,575 households. 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	Std. Dev.
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
Mean family assets	363,445	1,026,418
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

First, I take a number of parameters from the literature and external data sources. 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 young and middle age children need, I take a weighted average over each period. Young children in the model are between the ages of 0 and 10. From the ages between 0 and 4, I assume children need full-time childcare: 8 hours per day 7 days a week. While a day is 16 hours, I limit this to active care time, rather than time that would be spent with the child anyways (i.e. secondary care time). After age 4, children likely enter kindergarten, and thus some care time is taken up by school hours. Between the ages of 5 and 10, I assume children need 4 hours of active care time 5 days a week and 8 hours two days a week (on the weekends). Averaging these, we get 2,400 hours annually.

Middle children in the model are middle and high school aged, and thus even outside of school time need fewer active care hours. I assume they need four hours per day five 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. Thus, 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. Assuming 8 hours a day, this is 3 to 7.5 per hour. Half-day care ranges from $5,900 to $9,200, which works out to 5 to 9 per hour. Hourly caregivers 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) which 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
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, is based on the value in Lee and Seshadri (2019). The mean and standard deviation of the component of initial skills that are drawn randomly from a normal distribution with mean μ_d and standard deviation σ_d, are based on the distribution of the letter-word tests in the PSID-CDS. The weight on child consumption in the parent's utility function λ is also based on the value in Lee and Seshadri (2019).

In the young and middle-age child skill (Equation 5), I assume a skill depreciation rate

of δ_k, which represents the fact that not all skills carry over into the next period. I also assume that investment in children is weighted by ω_s relative to the child's skill. I set this parameter to weight investments much more than current skills. While the function still incorporates dynamic complementarity because the child's current skills impact their 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.

In the function that aggregates time and monetary investments (Equation 6), the weights on time investments relative to monetary investments, ω_1 and ω_2, 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.

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.

Parent time also scales with skill, which is scaled by median parent skill, $\hat{s}$, so that more time from higher-skilled parents is more productive in the child's skill development. This reflects finding in 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", or 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., 2014). Thus, the scaling of parental time by skill in my context also helps capture that the fraction of childcare time spent on "productive time" may be higher in more highly educated families.

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_1	Weight on time (young)	0.81
ω_2	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.

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 is set to σ_μ.

To give a sense of the implications of the size of the preference shock, I compute the size and probability of the the preference shock needed to push an average family[6] 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 the price of college attendance. Given the scale of the distribution, the likelihood of a shock of that magnitude is approximately

[6]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.

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 based on a regression 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) comes from the variance of the residual in a regression of family income on age, year, and education for working-age parents of CDS children. 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
$I(s_t^p)$	Spousal 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 is a combination of the parent's earnings and her spouse's income. I model this as a step function based on the parent's skill, with annual spousal income of the parent defined by levels of the parent's skill:

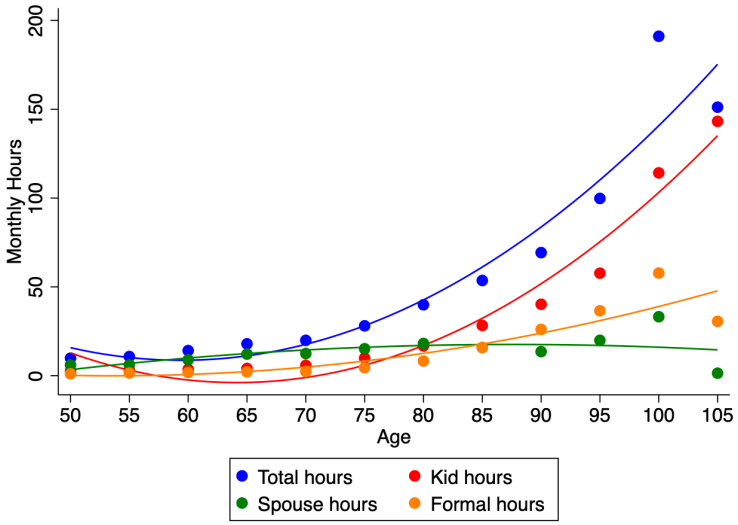
$$I(s_t^p) = \begin{cases} 0 & s_t^p < 1.25 \\ 20,000 & s_t^p \geq 1.25 \text{ and } s_t^p \leq 2.55 \\ 40,000 & s_t^p \geq 2.55 \text{ and } s_t^p < 3.95 \\ 60,000 & s_t^p \geq 3.85 \end{cases} \tag{28}$$

This functional form is captures positive assortative matching in the marriage market and is on the correlation between spouses education levels in the data. 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.

Long-term care & grandparent income

For information on long-term care risk, I turn to the HRS sample. The HRS reports hours of eldercare respondents and their spouses receive across many different sources. I aggregate long-term care needs of grandparents to the household level, such that I use the total hours of care needed by a both grandparents in a household if two are present. The number of hours of care across each care source is summarized in Figure 8. The parameters related to grandparent income and long-term care are summarized in Table 11.

Figure 8: 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 asking about the long-term care needs of respondents, The HRS asks about the hours of care an individual received over the past month. When 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 cover 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 (two years). I assume that the hours reported in the past month are representative of care hours over the entire period. I then aggregate the total number of hours of care a grandparent household needs in each corresponding stage of the model.

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 then 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.

Turning to long-term care costs, part-time care costs $20,000 annually which is $20/hour and full-time care is $61,700 annually or $30/hour (Brown and Finkelstein, 2007). Further, 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, 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.

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). Thus, 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. To do so, I calculate the additional consumption a grandparent receiving formal or Medicaid care would need to be indifferent between receiving formal care and median consumption and 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 value of Supplemental Security Income (SSI), which is \$7,800 annually.

Agents in the model weight leisure by 0.56, relative to consumption, and the curvature on consumption and leisure are both around 1.5. This is slightly lower than what is typ-

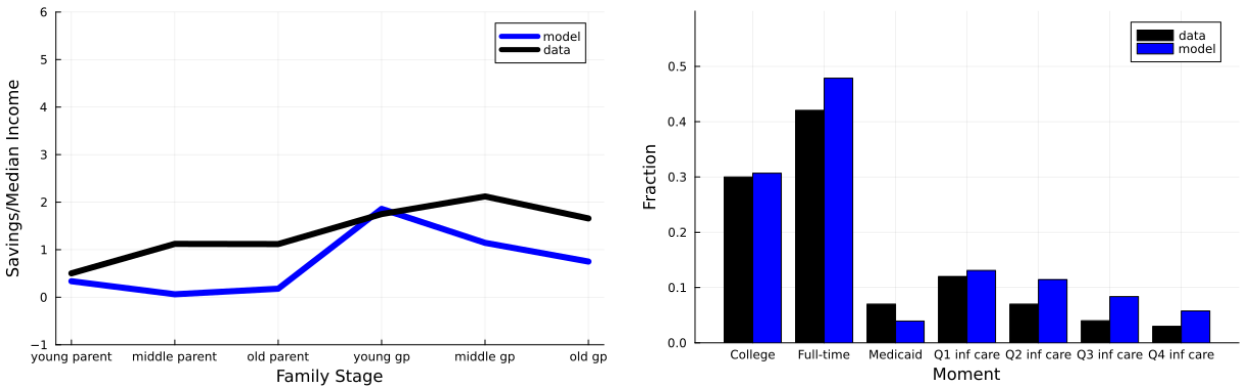
ically found in the literature using dynamic games between family members. Barczyk et al. (2022), Barczyk and Kredler (2018), and Boar (2021) fix the coefficient on consumption to 2.0 and (Mommaerts, 2024) estimates a value of 2.1. On the other hand, many models of overlapping generations assume log utility over consumption (Anstreicher, 2024; 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 (2024) 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.

5.4 Model fit

To estimate the parameters, I target the the fraction of parents working full-time, the college-going rate, the Medicaid rate, and informal care rates over the wealth distribution. I also target the savings of families over the life course. The model fit is summarized in Figure 9. These moments are chosen to identify the key parameters, and identification is discussed in subsection 5.5.

Figure 9: Targeted moments



(a) Savings rate

(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 over time. The left panel reports the savings rate, scaled by median income. 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.

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 fairly well.

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. The model is also able to fit key moments that are not targeted by the estimation procedure. Figure 10 shows moments related to time and monetary investments in children, parental labor supply, and grandparent long-term care over the wealth distribution. Figure 11 shows that the model is able to match the rank-rank correlation between parent and child income.

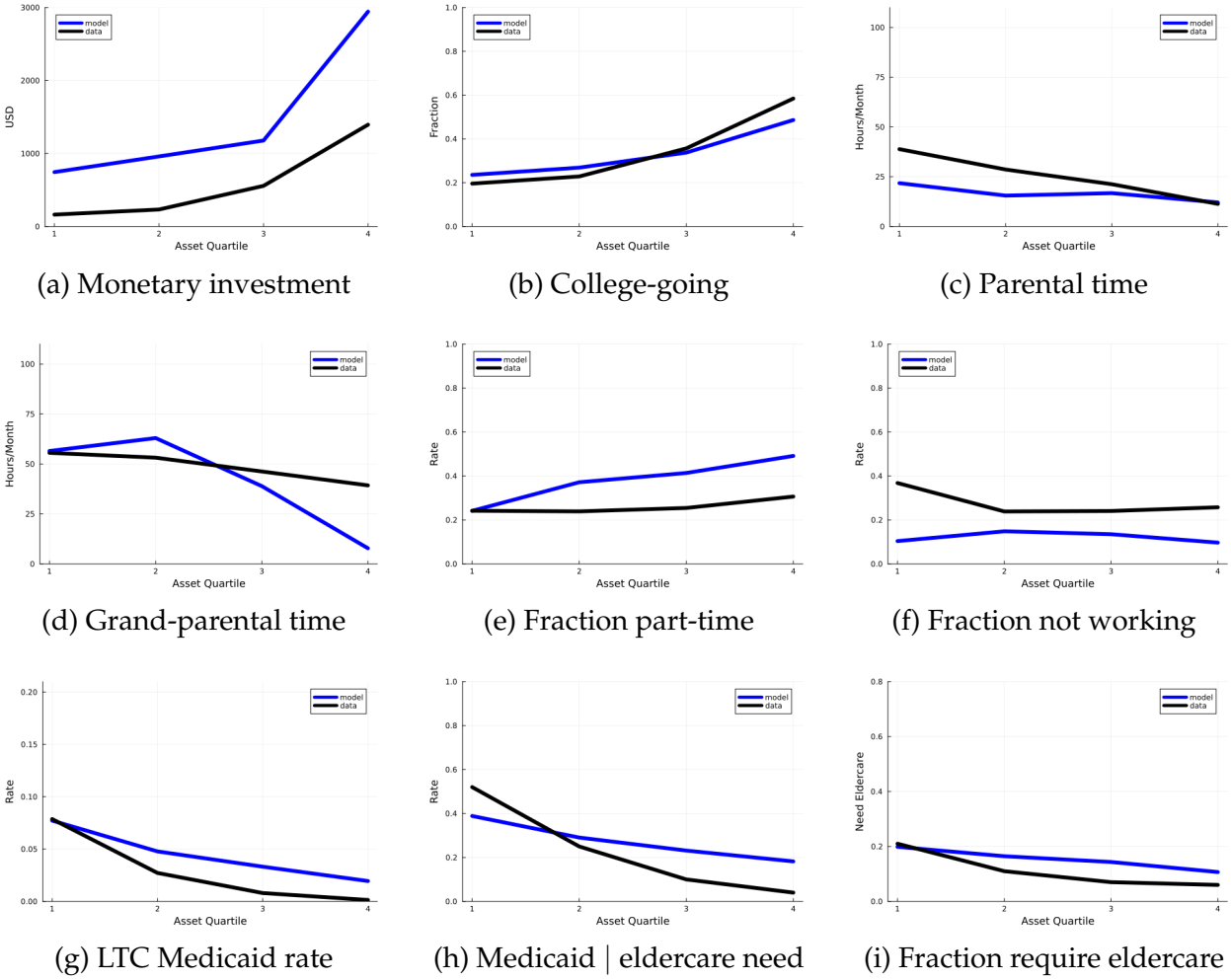
Moments over the wealth distribution

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 use the HRS. I use the corresponding asset distribution in the model (i.e. moments related to parents use the PSID data, and I use the wealth distribution of the parents in the model).

Turning first to monetary investments in children, investments during the young and middle-age period (Figure 10a) match the gradient in the data quite well, albeit at different levels. The model is able to match college-going rates across the wealth distribution quite well (Figure 10b). Time investments from parents and grandparents (Figure 10c and Figure 10d) are largely consistent with the patterns seen 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 slightly overstates the fraction of parents working part-time (Figure 10e) and understates the fraction not working (Figure 10f).

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 10g and Figure 10h). Finally, the model matches the fact that less wealthy grandparents need more care than their wealthier counterparts.

Figure 10: Non-targeted moments over the wealth distribution



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

(d) Grand-parental time (e) Fraction part-time (f) Fraction not working

(g) LTC Medicaid rate (h) Medicaid | eldercare need (i) Fraction require eldercare

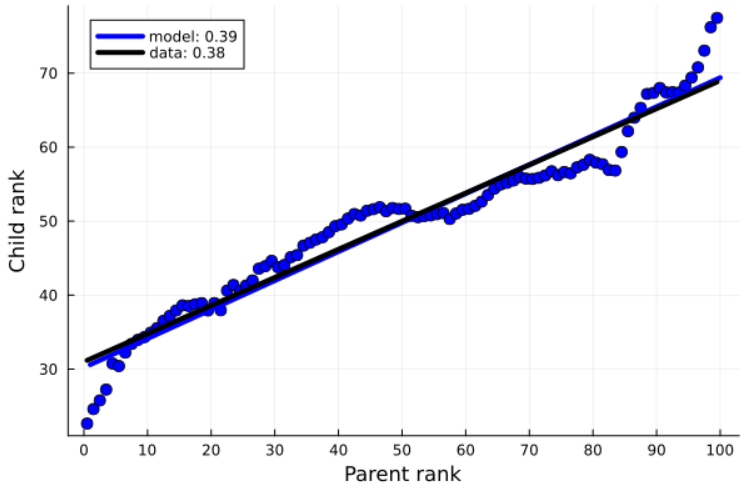
Notes: The figure reports how non-targeted moments vary over the wealth distribution in the model (in blue) and the data (in black). Moments on monetary investments in children, college-going, parental time, and the fraction of parents working part-time and not working are computed from the PSID sample. 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.

Broadly matching trends over the wealth distribution is important for correctly capturing the impact of long-term care on intergenerational mobility. Further, 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 next show that the model is able to match one main measure of intergenerational mobility, the correlation between parent and child income rank.

Intergenerational mobility

In the model, the rank-rank correlation between parent and child income is 0.39, compared to 0.38 in the PSID data. In Figure 11, 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.

Figure 11: 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, and in todel I use young parent income (which corresponds to the age of 30-40).

In the Section 6, I quantify the impact that long-term care has on the rank-rank correlation between parent and child income, but 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.

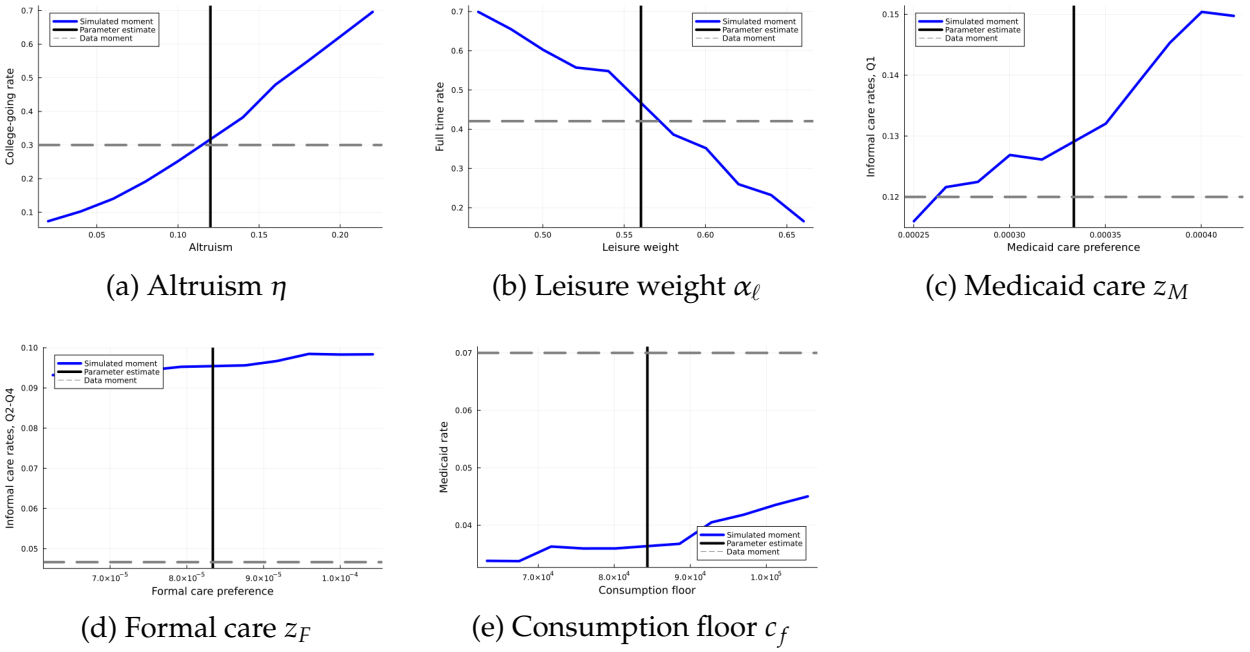
The altruism parameter η governs how much families care about the future of the dynasty, and thus how much they invest in their children. More weight on the future of the dynasty results in higher investments in children which in turn translates into higher future earnings. Therefore, the rate at which 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, all else equal, it is likely that grandparents would prefer to receive care from someone they know rather than a stranger. I use the rates of informal care over the wealth distribution to identify the degree to which grandparents wish to avoid formal care z_F. Additionally, given Medicaid-funded care is of a lower quality than formal care paid out of pocket, the informal care rate of lowest wealth quartile as well as the overall Medicaid rate help identify grandparent's dis-utility from Medicaid funded care, z_M. The Medicaid consumption floor c_f is identified by the overall Medicaid rate.

Turning to the parameters that govern how agents in the model value leisure, the rates of full-time work as well as informal care help identify the curvature on leisure γ_ℓ. 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 consumption γ_c governs risk aversion as well as how much families are willing to substitute consumption over time. A family's savings over each stage in the model helps 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. This exercise is based on testing for the sensitivity of parameter estimates to changes in moments as described in Andrews et al. (2017). The results for the altruism, leisure weight, formal and Medicaid eldercare preferences, and consumption floor parameters are reported in Figure 12.

Figure 12: Identification of key parameters



(a) Altruism η (b) Leisure weight α_ℓ (c) Medicaid care z_M

(d) Formal care 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 12a, it is clear that as altruism rises, so does the rate of college-going. Further, the rate of full-time work is decreasing in the weight on utility from leisure (Figure 12b), informal care is increasing in dis-utility from Medicaid (Figure 12c) and formal care (Figure 12d), and the Medicaid rate is increasing in the generosity of the program (Figure 12e). 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 three asset quartiles. 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 long-term care risk: insurance that covers only formal care costs and insurance that provides compensation for informal caregivers. I evaluate the effects of both full insurance against long-term care risk and changes to the Medicaid program.

6.1 The impact of long-term care on intergenerational mobility

I first use the model to quantify the impact of long-term care on intergenerational mobility. Long-term care may impact the outcomes of children not only through the presence of long-term care needs, also through families' expectations aroung long-term care needs.

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 they have no expectations of developing long-term care needs. This results in a 12.2% reduction in the correlation between parent and child income rank.

To evaluate the extent to which this comes from behavioral changes due to expectations about long-term care, I use the baseline policy functions and simulate the model without realizations of long-term care need, but maintaining the expectation of long-term care. In this case, grandparents maintain the expectation of long-term care risk, but the shock is never realized. In this case, there is a 5.1% decrease in the correlation between parent and child income rank. This indicates that while realizations of long-term care needs are important, families do adjust their behavior in the presence of risk, even when that risk is never realized. In subsection I.1 I break down the changes in families' decisions in the wake of a long-term care shock.

Table 13: Long-term care & intergenerational mobility

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

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.

6.2 Willingness-to-pay for full insurance

Given that long-term care shocks negatively impact the investments families make in their children and their children's earnings later on, I use the model to quantify how much families are willing to pay to live in a world with full insurance against long-term

care risk. There are two ways to provide insurance against long-term care. One is to subsidize formal care, the other is to subsidize informal care.

Covering formal care

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 social safety net. The Medicaid benefit becomes

$$M_t = \max\{0, c_f - max\{a_t^g - a_{lim}, 0\} - I^g\} \tag{30}$$

Formal care costs ($p^g \times hm_m^g$) are covered whenever they are incurred, and while there is no Medicaid long-term care coverage, agents still have a preference for informal care. I assume that each family pays the expected cost of long-term care, split evenly across the three stages. I measure willingness-to-pay as the 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.

Covering 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. To measure the effects of subsidizing informal care in the model, I introduce a subsidy, S. The amount of the subsidy is equal to 75% of the mean hourly wage of parents. Parents who provide informal care receive $S \times hp_t^g$ such 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, split evenly across the three stages.

Results

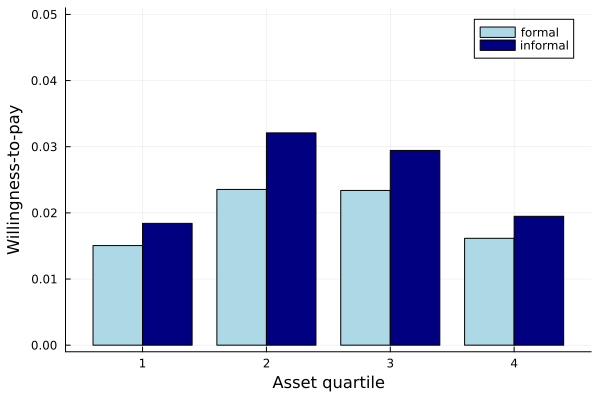
I find that the families that benefit the most from coverage for formal and informal care subsidies are those in the middle of the wealth distribution, though low-wealth and high-wealth families also benefit. In Figure 13a, I report the willingness-to-pay for full insurance across the wealth distribution.

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

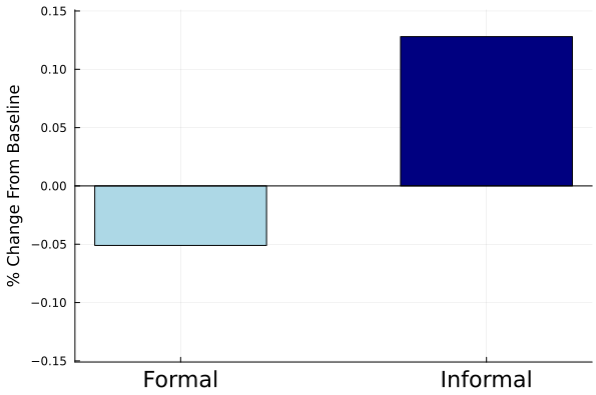
the effects of a long-term care shock, families' still lose access to grandparent-provided child care, and thus insuring the cost does not fully negate the effects of the shock. On the other hand, providing a subsidy for informal caregivers *increases* the rank-rank correlation between parent and child income by 5 percentage points.

Figure 13: Impacts of full insurance

(a) Willingness-to-pay by wealth



(b) Intergenerational mobility



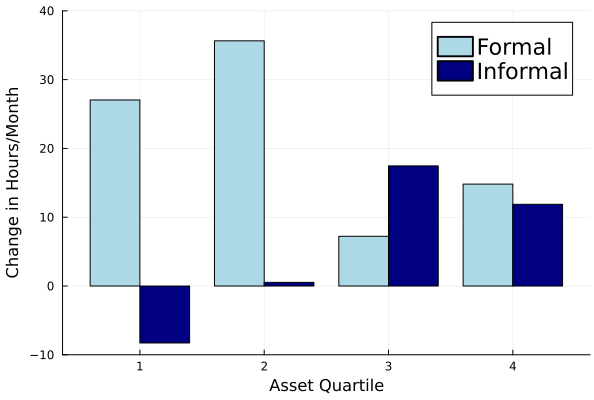
Notes: Willingness-to-pay is measured as the amount of assets a family in the baseline model would need to be indifferent between the baseline model and the counterfactual model. WTP is reported as a fraction of consumption.

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 at 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.

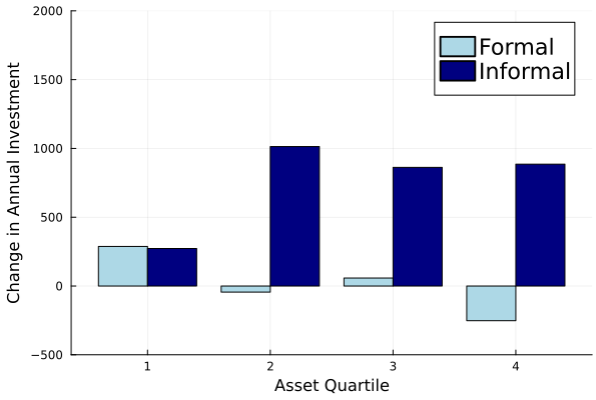
In Figure 14a and Figure 14b I show how time and monetary investments change under each counterfactual policy. Under the informal care subsidy, time investments from parents decrease for the least wealth. At the same time, monetary investments made by all families increase, though the gradient over the wealth distribution steepens. Thus, low wealth parents provide more informal eldercare and spend less time on childcare, and 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

(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. Both are averaged over the first two stages of the model, when parents make these time and monetary investments in their children.

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 gradient in college-going over wealth follows a similar pattern across the counterfactuals (flattening under the formal care subsidy, steepening under the informal care subsidy). 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 that shows 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 in 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 I.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 Policy changes

Given that full insurance for long-term care is hard to implement in practice (Brown and Finkelstein, 2007), I evaluate the impacts of more realistic policies that provide insurance

formal and informal insurance against long-term care risk.

First, I evaluate 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 the same means-testing to provide a subsidy for informal caregivers. This allows Medicaid-eligible grandparents to receive informal care, and informal caregivers are compensated for their time. I implement income taxes to pay for these policies. The results are summarized in Table 14

Medicaid 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:

$$M_t = \max\{0, c_f + p^g hm_t^g - max\{a_t^g - a_{lim}, 0\} - I^g\} \tag{31}$$

I evaluate the impact of raising Medicaid's asset limit from \$2,000 to \$25,000. I also implement an income tax to cover the costs of the program.

Subsidies for informal care

While in subsection 6.2 I show that informal insurance increases the rank-rank correlation between parent and child income, I evaluate the effects of a means-tested subsidy for informal caregivers. I introduce a subsidy, $\hat{S}$, with the amount of the subsidy equal to 50% of the mean hourly wage of parents. Parents who provide informal care receive $\hat{S} \times hp_t^g$ such that the subsidy amount scales with the amount of eldercare a parent provides. The policy is funded by an income tax.

Results

The results are summarized in Table 14. These results mirror the impacts above, wherein both policies increase welfare, but subsidizing formal care decreases the correlation between parent and child income rank and subsidizing informal care raises the correlation between parent and child income rank.

Table 14: Policy costs

	Medicaid asset limit	Informal care subsidy
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 in which families make care and savings decisions, as well as 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 of parents and grandparents.

I find that the presence of long-term care needs increases the correlation between parent and child income by 12.2%. Further, while many families will eventually face long-term care needs, there is significant heterogeneity in the timing and amount. Since it is risky, there may be effects on behavior even if this risk is never realized. I find that these expectations account for 5.1% of the correlation between parent and child income. This result highlights the fact that insurance may be beneficial for families, even if they never face long-term care needs.

More broadly, when designing these insurance policies, taking into account the effect on children is important. While providing insurance against long-term care risk is welfare-improving, the type of care covered has implications for intergenerational mobility. I find that subsidizing formal care increases economic mobility. This 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 intergenerational mobility. In this case, there is steeper gradient in investments in children over the wealth distribution. The decreases in time investments made by parents are more concentrated among less wealthy families who rely more on informal care. Further, these decreases are not fully offset by increases in monetary investments. These results are

mirrored in 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.

This is particularly important as the US population ages, life expectancies rise, and families have fewer children which will all likely increase the burden of long-term care on families. 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. This is an important limitation, but the results of this paper shed light on how long-term care policies impact future generations, and I leave complications related to family structure for future work.

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Appendix

A Model details

Appendix Table A.1: State and Choice Variables

Type	Variable	Elements
State	z_y	$\{\theta_y, a_y^p, a_y^g, s_y^p, s_y^k, \epsilon_y\}$
State	z_m	$\{\theta_m, a_m^p, a_m^g, s_m^p, s_m^k, \epsilon_m, H_m^g\}$
State	z_o	$\{\theta_o, a_o^p, a_o^g, s_o^p, s_o^k, \epsilon_o, H_o^g\}$
Choice	j_y	$\{c_y^k, c_y^p, c_y^g, a_m^p, a_m^g, L_y^p, \ell_y^p, x_y, hm_y^k, hp_y^k, hg_y^k, \ell_y^g, \mu_y^p, \mu_y^g\}$
Choice	j_m	$\{c_m^k, c_m^p, c_m^g, a_o^p, a_o^g, L_m^p, \ell_m^p, x_m, hm_m^k, hp_m^k, hg_m^k, hm_m^g, hp_m^g, \ell_m^g, \mu_m^p, \mu_m^g\}$
Choice	j_o	$\{c_o^k, c_o^p, c_o^g, a_y^p, a_y^g, L_o^p, \ell_o^p, X_o, hm_o^g, hp_o^g, \ell_o^g, \mu_o^p, \mu_o^g\}$

B 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.

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

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.

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

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:

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

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

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

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

C 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

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

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

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

and the probability of college-going is given by

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

D 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, 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.

D.1 Parents

Parents maximize

$$W^p_t(z_t) = \max_{j^p_t} \frac{c^{p(1-\gamma_c)}}{1-\gamma_c} + \lambda \frac{c^{k(1-\gamma_c)}}{1-\gamma_c} + \alpha_\ell \frac{\ell^{p(1-\gamma_\ell)}}{1-\gamma_\ell} + \beta E W^p_{t+1}(z_{t+1}) \tag{D.1}$$

subject to their own budget constraint

$$c^p_t + c^k_t = w_t L_t + R a^p_{t-1} - a^p - p^k h m^k_t - x_t - p^X X_t \tag{D.2}$$

and time constraint

$$T = h p^k_t + L^p_t + \ell^p_t \tag{D.3}$$

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

$$H_t^k = hp_t^k + hm_t^k \tag{D.4}$$

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 $j_t^p = \{c_t^p, c_t^k, hk_t^p, hk_t^m, X_t, a_t^p\}$.

D.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.

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

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

$$c_t^g = I^g + Ra_{t-1}^g - a_t^g - M_t \mathbb{1}_{hm_t^g>0} - p^g hm_t^g \tag{D.6}$$

and time constraint, given by:

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

Any eldercare hours must be met formally, such that

$$H_t^g = hm_t^g \tag{D.8}$$

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 $j_t^g = \{c_t^g, a_t^g, hm_t^g\}$.

E 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:

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

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).

F Limited commitment details

Why no break-up?

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 default to the allocations in the outside option. 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. 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.

G 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 G.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 G.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 G.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 G.2: Timing

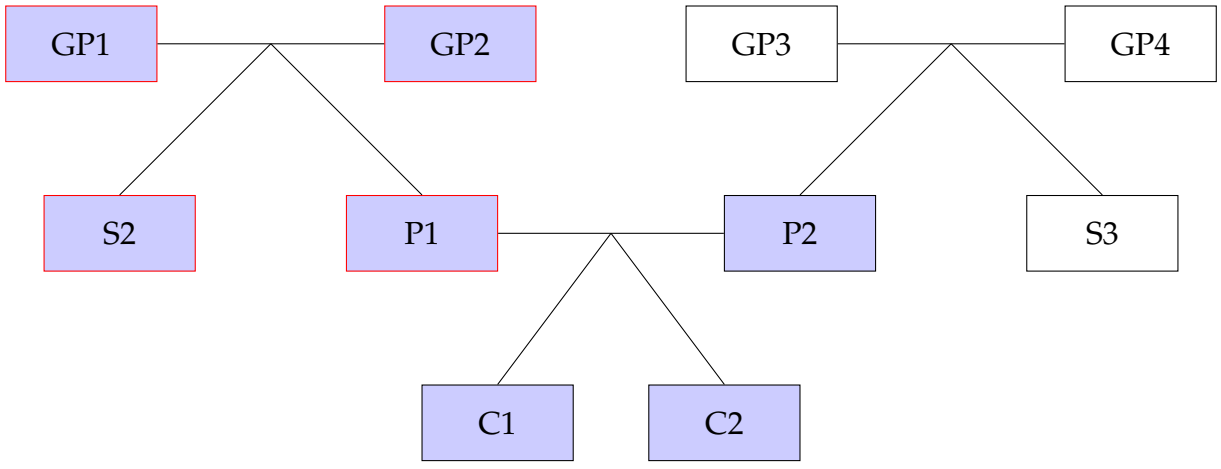
Asset quartile	First care need - first birth	Death - first care need	Death - first birth
Q1	47.6	14.5	62.1
Q2	48.9	13.6	62.5
Q3	50.4	12.9	63.3
Q4	49.9	12.0	61.9
Q5	28.9	11.2	60.1
Observations	25,236	56,484	56,484

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.

H 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 H.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 H.1: Family Tree: Data

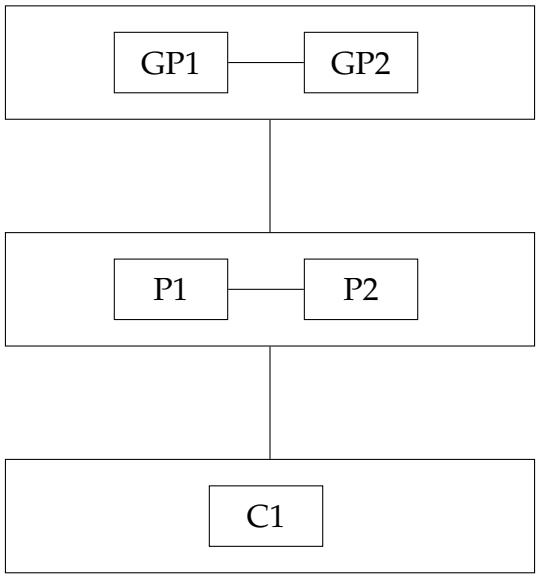


Notes: Red boxes indicate data available in the HRS. Blue shading indicates data available in the PSID.

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 grand-

parents, a parent generation, made up of two parents, and a child generation, currently made up of one child. This is described in Figure H.2.

Appendix Figure H.2: Family Tree: Model



I The impact of a long-term care shock

I.1 Baseline model

To measure 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 I.1 shows how outcomes diverge after the realization of a long-term care shock across generations.

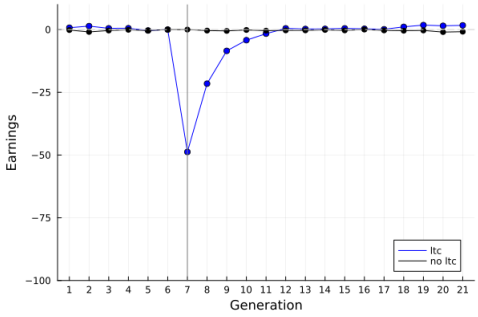
As expected, earnings and labor supply fall in the period in which the shock is realized (Figure I.1a and Figure I.1b). Labor supply rebounds the fastest, returning to the pre-shock level the following generation. However, earnings do not rebound fully in the following generation. This is because the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

Figure I.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 I.1c). This happens as a result of a large dip in monetary investments in children (Figure I.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 I.1f).

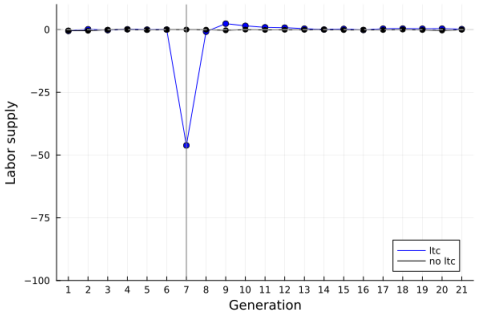
Time investments in children are also affected. Because grandparents with care needs are unable to provide childcare, care from parents increases in the period of the shock and rebounds in the following period (Figure I.1g). Care from grandparents decreases in the period of the shock as expected (Figure I.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 I.1d, which shows that savings are the slowest to rebound in the aftermath of the long-term care shock.

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

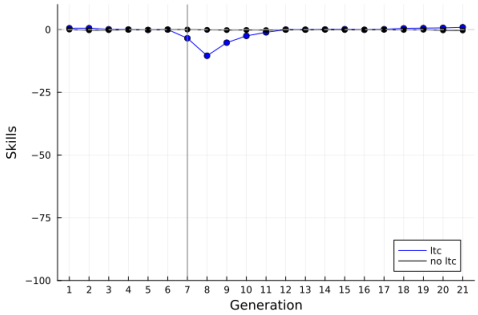
(a) Earnings



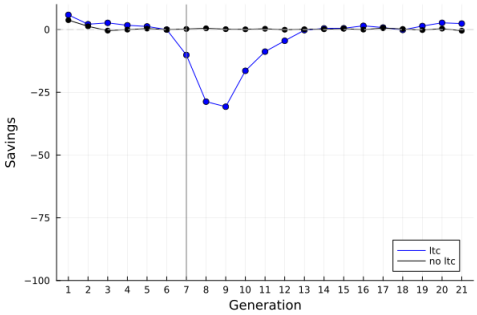
(b) Labor supply



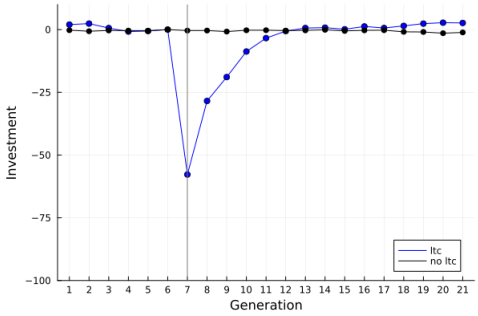
(c) Parent skill



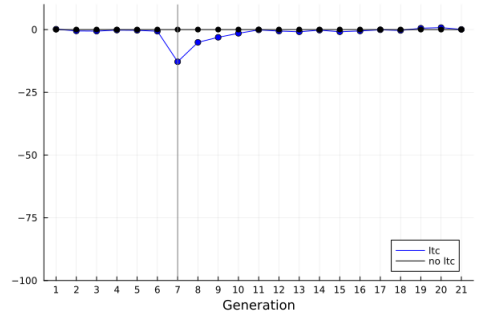
(d) Family savings



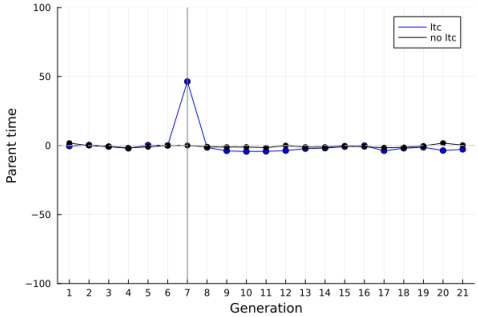
(e) Monetary investment in children



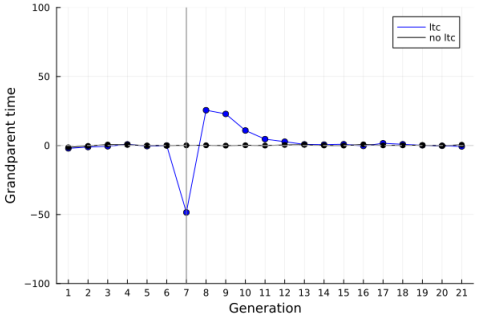
(f) College-going



(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.

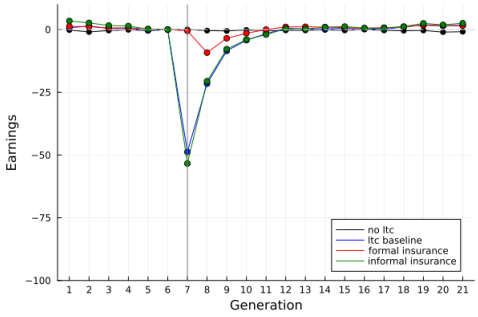
I.2 Policy changes

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.

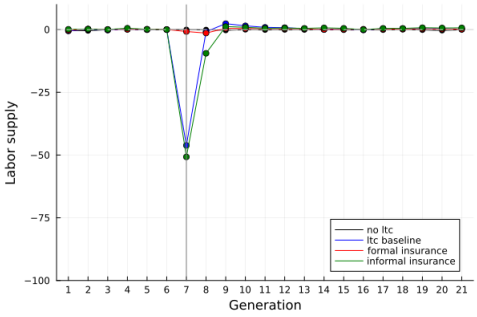
These figures show how the insurance policies blunt the impacts of the long-term care shock. These results indicates the importance of accounting for the impact on children when thinking about long-term care insurance policies. Under full insurance, the earnings and labor supply of the parent in the 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 I.2: Impact of a long-term care shock by policy

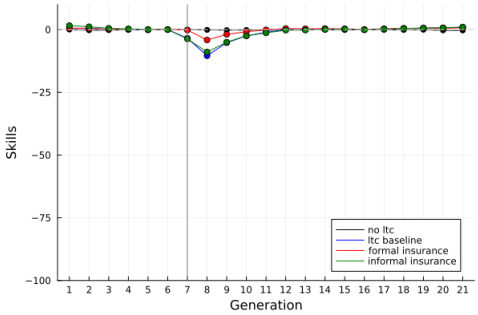
(a) Earnings



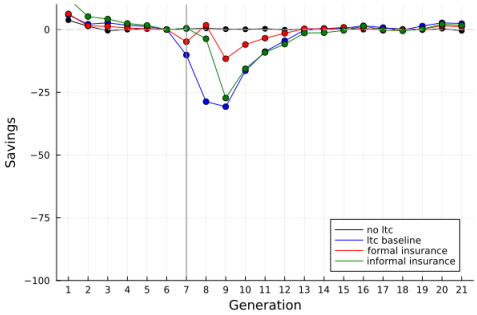
(b) Labor supply



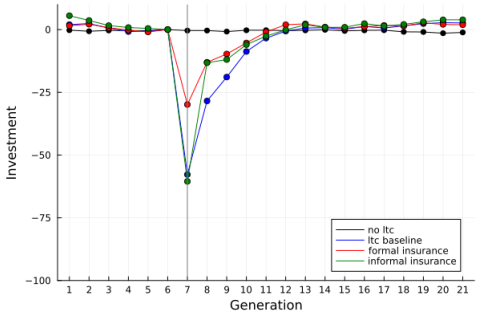
(c) Parent skill



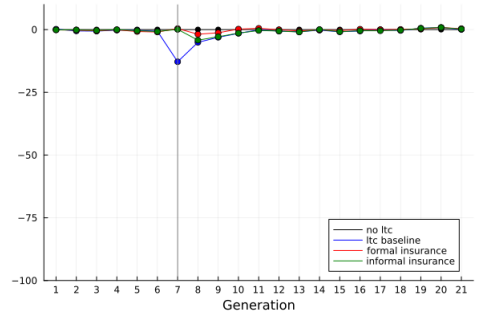
(d) Family savings



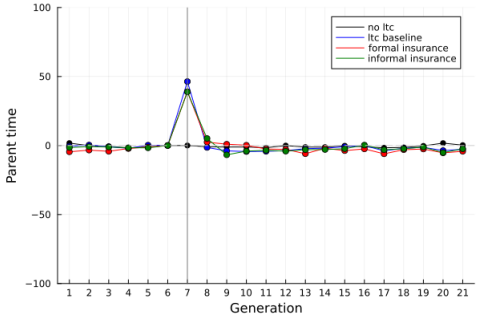
(e) Monetary investment in children



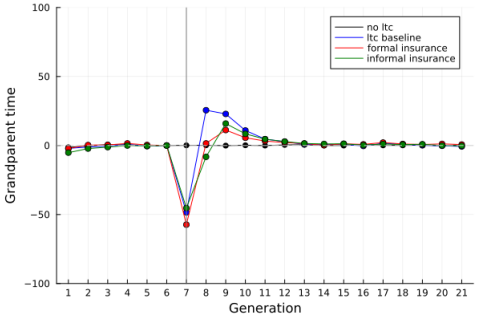
(f) College-going



(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.