Childcare and Long-Term Care: Altruism and Strategic Motives within the Family*

Chao Fu† Ami Ko‡ Chamna Yoon§

January 30, 2026

Abstract

In the U.S., families play a central role in the provision of childcare and long-term care (LTC), with grandparents frequently assisting their adult children with childrearing and middle-aged children providing much of the care for elderly parents. This paper studies the motives underlying these intergenerational time transfers and evaluates their policy implications. Using HRS data and exogenous variation in childcare costs, we first document evidence consistent with strategic implicit contracting, whereby early childcare assistance is repaid with later LTC. To quantify the underlying mechanisms and assess policy impacts, we estimate a dynamic model of an extended family who interact over care arrangements and bequests with both altruistic and strategic concerns. The estimated model shows that strategic reciprocal motives play a central role in shaping the intertemporal linkage between childcare and LTC. These mechanisms generate meaningful policy spillovers across care sectors. In particular, childcare subsidies that reduce grandparental involvement crowd out future family-provided LTC, while conditional expansions of old-age social insurance that reward past childcare provision reinforce the family's role in both care sectors.

*Preliminary and incomplete. Do not circulate.

†University of Wisconsin-Madison and NBER, cfu@ssc.wisc.edu.

‡Georgetown University, ami.ko@georgetown.edu.

§Seoul National University, chamna.yoon@snu.ac.kr.

1 Introduction

Even in economies with well-developed markets for childcare and long-term care (LTC), a large share of care continues to be provided informally by family members. For example, in the U.S. Health and Retirement Study (HRS) data, about one-third of working women with young children obtain childcare provided by their parents, and nearly two-thirds of retirees with LTC needs receive assistance from their middle-aged children. More remarkably, among retirees with LTC needs, those who previously helped their adult children with childcare are 26% more likely to receive LTC provided by these adult children.[1] These patterns suggest that families allocate time-intensive care across generations and across different stages of the life cycle, raising the question of how these care decisions are linked within the family.

This paper studies the motives underlying intergenerational time transfers of childcare and long-term care. We ask whether these transfers are primarily driven by altruism or whether they reflect strategic behavior across life stages. Under altruism, family members provide care because they value each other's well-being. Under strategic motives, care provided at one stage of life influences future behavior—for example, grandparents may help with childcare in anticipation of receiving long-term care from their adult children later in life. Understanding the relative importance of these motives is important for interpreting observed family behavior and for the optimal design of public policies. In particular, when strategic motives are strong, policies targeting one care sector can indirectly affect the other through strategic family dynamics.

We begin by documenting a set of empirical facts about intergenerational time transfers. Leveraging cross-state and cross-time policy variation in the Child Care and Development Fund (CCDF), which subsidizes childcare for low-income families, we examine how CCDF generosity affects childcare and LTC among low-educated women with young children. We compare this treatment group to otherwise similar women with older children, who are less likely to be affected by CCDF and therefore serve as a control group. Our results show that as CCDF generosity increases from its lowest to highest level, grandparent-provided childcare declines by 13 percentage points, consistent with altruistic responses. At the same time, grandparents' subjective beliefs about receiving future LTC from their daughters decline by 16 percentage points, indicating a reciprocal link between the two time transfers.

Motivated by these data patterns, we develop and estimate a dynamic model of intergenera-

[1] Authors' calculations from HRS data, 1996–2014.

tional care provision within a family, consisting of two active players—a retired grandparent (G) and a parent (P)—and a passive child. The model has three stages: an initial stage when childcare is needed, an intermediate stage, and a later stage when long-term care (LTC) may be needed. Throughout all stages, P makes labor supply decisions (full-time, part-time, nonworking), recognizing the value of accumulated experience for future wages; G, who faces health and mortality risks, makes consumption and savings decisions. In addition, in the first stage, P chooses the amount of childcare to purchase from the market, while G chooses the amount of childcare to provide, with P being responsible for the remaining childcare needs. In the third stage, a surviving G might have LTC needs, in which case, P chooses the amount of informal LTC to provide, with the remaining need purchased by G from the formal LTC market.

Consistent with findings from our design-based analysis, our model accounts for both altruistic and strategic motives for intergenerational time transfers. Altruistic motives are embedded in the model by allowing P and G to care about each other's well being, governed by altruistic parameters that vary across families of different unobserved types. This unobserved heterogeneity leads to a pure correlation between family-provided childcare and LTC. Care can also be provided for strategic motives. P may feel guilty for not providing LTC to a needy G who helped with childcare in the past. Anticipating this, G may strategically provide childcare in the first stage to increase the chance of receiving informal LTC when needed. This would lead to a causal relationship between the two time transfers. In addition, P may provide LTC to reduce G's medical expenses, thereby increasing bequests.

We use three datasets to estimate the model. First, we rely on the HRS for information on G's assets, LTC arrangements, and the correlation between the two time transfers. Second, we use the Survey of Income and Program Participation (SIPP) to gather detailed data on P's employment, income, and childcare arrangements. Third, we use Add Health, a panel survey tracking teenagers into adulthood, to obtain measures of parent-child closeness, which we use to estimate the conditional distribution of family altruistic types via K-modes clustering.

Given the estimated distribution of family types, we estimate the rest of major model parameters via indirect inference. To identify parameters critical for policy implications, i.e., parameters governing the relative importance of altruistic versus strategic motives, we exploit the dynamic nature of the model combined with exclusion restrictions. For example, using childcare prices as an instrument for G-provided childcare, the associated change in P-provided LTC provides identifying information on P's guilt for not "paying back." Furthermore, how G-provided childcare responds

to changes in childcare prices reveals G's altruism toward P. To identify the extent to which P's informal LTC decisions are driven by a desire to protect bequests from formal care costs, we exploit variation in P-provided care in response to formal LTC costs.

The estimates reveal a pronounced asymmetry in altruism across generations, with grandparents displaying strong altruism toward their adult children and much weaker altruism in the reverse direction. Consequently, adult children's care decisions are shaped less by altruism and more by guilt and bequest incentives. The estimates also indicate that grandparents strongly prefer family-provided LTC to formal care services such as nursing homes. As a result, grandparents have incentives to provide childcare earlier in life to activate guilt on their children's side or to accumulate savings and use bequests to elicit elderly care when needed.

Using the estimated model, we conduct simulations to examine the effects of counterfactual care policies, with a focus on spillovers across care sectors. In the childcare sector, we consider an unconditional subsidy that does not require parental employment, as well as an expansion of the eligibility income threshold. In the LTC sector, we analyze a conditional Medicaid expansion that raises the Stage-3 consumption floor for grandparents who previously provided childcare in Stage 1. All counterfactual policies are financed by a proportional income tax on parents and are calibrated to be budget balanced.

Our findings reveal substantial spillovers across the childcare and LTC sectors. Expansions of childcare subsidies, such as removing work requirements or raising the eligibility income threshold, increase the use of formal childcare and crowd out care provided by grandparents. As Ps rely less on family support early in life, they become less committed to providing informal LTC later, leading to greater reliance on formal LTC and higher Medicaid recipiency among Gs. In contrast, a conditional Medicaid expansion that rewards grandparent-provided childcare strengthens intergenerational reciprocity. It increases G's childcare provision and modestly raises P's labor supply. At the same time, higher earnings and greater availability of grandparental care reduce childcare subsidy take-up. Informal LTC provision by P also increases later in life, reflecting stronger intrafamily commitments. Taken together, these results highlight that policy interventions in one care sector can generate sizable and unintended effects in the other through dynamic family interactions over the life cycle.

Related Literature There is a long-established literature on intergenerational transfers that focuses on two foundational motives: pure altruism and strategic exchange. The altruism model,

most famously articulated in the "Rotten Kid Theorem" by Becker [1974], posits that an altruistic parent's financial transfers are sufficient to align the incentives of all family members. In contrast, the strategic view, exemplified by strategic bequest motives in Bernheim et al. [1985], models transfers as an explicit exchange in which parents use the threat of disinheritance to purchase services, such as care, from their children. In his Nobel Prize lecture [Becker, 1993], Gary Becker argued that parents concerned about old-age support can invest in their children by instilling "feelings of guilt, obligation, duty, and filial love," which effectively commit children to provide support later in life. This concept, later formalized as a rational manipulation of preferences [Becker et al., 2016], provides a powerful explanation for non-financial transfers. Our paper builds on this insight by structurally modeling this guilt channel and quantifying its importance, relative to altruism and bequest motives, in explaining the dynamic, two-way exchange of care within the family.

More recently, a growing literature uses structural models to understand families' role in caregiving, focusing either on childcare provision by grandparents [Cardia and Ng, 2003, Bick, 2016, García-Morán and Kuehn, 2017] or on LTC provision by adult children [Barczyk and Kredler, 2018, Ko, 2022, Mommaerts, 2025]. Given the highly bi-directional nature of these two types of caregiving within a family, we contribute to this literature by providing a unified framework to study both types of transfers in a dynamic setting. Our policy simulations suggest that policy designs could be more effective by accounting for the intrinsic and endogenous linkage between these two types of transfers.

Finally, our paper also relates to studies on the relationship between female labor supply and caregiving. A vast literature documents the "child penalty," showing that the availability and cost of childcare are first-order drivers of mothers' labor force participation and career trajectories [Angrist and Evans, 1998, Kleven et al., 2019]. Within this, a specific strand has highlighted the crucial role of grandparent-provided childcare in easing this constraint and enabling mothers to work [Compton and Pollak, 2011, Anstreicher and Venator, 2024]. In parallel, a separate but analogous literature documents the significant negative impact of informal LTC on the careers of prime-age women, finding that daughters who become primary caregivers often reduce hours, exit the labor force, or suffer wage penalties [Skira, 2015, Cil and Tuncbilek, 2018]. While both literatures confirm that female labor supply is highly elastic to caregiving needs, they have largely proceeded on separate tracks. As a result, they do not account for the fact that grandmothers' provision of childcare and their subsequent receipt of informal long-term care are dynamically linked decisions.

The remainder of the paper is organized as follows. Section 2 presents descriptive evidence. Section 3 introduces the model. Section 4 describes the data used to estimate the model. Section 5 presents the estimation strategy and results. Section 6 uses the estimated model to conduct counterfactual policy experiments. Section 7 concludes.

2 Descriptive Evidence

2.1 Summary Statistics on Intergenerational Transfers

In this section, we use HRS data to report summary statistics on intergenerational transfers. The HRS surveys a nationally representative sample of Americans ages 50 and older every two years beginning in 1992. We use ten biennial waves from 1996 to 2014. The sample is restricted to respondents who were age 50 or older in wave 3, remained alive over the sample window, and did not miss any interviews while alive. We refer to the HRS respondent as G (grandparent). We consider the adult children of G, denoted P, who were age 21 or older in wave 3, were alive whenever their parent was alive, and remained out of school throughout the sample period. Respondents without any adult children in wave 3 are excluded.

Table 1 summarizes transfers at the G-P-wave level. Time transfers are prevalent. For younger families where P's youngest child is aged under five, 29% report relying on grandparent-provided childcare.[2] On the elder-care side, 26% of Ps provide informal long-term care to a G with care needs.[3] Financial transfers are comparatively modest. The mean annual financial transfer from G to P is \$672, and that from P to G is even smaller at \$52.[4] In contrast to these small inter vivos amounts, 27% of Ps are listed as beneficiaries of G's life insurance.

Columns (1) in Tables 2 and 3 characterize the childcare stage, whereas Columns (2) in both tables pertain to the long-term care stage. In the childcare stage, Column (1) of Table 2 reports characteristics of Ps who receive childcare assistance from G, and Column (1) of Table 3 describes Gs who provide such assistance to any of their children. The average P is 37 years old. Only 6%

[2] In the HRS, we do not observe the ages of P's children, but we do observe the number of children P has. We infer new births from changes in the reported number of children and use this information to impute the age of the youngest child.

[3] We classify G as having long-term care needs if they have activities of daily living (ADLs) limitations or cognitive impairment and receive some form of long-term care, including formal services or informal family care.

[4] Brown [2006] find that 14% of respondents aged 69 and older receive regular care from their children, while only 1% pay a child for informal care. Groneck [2017] find that the correlation between informal care provision and inter vivos transfers made in the previous wave before a parent's death is not statistically significant.

Table 1: Summary Statistics on Transfers

	Mean	SD
$G \to P$: grandchild care	0.10	0.30
: P has a young kid	0.29	0.46
$G \to P$: annual financial transfer	671.87	6514.59
$G \to P$: beneficiary of G's life insurance	0.27	0.45
$P \to G$: informal LTC	0.04	0.20
: G has LTC needs	0.26	0.44
$P \to G$: annual financial transfer	52.30	718.77
Unique G	11567	
Unique G-P pairs	34394	
Unique G-P-wave combinations	222647	

Notes: Statistics are computed from G-P-wave–level data.

coreside with a G despite receiving childcare help. A much bigger share of 55% live within 10 miles to the G. The average G is 65 years old, and most (71%) are retired at this stage.

In the long-term care stage, Column (2) of Table 2 reports characteristics of Ps who provide care to a G with long-term care needs, while Column (2) of Table 3 describes the disabled Gs who receive such care. The average P is 53 years old, and the average G is 81, indicating a 16-year gap between the childcare and long-term care phases.

Among caregiving Ps, 64% are daughters (Table 2). Of the 95.5 average hours of care received by G, 70.6 hours (74%) come from daughters, underscoring their central role in meeting retirees' long-term care needs (Table 3). Moreover, 79% of disabled Gs who receive long-term care from their children are female, consistent with women's higher long-term care risk and their greater likelihood of outliving a spouse and relying on children rather than spousal care [Chang and Ko, 2026].

2.2 Relationship between Childcare and LTC Provision

We next examine how the two intergenerational transfers are related. Using a sample of disabled Gs with long-term care needs, we assess whether their receipt of informal long-term care from their Ps is correlated with whether G provided childcare help in the past when P had young children. Column (1) of Table 4 reports the results.[5] All else equal, past childcare help is associated with a 6.7 percentage point higher likelihood that G receives informal long-term care from P, which is substantial given the care rate of 25.6%.

The positive correlation may reflect either unobserved heterogeneity in altruism or implicit

[5] See Table B.1 for the full list of coefficient estimates.

Table 2: P Characteristics by Caregiving Role

	(1) P receives childcare help		(2) P provides LTC	
	Mean	SD	Mean	SD
Female	0.54	0.50	0.64	0.48
Age	36.73	5.62	52.93	10.61
Education (years)	13.96	2.27	13.10	2.55
Married	0.81	0.39	0.60	0.49
Coresides w/ parent	0.06	0.23	0.28	0.45
Lives within 10 mi to G	0.55	0.50	0.73	0.44
# Children	2.38	1.19	2.13	1.70
Observations	9222		7430	

Notes: Sample is at P-wave level. Column (1) includes Ps whose youngest kid is age 5 or younger and who receive childcare help from G. Column (2) includes Ps who provide care to their G with long-term care needs.

Table 3: G Characteristics by Caregiving Role

	(1) G provides childcare		(2) G receives informal LTC	
	Mean	SD	Mean	SD
Female	0.55	0.50	0.79	0.41
Age	65.37	6.48	81.39	10.14
Education (years)	12.42	3.09	10.06	3.82
Monthly LTC hrs from children	2.05	28.55	95.47	176.42
Monthly LTC hrs from daughters	1.65	27.10	70.57	159.01
Retired	0.71	0.45	0.99	0.09
Assets (in thousand)	753.43	2257.35	200.33	727.21
Annual income (in thousand)	89.82	152.64	29.77	102.27
# Children	3.25	1.86	3.33	2.14
Have LTC needs	0.12	0.33	1.00	0.00
Observations	7819		5698	

Notes: Sample is at G-wave level. Column (1) includes Gs who provide childcare to any of their children with young kids. Column (2) includes Gs with long-term care needs that receive informal long-term care from any of their children.

Table 4: Relationship between Intergenerational Time Transfers

	(1)		(2)		(3)	
	P provides LTC		G provided childcare		P provides LTC	
G provided childcare	0.067***	(0.018)				
Childcare price was high			0.069***	(0.015)	0.068*	(0.041)
Observations	13045		13175		13045	
Adjusted R^2	0.338		0.558		0.336	
Mean of dependent variable	0.256		0.222		0.256	
Family fixed effects	Yes		Yes		Yes	

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the household level and are in parentheses. The sample consists of families in which the respondent (G) has long-term care needs. Not all coefficients shown. See Table B.1 for full estimation results.

contracting, in which providing childcare help increases the likelihood of receiving long-term care later. To explore the latter mechanism, we instrument for G's provision of childcare help using plausibly exogenous variation in childcare prices, exploiting both cross-time and cross-sectional differences.

2.2.1 Leveraging Cross-time Variation in Childcare Prices

We use the Consumer Expenditure Survey Public Use Microdata to measure cross-time variation in inflation-adjusted childcare prices. Based on average formal childcare spending, we categorize the years 1996–2014 into periods of low and high childcare prices. During this period, childcare costs rose sharply in 2005 (see Figure B.1 in the Online Appendix). We therefore classify Ps with young children in 2004 and earlier as facing low childcare prices, and those with young children in 2005 and later as facing high prices.

Column (2) of Table 4 confirms the first-stage relationship: Ps that faced high childcare prices are 6.9 percentage points more likely to have received childcare help from G. Column (3) then regresses P's current long-term care provision to their disabled G on whether P faced high childcare prices several years ago when their kid was young. The result reveals that P is indeed 6.8 percentage points more likely to provide care if they faced high childcare prices. Together, these results suggest that when formal childcare was relatively expensive, families relied more on G for childcare, and these earlier transfers are associated with greater long-term care support later in life.

2.2.2 Leveraging Cross-sectional Variation in Childcare Prices

The previous analysis used temporal changes in childcare prices to identify the link between childcare and elderly care. We now complement this by exploiting cross-state variation in childcare costs arising from differences in the generosity of childcare subsidy programs. Specifically, we use the Child Care and Development Fund (CCDF), the primary program providing childcare subsidies to low-income families in the U.S. In 2010, about 5.5% of eligible children (ages 0–12) were served by the CCDF, which typically covered around 75% of childcare costs [Guner et al., 2020]. Although relative-provided care is eligible for reimbursement, most CCDF-supported children attend formal or licensed care. Reimbursement rates for informal care are much lower, and relative providers must meet health and safety requirements that can be burdensome.[6]

While states must meet federal guidelines, such as income eligibility below 85% of the state median and qualifying activities like work or education, they retain broad discretion in setting specific parameters. We compile state-level CCDF policy data for 2009–2014 from reports by the Administration for Children and Families.[7] We construct an index $Policy_{st} \in [0, 1]$ summarizing the generosity of each state's CCDF, averaging five binary indicators: (1) whether job search qualifies as an eligible activity, (2) whether no minimum work hours are required, (3) whether TANF income is exempt from eligibility calculations, (4) whether TANF families are exempt from copayments, and (5) whether families below 100% of the federal poverty line are exempt from copayments. For example, if a state in a given year has the value of one for all of the five indicators, then $Policy_{st} = 1$. If it has the value of one for only three indicators, $Policy_{st} = \frac{3}{5} = 0.6$.

To examine how childcare subsidy policy changes affect families, we use the restricted-access HRS, which reports the state of residence for respondents (G) and their children (P). Because the HRS questions are retrospective and CCDF policy data begin in 2009, we use the 2010, 2012, and 2014 waves. As the CCDF is means-tested, it primarily concerns low-income families.[8] We therefore restrict the sample to low-educated Ps, those without a high school diploma.[9] We further limit the sample to G–P pairs residing in the same state, which account for 81.5% of families with low-educated P. The treatment group includes Ps whose youngest child is not yet in school and therefore face the largest childcare expenses.

[6] In 1999, only about 15% of CCDF-subsidized children were cared for by relatives [Ho, 2015]. By 2016, 24 states required CPR certification, 22 required First Aid certification, and 21 mandated annual inspections for relative providers.

[7] https://www.acf.hhs.gov/opre/project/child-care-and-development-fund-ccdf-policies-database.

[8] In 2012, the average income of subsidy recipients was about $20,000 [Guner et al., 2020].

[9] Table B.2 in the Online Appendix shows results when this restriction is lifted.

Table 5: Childcare Subsidies and Intergenerational Time Transfers

	(1) P works full time		(2) G provides childcare		(3) G believes P will provide LTC	
Treat=1	0.001	(0.051)	0.030	(0.028)	0.038	(0.033)
Generosity of CCDF	-0.157	(0.142)	-0.012	(0.086)	0.148	(0.147)
Treat=1 × Generosity of CCDF	-0.025	(0.139)	-0.129**	(0.064)	-0.157*	(0.085)
Observations	2480		2616		2570	
Adjusted R^2	0.449		0.410		0.350	
Mean of dependent variable	0.481		0.070		0.235	
Family fixed effects	Yes		Yes		Yes	

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the household level and reported in parentheses. The sample consists of Ps with less than a high school education. See Table B.2 for results that include Ps of all education levels. The treatment group consists of Ps whose youngest child is not yet in school.

We estimate

$$Y_{ist} = \beta Treat_{it} \times Policy_{st} + \alpha Treat_{it} + \gamma Policy_{st} + \eta_2 Other_{st} + \eta_1 X_{ist} + \lambda_t + \theta_s + \varepsilon_{ist}, \quad (1)$$

where i indexes P, s is P's state of residence, and t the year. The dependent variables are: (1) whether P works full-time, (2) whether G provides childcare help, and (3) whether G expects P to provide informal long-term care in the future when G becomes disabled. $Treat_{it}$ is the indicator for belonging to the treatment group, $Policy_{st} \in [0, 1]$ captures the generosity of the CCDF, $Other_{st}$ includes state-level controls (unemployment rate, minimum wage, state EITC supplement), and X_{ist} includes individual and parental demographics. Year (λ_t) and state (θ_s) fixed effects are included.

Table 5 presents the results. Column (1) shows that CCDF generosity does not significantly affect labor supply among low-educated Ps. Column (2) indicates that more generous CCDF programs substantially reduce grandparent-provided childcare for the treatment group: moving from the least to the most generous program lowers this rate by 12.9 percentage points among families with young children. Because greater CCDF generosity effectively reduces the out-of-pocket price of childcare, this result mirrors the earlier finding that G-provided childcare increases when childcare prices are higher (Table 4, Column 2). These results together imply G's caregiving decisions are partly motivated by altruism, as they increase help when formal childcare becomes more costly for Ps.

Column (3) of Table 5 shows that, among the treatment group, G's expectations of receiving

informal long-term care decline by 15.7 percentage points as the CCDF programs move from the least to the most generous. This finding aligns with the earlier results in Column (3) of Table 4, where higher past childcare prices are associated with greater provision of long-term care. In the CCDF analysis, because program generosity does not increase P's employment, the effects are unlikely to operate through higher opportunity costs. Instead, the findings suggest a causal link between intergenerational time transfers: reduced grandparental childcare due to exogenous shocks lowers the perceived likelihood of elderly care later, consistent with an implicit family contract in which Ps repay earlier childcare help with subsequent long-term care.

Table B.2 in the Online Appendix reports results when Ps of all education levels are included. CCDF generosity continues to reduce both G-provided childcare and G's expectations of receiving informal long-term care from P. However, the estimates are considerably noisier, as expected, because the broader sample includes many Ps with incomes too high for CCDF programs to be relevant.

To summarize, the descriptive results presented thus far suggest that accurately evaluating policies targeting either child care or elder care requires a unified framework that accounts for family interactions in caregiving across different stages of the life cycle. We now turn to an intergenerational model that serves this purpose.

3 Model

In a dynamic non-cooperative game framework, we study two-way time transfers of childcare and LTC in an extended family, consisting of two active players—a retired grandparent (G) and a parent (P)—and a passive child. The model has three stages: a first stage when childcare is needed, a third stage when LTC may be needed, and a stage in between. Throughout all stages, P makes labor supply decisions; G, who faces health and mortality risks, makes consumption and savings decisions. In addition, in the first stage, P chooses the amount of childcare to purchase from the market, G chooses the amount of childcare to provide, with P being responsible for the remaining childcare responsibilities. In the third stage, a surviving G might face LTC needs, in which case, P chooses the amount of informal LTC to provide, with the remaining need purchased by G from the LTC market. The two-way transfers can arise from altruistic motives and strategic motives: First, P may provide LTC to reduce G's medical expenses, thereby increasing bequests. Second, P may feel guilty for not providing LTC to a needy G who helped with childcare in the past; foreseeing

this, G may provide childcare strategically to increase the chance of receiving informal LTC when needed.

3.1 Primitives

A household is characterized by $\left(X_1, \chi, H_0^P, a_0^G\right)$. The vector X_1 consists of 3 subvectors: X_1^P (P's demographics), X_1^G (G's demographics, initial health, and retirment income), and X_1^{PG} (household-level observables). The variable χ is unobserved by the researcher, which captures permanent heterogeneity across households in terms of their altruism; we model χ as an unobserved discrete type that is correlated with X_1. Finally, H_0^P is P's initial work experience and a_0^G is G's initial asset level. Overtime, G's health (part of X_t) evolves exogenously, while H_t^P and a_t^G evolve endogenously.

3.1.1 Timing and Decisions

The model has three stages, starting from the child's birth. Stage 1 corresponds to the first five years of the child's life. Stage 3 corresponds to years when the grandparent, if still alive, may need LTC (G is aged above 73). Stage 2 corresponds to years in between. To ease exhibition, we present the model as if all stages have the same length; our empirical analysis accounts for stage-specific lengths, detailed in Online Appendix.

At each stage, P and G move sequentially, with P moving first. The specific timing and decisions to be made in these stages are as follows:

Stage 1: The child requires Q hours of care per week, which can be provided by P, G, and/or the market in the form of paid childcare.

Stage 1.1: P observes her Stage-1 choice-specific shocks and chooses her work hours $h_1^P \in \{0, 20, 40\}$ and the hours of market-provided childcare $q^M \in \{0, 20, 40\}$.

Stage 1.2: G observes her choice-specific shocks related to childcare provision $\left(q^G\right)$ and chooses $q^G \in \{0, .., Q - q^M\}$ and her asset level a_1^G.

Stage 2: G experiences a health shock. With probability $\lambda\left(X_1^G\right)$, G survives with an updated health status, governed by transition function $\Gamma(X_t^G | X_{t-1}^G)$; with probability $1 - \lambda\left(X_1^G\right)$, G dies and leaves bequest a_1^G to P. After G's survival and health status are realized, Stage 2 decisions are as follows.

Stage 2.1: P observes her Stage-2 labor-supply shocks and chooses her work hours h_2^P.

Stage 2.2: Surviving G chooses her asset level a_2^G.

Stage 3: G experiences another health shock. With probability $\lambda\left(X_2^G\right)$, G survives with an updated health status, which determines how many weekly hours of LTC G needs $N\left(X_3^G\right) \in \{0, ..., N_{\max}\}$; with probability $1-\lambda\left(X_2^G\right)$, G dies and leaves bequest a_2^G to P. After the realization of G's LTC needs, Stage 3 decisions are as follows.

Stage 3.1: P observes her Stage-3 choice-specific shocks and chooses work hours h_3^P and her LTC provision $n^P \in \left\{0, ..., N\left(X_3^G\right)\right\}$ if G needs it.

Stage 3.2: Surviving G pays the out-of-pocket expense for $N\left(X_3^G\right) - n^P$ hours of formal LTC and chooses her asset level (a_3^G). At the end of period 3, G dies and bequests a_3^G to P.

3.1.2 Constraints

Constraints for P We assume that the parent does not save and uses all her after-tax income to fund her consumption and, if $t = 1$, her expenses on market-provided childcare. P's after-tax labor and non-labor income $W\left(h_t^P, H_{t-1}^P, X_t^P\right)$ depends on her work hours h_t^P, past work experience H_{t-1}^P, and demographics X_t^P. At the beginning of next period, P's experience evolves such that

$$H_t^P = \widetilde{H}(H_{t-1}^P, h_t^P). \tag{2}$$

At $t = 1$, P's out-of-pocket expense on paid childcare depends on the sticker price of childcare p, P's usage of this service q^M, and childcare subsidies P may be eligible for given her income $W(\cdot)$, labor supply h_t^P, and demographics X_t^P. Considering income tax and childcare subsidy policies, we can write P's consumption in period t as given by

$$c_t^P = \begin{cases} Y\left(h_t^P, W\left(h_t^P, H_{t-1}^P, X_t^P\right), X_t^P, q^M, p\right) \text{ for } t = 1, \\ W\left(h_t^P, H_{t-1}^P, X_t^P\right) \text{ for } t = 2, 3, \end{cases} \tag{3}$$

where $Y(\cdot)$ is P's after-tax income net of out-of-pocket expenditure on paid childcare. Notice that $W(\cdot)$ enters $Y(\cdot)$ because it determines one's total available resources and because it determines one's eligibility for childcare subsidies. Similarly, h_t^P and X_t^P not only affect one's income $W(\cdot)$, they may also affect one's eligibility for childcare subsidies and hence enter $Y(\cdot)$ directly.

The parent allocates her endowed time $\mathcal{T}$ to work (h_t^P), childcare $\left(q^P\right)$, elderly care $n^P \in$

$\left\{0, ..., N\left(X_3^G\right)\right\}$, and leisure (l_t^P), such that

$$l_t^P = \mathcal{T} - h_t^P - I\left(t=1\right) q^P - I\left(t=3\right) n^P, \tag{4}$$

$$\text{with } q^P = Q - q^M - q^G, \tag{5}$$

i.e., at $t = 1$, P provides all childcare hours not covered by paid care or G.

Constraints for G The grandparent's consumption $\left(c_t^G\right)$ and savings $\left(a_t^G\right)$ decisions are subject to the following constraints:

$$c_t^G = \max\left\{(1+r)a_{t-1}^G + y^G - a_t^G - I\left(t=3\right) m\left(N - n^P\right),\ \underline{c}^G\right\} \tag{6}$$

$$a_t^G \geq 0 \tag{7}$$

$$a_t^G = 0 \text{ if } (1+r)a_{t-1}^G + y^G - I\left(t=3\right) m\left(N - n^P\right) \leq \underline{c}^G, \tag{8}$$

In 6, a_{t-1}^G is the G's assets at the beginning of Stage t, on which G earns interests at rate r, $y^G \in X_t^G$ is G's retirement income. These resources are used to fund G's consumption c_t^G and savings next period a_t^G, and if $t = 3$, the cost of formal LTC services $m\left(\cdot\right)$. In the case of large LTC expenditure needs, G is provided a consumption floor $\underline{c}^G$ by implicit governmental or societal insurance. We put two constraints on G's asset choice. First, G cannot borrow (7); second, G has to run down her asset to zero before she can resort to the consumption floor (8).

The grandparent splits her time $\mathcal{T}$ between leisure l_t^G and childcare $q^G \in \{0, .., Q - q^M\}$ in $t = 1$, and spends all her time on leisure in other periods, such that

$$l_t^G = \mathcal{T} - q^G I\left(t=1\right). \tag{9}$$

3.1.3 Preferences

P's Flow Utility

$$u^P(c_t^P, l_t^P, h_t^P) + I\left(t=1\right)\begin{pmatrix}\theta_q q^P + \\ \theta_K K\left(q^M, q^G, q^P\right)\end{pmatrix} - I(t=3)\begin{pmatrix}\psi\left(N(X_3^G), n^P\right) \times \\ \left(\omega_\chi^P + \rho q^G\right)\end{pmatrix}. \tag{10}$$

Common across all stages, P derive utilities $u^P(.)$ from her own consumption c_t^P, leisure l_t^P, and a fixed disutility if she works $(h_t^P > 0)$. In Stage 1, P derives additional utility θ_q from time

spent caring for her child and utility θ_K from her child's skill development $K(.)$, the latter being a function of childcare arrangement.[10] In Stage 3, the grandparent derives disutily $\psi(.)$ from spending time in formal LTC facilities, which is a function of G's LTC need $N(X_3^G)$ and P's LTC provision n^P. Being altruistic toward G, P also feels this disutility to a degree that depends on 1) ω_χ^P (a type-specific altruism parameter) and 2) G-provided childcare in Stage 1. The latter, governed by the parameter ρ, captures the guilt or indebtedness P feels toward G for G's time transfer.

G's Flow Utility

$$u^G(c_t^G, l_t^G) + \omega_\chi^G \left(u^P(.) + I(t=1) \left(\theta_q q^P + \theta_K K(.) \right) \right) - I(t=3)\, \psi\left(N(X_3^G), n^P \right). \tag{11}$$

Common across all stages, the grandparent, if alive, derives utility $u^G(.)$ from her own consumption and leisure and from P's flow utility weighted by a type-specific altruism parameter ω_χ^G. In Stage 3, G derives disutility from spending time in formal LTC facilities $\psi(.)$.

3.2 Value Functions

In this subsection, we specify the value functions and solve the family's problem backward. Recall that G's survival probability at the beginning of $t = 2, 3$ is $\lambda\left(X_{t-1}^G\right)$. Conditional on G's survival, we denote the transition probability from X_t^G to X_{t+1}^G by $\Gamma\left(X_{t+1}^G | X_t^G\right)$. We denote by Ω_t the common state variables faced by P and G at Stage t; they face their own choice-specific shocks when applicable. Notably, because P moves first, P's Stage-t choices become G's stage variables at t.

3.2.1 Stage 3

At $t = 3$, common state variables Ω_3 include X_3, χ, H_2^P (P's work experience), a_2^G (G's asset), and q^G (G's childcare time in Stage 1).

[10] Although only appearing in Stage-1 utility, θ_K captures the (sum of) P's discounted utility from child development from future period(s).

Surviving G's Problem Given Ω_3 and P's Stage-3 choices, G chooses her optimal asset level a_3^G, yielding the following value function:

$$V_3^G\left(\Omega_3, c_3^P, h_3^P, n^P\right) = \max_{a_3^G} \left\{ \begin{array}{c} u^G(c_3^G, \mathcal{T}) + \omega_\chi^G u^P\left(c_3^P, \mathcal{T} - h_3^P - n^P, h_3^P\right) \\ -\psi(N(X_3^G), n^P) + \beta\omega_\chi^G B\left(a_3^G\right) \end{array} \right\} \quad (12)$$
$$s.t.\ (6) - (8).$$

The first three components of (12) are G's flow utility as specified in (11). The last component reflects the fact that G will die and leave bequest at the end of Stage 3, providing P with a utility $B\left(a_3^G\right)$ discounted at rate β. Being altruistic, G feels this utility to the degree of ω_χ^G.

P's Problem If G survives, P chooses labor supply and LTC provision: $z_3^P \equiv \left(h_3^P, n^P\right)$, yielding the value function $V_3^P(\cdot)$ given by

$$V_3^P\left(\Omega_3, \epsilon_3^P\right) = \max_{z_3^P} \left\{ \begin{array}{c} u^P(c_3^P, \mathcal{T} - h_3^P - n^P, h_3^P) - \left(\omega_\chi^P + \rho q^G\right)\psi(N(X_3^G), n^P) \\ +\beta B\left(a_3^G\right) + \epsilon_3^P\left(z_3^P\right) \end{array} \right\}$$
$$s.t. \quad (3),$$

where $\epsilon_t^P(.)$ is an i.i.d. choice-specific shock.

If G dies at the beginning of Stage 3, P receives G's bequest a_2^G and chooses labor supply h_3^P, yielding the following value function $\widetilde{V}_3^P(\cdot)$ given by

$$\widetilde{V}_3^P\left(\Omega_3, \epsilon_3^P\right) = \max_{h_3^P} \left\{ u^P(c_3^P, \mathcal{T} - h_3^P, h_3^P) + B\left(a_2^G\right) + \epsilon_3^P\left(h_3^P\right) \right\}$$
$$s.t.\ (3).$$

3.2.2 Stage 2

At $t = 2$, common state variables Ω_2 include X_t, χ, H_1^P, a_1^G, and q^G.

Surviving G's Problem G chooses optimal asset a_2^G , yielding the value function

$$V_2^G\left(\Omega_2, c_2^P, h_2^P\right) = \max_{a_2^G} \left\{ \begin{array}{c} u^G(c_2^G, \mathcal{T}) + \omega_\chi^G u^P\left(c_2^P, \mathcal{T} - h_2^P, h_2^P\right) \\ +\beta(1-\lambda\left(X_2^G\right))\omega_\chi^G B\left(a_2^G\right) \\ +\beta\lambda\left(X_2^G\right)\sum_{X_3^G}\Gamma\left(X_3^G|X_2^G\right)E_{\epsilon_3^P}\left[V_3^G\left(\Omega_3, c_3^P, h_3^P, n^P\right)\right] \end{array} \right\} \quad (13)$$
$$s.t.\ (2), (6)-(8).$$

With probability $(1-\lambda\left(X_2^G\right))$, G dies at the beginning of Stage 3 and leaves bequest a_2^G to P (the second row of (13)). With probability $\lambda\left(X_2^G\right)$), G survives in Stage 3 (the third row of (13)). In this case, G's expected value accounts for two types of uncertainties. First, with transition probability $\Gamma\left(X_3^G|X_2^G\right)$, G's health evolves to a new status. Second, G takes expectations over shocks to P's Stage-3 choices, because $V_3^G(\cdot)$ depends on these choices.

P's Problem If G survives, P's value function is given by

$$V_2^P\left(\Omega_2, \epsilon_2^P\right) = \max_{h_2^P} \left\{ \begin{array}{c} u^P(c_3^P, \mathcal{T} - h_2^P, h_2^P) + \epsilon_2^P\left(h_2^P\right) \\ +\beta(1-\lambda\left(X_2^G\right))E_{\epsilon_3^P}\left[\widetilde{V}_3^P\left(\Omega_3, \epsilon_3^P\right)\right] \\ +\beta\lambda\left(X_2^G\right)\sum_{X_3^G}\Gamma\left(X_3^G|X_2^G\right)E_{\epsilon_3^P}\left[V_3^P\left(\Omega_3, \epsilon_3^P\right)\right], \end{array} \right\} \quad (14)$$
$$s.t. \quad (2), (3).$$

Parallel to (13) , the second row in (14) describes the case where G dies at the begining of $t=3$ and the third row describes the case where G survives in $t=3$.

If G dies at the beginning of $t=2$, P receives G's bequest a_1^G and chooses labor supply h_t^P for $t=2,3$, yielding the value function

$$\widetilde{V}_2^P\left(\Omega_2, \epsilon_2^P\right) = \max_{h_2^P} \left\{ \begin{array}{c} u^P(c_2^P, \mathcal{T} - h_2^P, h_2^P) + B\left(a_1^G\right) + \epsilon_2^P\left(h_2^P\right) + \\ \beta E_{\epsilon_3^P}\max_{h_3^P}\left\{u^P(c_3^P, \mathcal{T} - h_3^P, h_3^P) + \epsilon_3^P\left(h_3^P\right)\right\} \end{array} \right\}$$
$$s.t. \quad (2), (3).$$

3.2.3 Stage 1

At $t=1$, common state variables Ω_1 include X_1, χ, H_0^P and a_0^G.

G's Problem Given Ω_1, P's Stage-1 choices $\left(c_1^P, h_1^P, q^M\right)$, and her choice-specific shocks to childcare provision $\epsilon_1^G\left(q^G\right)$, G chooses her asset level and childcare provision q^G :

$V_1^G\left(\Omega_1, c_1^P, h_1^P, q^M, \epsilon_1^G\right) =$

$$\max_{a_1^G, q^G} \left\{ \begin{array}{c} u^G(c_1^G, \mathcal{T} - q^G) + \omega_\chi^G \left[u^P\left(c_1^P, l_1^P, h_1^P\right) + \theta_q q^P + \theta_K K\left(.\right)\right] + \epsilon_1^G\left(q^G\right) \\ +\beta(1-\lambda\left(X_1^G\right))\omega_\chi^G B\left(a_1^G\right) \\ +\beta\lambda\left(X_1^G\right) \sum_{X_2^G} \Gamma\left(X_2^G | X_1^G\right) E_{\epsilon_2^P}\left[V_2^G\left(\Omega_2, c_2^P, h_2^P\right)\right] \end{array} \right\} \tag{15}$$

$s.t.$ (2), (4), (5), (6) − (8).

The first row of (15) describes G's flow utility, including her choice-specific shock. With probability $1-\lambda(X_1^G)$, G dies in Stage 2 and leaves bequests to P (Row 2). With probability $\lambda(X_1^G)$, G survives in Stage 2; in this case, G forms expectations over her Stage-2 health shocks and shocks to P's Stage-2 choices.

P's Problem P chooses labor supply and paid childcare usage $z_1^P = \left(h_1^P, q^M\right)$, each choice z_1^P is associated with a preference shock $\epsilon_1^P\left(z_1^P\right)$, yielding the value function:

$V_1^P\left(\Omega_1, \epsilon_1^P\right) =$

$$\max_{z_1^P} \left\{ E_{\epsilon_1^G} \left[\begin{array}{c} u^P(c_1^P, l_1^P, h_1^P) + \theta_q q^P + \theta_K K\left(q^M, q^G, q^P\right) + \epsilon_1^P\left(z_1^P\right) \\ +\beta(1-\lambda\left(X_1^G\right)) E_{\epsilon_2^P}\left(\widetilde{V}_2^P\left(\Omega_2, \epsilon_2^P\right)\right) \\ +\beta\lambda\left(X_1^G\right) \sum_{X_2^G} \Gamma\left(X_2^G | X_1^G\right) E_{\epsilon_2^P}\left[V_2^P\left(\Omega_2, \epsilon_2^P\right)\right] \end{array} \right] \right\} \tag{16}$$

$s.t.$ (3) − (5).

Because G moves after P and because G's choices affect P's flow and future utilities, P takes expectation over G's choice shocks (ϵ_1^G), hence the operator $E_{\epsilon_1^G}(\cdot)$. Inside of $E_{\epsilon_1^G}(\cdot)$, (16) describes P's flow utility (Row 1) and expected value in Stage 2 if G dies (Row 2) and if G survives (Row 3).

4 Estimation Data

4.1 HRS

From the HRS 1996–2014 data introduced in Section 2, we build an estimation sample by imposing the following restrictions. Our model considers interactions between one retired G and one P.

Table 3 shows that informal long-term care is provided mostly to female Gs. For each household in the HRS, we therefore choose a female G who is retired. Regarding P selection, we consider daughters. This is based on the fact that daughters account for most of the informal long-term care hours provided by children. Furthermore, as one goal of the paper is to examine how childcare policies affect employment decisions among the working generation, we focus on female Ps whose labor supply is more elastic than men's to these changes. Applying these gender restrictions results in 5,082 Gs and 9,483 Ps.

For each G, we need to pick one P. If we were to pick the P who is observed to provide the most long-term care hours to G, then she is likely to be too old for us to observe whether G provided childcare help when P had young kids. In contrast, if we picked the P based solely on childcare hours from G, then we risk picking the wrong P who might not be the primary long-term caregiver for G. Our solution is a compromise between the two. In the first step, using families that are observed to rely on informal long-term care, we regress the dummy for whether the child is the primary caregiving child on a vector of child characteristics that are exogenous to the model.[11] Then, we use the estimated coefficients to predict each P's probability of being the major caregiver.

In the second step, we restrict the sample to Ps for whom we have credible information about G's childcare provision. This is not a trivial task, as we do not observe the ages of P's children and can only infer new births from changes in the reported number of children. We first keep Ps for whom we observe their first birth.[12] Assuming they have all of their subsequent children during the sample period (mean number of children P has is around two), we can infer G's entire childcare history. For Ps that enter the sample with kids already, we keep them if they ever receive childcare help from G at some point during the sample period. Applying this second-step restriction results in 2,426 Gs and 3,341 Ps.[13]

In the third step, for each of the 2,426 Gs, we select the P with the highest predicted probability of being the primary caregiver computed in the first step. The final sample includes 2,426 families

[11] To construct the dependent variable, we use the following criteria until ties are broken: (i) the number of waves where the child is reported to provide informal LTC, (ii) the number of help days, and (iii) the number of help hours. The regressors include the child's age, proximity to the parent, education, marital status, number of kids, number of siblings, and whether the child is the oldest child.

[12] We treat a case as a first birth when P's reported number of children increases from zero in the previous wave to a strictly positive value.

[13] The second-step restriction excludes Gs for whom we cannot credibly impute their childcare provision to any of their daughters. That is, their daughters enter the sample already with kids, and G never provide childcare to them over the sample period. We do not use these families because if we did, we would treat G as never providing childcare, when in fact, they could have provided care before the sample period started, when P's kids were young.

and 19,940 family-wave observations. After excluding observations where G's assets are in the top 1.5% of the distribution, we have 2,419 families and 19,646 family-wave observations. Tables B.3 and B.4 in the Online Appendix provide summary statistics of the families in the HRS estimation sample.

4.2 SIPP

While the HRS is informative about how childcare and long-term care transfers within a family are linked, it does not contain detailed information on childcare arrangements. For example, it lacks measures of the intensive margin of grandparent-provided childcare and information on the use of formal childcare services. Furthermore, Gs report on P's employment and earnings, which may be less accurate. To complement, we use the Survey of Income and Program Participation (SIPP) which is a nationally representative longitudinal survey conducted by the U.S. Census Bureau. The dataset provides information on income, employment and a wide variety of subjects. Panels were drawn annually from 1984 to 1993, and there were usually several panels in progress simultaneously. Starting in 1996, they had larger non-overlapping panels drawn every few years. Prior to the 2014 panel, data were collected at 4-month intervals ("waves"), and most panels consisted of between 8 and 16 waves.

The survey consists of "core" questions that are asked every wave and Topical Module (TM) questions that are not repeated in each wave. TM questions gather specific information on a wide variety of subjects, including child care arrangements. We construct the SIPP TM sample using waves from 2001, 2004 and 2008 panels where TMs included questions on child care arrangements.[14] A designated parent is selected from each household to answer questions about care arrangements for each and every child. In married couples, the mother is the designated parent. Among TM respondents, 97% are women, and we exclude the remaining 3% from the sample. We further restrict to respondents with children of ages 0-5 years who are not yet in school. As our model considers only one grandchild, in cases with multiple children, we first select the child for whom the grandparent provides the most hours of care, and then we choose the youngest child to break the ties. The SIPP TM sample consists of 15,136 parents and the number of parent-wave observations is 21,250.

Table 6 reports summary statistics on child care arrangements obtained from the SIPP TM

[14] While TM questions for child care arrangements were asked to earlier panels, we do not use them due to inconsistencies in questions. For example, care arrangements were asked only to parents working or in school.

Table 6: Child Care Arrangements in the SIPP TM Sample

	(1) All		(2) P works full-time		(3) P works part-time		(4) P unemployed	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
	mean	sd	mean	sd	mean	sd	mean	sd
Use grandparent care	0.24	0.43	0.29	0.45	0.31	0.46	0.17	0.37
Use formal childcare	0.30	0.46	0.47	0.50	0.34	0.48	0.11	0.32
Grandparent hrs per week	4.98	12.08	7.66	14.86	5.01	10.29	2.50	9.00
Formal care hrs per week	8.93	16.40	16.73	20.58	7.68	13.07	2.25	8.12
Observations	21250		8357		3844		9049	

Notes: The sample is at the SIPP respondent-wave level. The sample is constructed using waves from 2001, 2004 and 2008 panels where Topical Modules included questions on child care arrangements. The sample consists of female designated parents who answered questions on child care arrangements and have at least one child aged 0-5 and not yet in school.

sapmple. The usage rate of grandparent-provided care is about 24% and that of formal childcare services is 30%.[15] Grandparents provide about 5 hours of childcare per week, while formal services provide 9 hours. Both formal childcare and grandparent-provided care increase in young mothers' work hours, although the gradient is less steep for grandparent-provided care.

Information about P's employment and earnings are asked in "core" questions, which were asked in all waves for panels 2001, 2004 and 2008. We restrict to female respondents aged between 21-64. The SIPP Core sample consists of 111,765 respondents and the number of respondent-wave observations is 865,484. We use this sample to estimate P's income function and to construct P's employment moments. Table B.5 in the Online Appendix reports the summary statistics of the respondents in the SIPP Core sample. Compared with Ps in the HRS sample, the mean age is lower by one year at 42.5. The share working full-time is 0.52, which is lower than the value of 0.64 observed in the HRS estimation sample. This difference may partly reflect that the cutoff for full-time work is higher in the SIPP (35 hours per week) than in the HRS (30 hours per week). The labor force participation rate is $0.52 + 0.16 = 0.68$, which is also lower than that in the HRS sample ($0.64 + 0.12 = 0.76$) as reported in Table B.3 of the Online Appendix.

4.3 Add Health

To estimate the distribution of unobserved altruism type, we use the publicly available survey data of the Add Health study, administered by the National Longitudinal Study of Adolescent to Adult Health. It is a longitudinal study of a nationally representative sample of adolescents in the U.S.

[15] Formal childcare services include daycare centers, nursery/preschool, family day care, and nannies.

and asks questions about how children and parents perceive their relationship. Online Appendix A provides details on the data.

5 Estimation Strategy and Identification

5.1 Empirical Definitions

Time horizon. We consider three values of P's age when the first stage of the model starts: 25, 29 and 34 years old. These are the first three quartiles of the maternal age distribution in the SIPP sample when their child is born. The grandparent G is assumed to be 29 years older than P, which is the mean age difference in the HRS estimation sample.[16] The first stage lasts 5 years which captures the time until free public education starts. The third stage starts when G is aged 73 and above, which is when the risk of developing LTC needs starts to become substantial.[17] Grandparents are assumed die with probability one once they reach the age of 95.

G's income We closely follow De Nardi et al. [2025] in specifying G's income process. We model log income as the sum of a flexible age profile and a permanent income (PI) component. We first estimate household fixed effects from a regression of log income on age polynomials. To identify PI, we rank households by these estimated fixed effects and assign them to terciles of the distribution.

P's income P's income process is estimated using the data from SIPP. Labor income is modeled as a function of hours worked (part-time or full-time), work experience, education, age and two-way interactions among these variables. Non-labor income is modeled as a function of education and age. We impute the federal income tax liabilities using the Internet TAXSIM program provided by NBER. We use the tax schedule in 2005. The tax liabilities are calculated as a function of age, labor income, non-labor income, and child age.

Care prices As described in Section 2, we use the Consumer Expenditure Survey Public Use Microdata to measure cross-time variation in inflation-adjusted childcare prices. Low formal childcare prices are set at \$4.3 per hour, which represent the mean costs between years 1996-2004. High child care prices are set at \$5.5, which are the mean costs between years 2005-2014. For information about formal LTC prices, we use Genworth's Annual Cost of Care Survey. The average cost of

[16] Grandparents are therefore either 54, 58 or 63 years old when the model starts.
[17] Consequently, the second stage lasts 14 years.

nursing homes is $232 per day during our sample period, which translates into the hourly rate of $46.[18] We incorporate variations in the cost of LTC based on whether the respondent (G) in the HRS sample has daughters other than the matched child (P). Conditional on having long-term care needs, the average nights spent in a nursing home is higher by 37% when the selected child is the only daughter that the respondent has. We therefore reflect this variation by increasing the cost of LTC for HRS respondents with just one daughter relative to those with multiple daughters.

Government transfers for care spending We model CCDF as childcare subsidies available to low-income parents who satisfy work requirements by being in the labor force. We set the threshold at 22% of the mean household income to match the 6% recipiency rate, and we use the 75% subsidy rate as in Guner et al. [2020]. Medicaid is modeled as providing a consumption floor for G, and we follow Brown and Finkelstein [2008] to calibrate this value which is $545 per month in 1999 dollars.

Care hours The total required childcare is 84 hours per week. In the SIPP sample, among individuals that use formal child care for more than 35 hours week, the majority report using the service 40 hours. For those that use less than 35 hours, the average hour is 17. We therefore allow formal childcare hours to be 0, 17 or 40 hours per week. Likewise, we allow grandparental childcare hours to be 0, 12, and 40 hours per week, where 12 is the mean among those that report receiving less than 35 hours of help. G in $t = 3$ can be healthy, lightly disabled or severely disabled. For the lightly disabled state, G needs 15 hours of care, while in the severe care, 40 hours of care are needed. When G is disabled, P can choose to provide 0%, 50% or 100% of required LTC hours.

Other values The total available time $\mathcal{T}$ for both P and G is set at 124 hours per week. P's part-time and full-time work requires 15 and 40 hours per week, respectively. The annual real interest rate is set at 3% as in Brown and Finkelstein [2008].

5.2 Parameters Estimated or Pre-Set Outside of the Model

G's health risks We use the HRS data to estimate G's health and mortality risks outside the model. G is assumed to be healthy in the first stage. In the second stage, conditional on being alive, G's health can be either good or bad. We use self-reported health in the HRS to measure this. In the third stage, conditional on being alive, G can be healthy, lighlty disabled or severely disabled. We treat an individual (1) as being healthy if the individual has zero or one limitation

[18] This is based on the assumption that nursing homes provide 40 hours of care per week.

carrying out activities of daily living (ADL); (2) as lightly disabled if the individual has two or three ADL limitations without cognitive impairment; and (3) as severely disabled if the individual has four or more ADL limitations or cognitive impairment.[19] G's health transition probabilities follow a Markov process where the next period's health depends on the current health and permanent income. We adopt a logit function and recover the transition by maximum likelihood estimation.

Child skill production function Rather than allowing the parent to have direct preferences over specific combination of $q = \left(q^M, q^G, q^P\right)$ of childcare arrangement, we discipline our model using the child skill development $K\left(q^M, q^G, q^P\right)$ function, such that P's preference over q arises through q's effect on child skill development. The function $K(\cdot)$, however, is neither the focus of this paper nor creditably identifiable using our data. Therefore, we borrow the estimates from Bernal and Keane [2011], who use variation in welfare policy rules to estimate the effect of different childcare inputs on young children's cognitive outcomes. Specifically, they find that relative-provided care adversely affects children's cognitive outcomes compared to parental time: one additional year of relative-provided care causes a 3% reduction in test scores. In contrast, they find positive effects of formal care (1.8% increase), although the estimate is less precise. The results are consistent with Flood et al. [2022], who document that relative-provided childcare has the lowest average quality among all non-parental care arrangements.

Type distribution We estimate the type distribution $\Xi(\chi|X_1)$ using measures of parent-child closeness from Add Health. We largely follow the idea from Bonhomme et al. [2022], with two differences. First, Add Health survey measures are categorical; instead of K-Means clustering, we use K-Modes clustering. Second, these measures are obtained from Add Health data, rather than our main estimate sample, preventing us from identifying types at the household level as in Bonhomme et al. [2022]. Instead, using the variables existing in both data sets—G's and P's education—as conditioning variables, we (nonparametrically) estimate the distribution of types $\Xi(\chi|X_1)$. In Online Appendix A, we provide details about this procedure.

[19] The HRS asks respondents whether they have a difficulty carrying out each of five ADLs, which are bathing, dressing, eating, getting in/out of bed, and walking across a room. The HRS also provides a cognitive score based on several tests including word recall, subtraction, backward number counting, object naming, date naming, and president naming. We treat an individual as cognitively impaired if the individual's test score is in the bottom 10%.

5.3 Structural Estimation via Indirect Inference

Given the estimated distribution of types conditional on household observables, we estimate the rest of model parameters (Θ) using the indirect inference estimation method. The estimated vector of structural parameters is the solution

$$\widehat{\Theta} = \text{argmin}_{\Theta} \left\{ [\widehat{\beta}(\Theta) - \overline{\beta}]' W [\widehat{\beta}(\Theta) - \overline{\beta}] \right\},$$

where $\overline{\beta}$ is our chosen set of auxiliary model parameters computed from data, $\widehat{\beta}(\Theta)$ is the corresponding auxiliary model parameters obtained from a large dataset simulated from the model, and W is a weighting matrix. In particular, the vector Θ to be estimated in Step 2 includes parameters governing 1) P's and G's consumption-leisure preference function $u^P(\cdot)$, $u^G(\cdot)$, 2) P's preferences over time spent with the child and child development, 3) G's disutility from using formal LTC, 4) household-type specific altruism parameters ω_χ^P and ω_χ^G, and 5) parameters governing strategic motives: P's guilt parameter ρ and utility from bequests.

5.4 Identification

We begin with an overview of our strategy to identify the rest of the model parameters, given $\Xi(\chi|X_1)$. Assuming households' χ types are permanent, our identification relies on the dynamic nature of the model and the panel data structure, combined with exclusion restrictions. As shown in Lewbel (2000), discrete choice models with unobserved types can be identified semiparametrically if there exists a variable, with a large support, that affects choice-specific payoffs but is excluded from the type distribution.

In our application, we exploit the following exclusion restrictions: Conditional on X, households of different types face the same (1) prices and (2) survival probabilities and health status transition probabilities for G. Given (1), the sensitivity of households' choices with respect to market care prices provides information on how households trade off consumption against the (dis)utility from using different care arrangements. Given (2), households of the same unobserved type, due to different realizations of G's health shocks, will face different choice-specific payoffs. However, the supports of these excluded variables are bounded; we therefore impose functional form assumptions. In addition, we also impose a perfect correlation between ω_χ^P and ω_χ^G. This is consistent with the data patterns in Add Health: the closeness measures reported by parents and by children are highly correlated.

With the assumptions above, we discuss how we identify households' preference parameters, particularly those essential for our counterfactual policy analysis, i.e., the relative importance of the two motives underlying households' two-way time transfers: altruistic motives (governed by the type-specific ω_χ) and strategic motives (governed by the common guilt parameter ρ and P's utility from bequests). To distinguish these two motives, we fully exploit the dynamic nature of the model and the exclusion restriction.

To the extent that G cares about P's utility, a higher market childcare price would induce G to provide (more) childcare. Given that prices are uncorrelated with types conditional on X, we can use child-care price as an instrument for G-provided childcare q^G. Conditional on X, the correlation between the instrumented q^G and P-provided LTC n^P provides identifying information on P's guilt parameter, ρ: an exogenous shift in q^G should not induce variation in n^P if $\rho = 0$.

The first stage of the above IV procedure is also informative. Conditional on X_1, households' types are uncorrelated with G's expected LTC need and prices they face. As such, the responsiveness of G-provided childcare to exogenous childcare price variation provides information on how much G cares about P's utility (ω_χ^G) relative to her own leisure, on average, where the average is taken over the known distribution of types $\Xi(\chi|X_1)$.

Given that P is forward-looking, how the random realization of G's Stage-2 health status affects P's Stage-2 choices is informative. If G's Stage-2 health status predicts high LTC needs in Stage 3, a highly altruistic P, who is more likely to provide LTC and hence work less in Stage 3, may reduce her labor supply because work experience is likely to be less valuable in Stage 3.

Consider an OLS regression of parent-provided LTC, n^P, on grandparent-provided childcare, q^G, and X. Unlike the IV estimate, the OLS estimated coefficient on q^G does not have a causal interpretation, due to omitted variable bias from unobserved heterogeneity; the omitted variable also contaminates the estimated coefficients on X. The difference between the OLS and IV estimates provides identifying information on unobserved heterogeneity. In other words, given $\Xi(\chi \mid X_1)$, type-specific altruism parameters must rationalize the discrepancy between OLS and IV estimates.

The identification of the rest of (type-independent) parameters is relatively straightforward. Consider a case where G has no LTC need in the third stage, an probablistic event that happens equally across types conditional on X. In this case, P's labor supply in the third stage provides information about P's consumption-leisure preference. Given this and the pre-set skill development function $K(q^M, q^G, q^P)$, the choice of childcare time helps identify P's direct utility from childcare provision and the weight on the child's skill. Variation in P's LTC provision rates by formal LTC

price is useful for identifying P's inheritance motive. After disciplining G's altruism using childcare price variation, the extent of G's childcare provision and saving behavior provides useful information on G's distaste for formal LTC.

5.5 Auxiliary Models

Reflecting the argument in Section 5.4, we target the following auxiliary models. It should be noted that our model parameters are jointly identified from information contained in *all* of our auxiliary models; yet, some auxiliary models are relatively more informative of certain sets of parameters than others.

Aux 1: G's Childcare Supply Response to Childcare Price Coefficients from the following OLS model:

$$q_i^G = \alpha_1 p_i^M + \alpha_2 X_i + \varepsilon_i \tag{17}$$

where q_i^G is G's childcare provision and p_i^M is the price of market-based childcare. Aux 1 is particularly informative of how G trades off between leisure and P's utility.

Aux 2: P's LTC Provision and G's Childcare Provision Coefficients from both the OLS and the reduced-form regressions of n_i^P:

$$n_i^P = \gamma_1^{OLS} q_i^G + \gamma_2^{OLS} Xi + \varepsilon_i \tag{18}$$

$$n_i^P = \gamma^R p_i^m + \gamma_2^R Xi + \varepsilon_i \tag{19}$$

As explained earlier, the discrepancy between the two estimates is informative about heterogeneity in altruism.

Aux 3: P's Labor Supply Response to G's Health Coefficients from the following regression of P's Stage-2 labor supply:

$$h_{i2}^P = \beta_1 X_{i2}^G + \beta_2 X_{i2} + \varepsilon_i \tag{20}$$

where X_{i2}^G is G's health in Stage 2, which predicts G's LTC need in Stage 3.

Aux 4: G's Wealth Accumulation First moment of G's wealth in each stage, conditional on G's retirement income.

Aux 5: P's Informal LTC Provision Moments that help pin down P's altruism (ω_χ^P) and inheritance motive, which are informal LTC provision rates by P's education, by G's LTC need severity, and by the price of formal LTC.

Aux 6: Childcare Arrangement Moments that help identify P's utility from different care modes (θ_q, θ_K) and G's leisure preference:

(a) Rate of G's childcare provision by P's education level, and by G's retirement income.

(b) Share of market-based childcare out of total non-G care ($q^M/(q^M + q^P)$), by P's education level.

Aux 7: P's Labor Supply Moments Full-time and part-time employment rates in each stage by P's education.

5.6 Estimation Results (PRELIMINARY)

Table 7: Parameter Estimates

Parameter Name	**Estimate**
G: altruism if Type A	0.8909
G: altruism if Type B	0.5583
P: altruism scale	0.0459
P: guilt when child care received	2.0836
P: weight on bequest utility	1.0713
G: leisure utility	1.7763
P: leisure utility	2.4646
P: direct utility from child care	3.6560
P: weight on child's skill	0.0019
G: formal LTC disutil when lightly disabled	0.0430
G: formal LTC disutil when severely disabled	2.0938
P: FT utility cost of employment when edu = HS or less	0.3072
P: FT utility cost of employment when edu = Some college	0.0556
P: FT utility cost of employment when edu = College+	-0.2246
P: additional utility cost of PT employment	0.9383

Table 7 reports estimates of the structural parameters obtained via indirect inference. A central finding is a pronounced asymmetry in altruism across generations. G exhibits a high degree of altruism toward P. In contrast, P's altruism toward G is substantially lower. This asymmetry implies that time and care transfers from P to G are not primarily motivated by direct concern for G's utility. Instead, P's time transfers are driven by a strong desire to avoid guilt, which is estimated to be large, as well as by financial incentives to protect bequests from being depleted by formal LTC expenses, captured by P's weight on bequest utility.

Table 8: Model Fit for Care Arrangements

	Empirical	Simulated
Formal childcare rate		
P's edu = HS or less	0.19	0.28
P's edu = Some college	0.31	0.33
P's edu = College +	0.41	0.51
G-provided childcare rate		
G's income = low	0.45	0.51
G's income = mid	0.52	0.64
G's income = high	0.57	0.58
P-provided LTC rate		
G did not provide childcare	0.44	0.47
G provided childcare	0.61	0.64

G's distaste for formal LTC is negligible when disability is mild but becomes large in the severe state. This pattern is intuitive, as severe disability is more likely to result in institutionalization in a nursing home, a form of formal LTC that is well documented to generate substantial disutility for retirees [Barczyk and Kredler, 2018, Mommaerts, 2025, Ko, 2022]. To reduce the risk of nursing home entry, G therefore has strategic incentives to provide childcare earlier in life to activate the guilt mechanism on P's side or to accumulate savings and use bequests to elicit informal LTC from P.

P derives high utility from spending time with their children. This preference appears to be driven by the act of caregiving itself rather than by its long-run consequences, as the estimated weight on the child's future skill is small.

Table 8 reports the fit for childcare and LTC arrangements. Table 9 reports the fit for P's employment conditional on her education. Figure 1 reports the fit for G's wealth evolution conditional on permanent income terciles.

6 Counterfactual Policy Experiments (PRELIMINARY)

We conduct counterfactual policy experiments to evaluate the impact of alternative childcare and LTC policies. All counterfactuals are financed by a proportional flat-rate income tax applied to all P households.

The first policy (C1) replaces the existing means-tested childcare subsidy with an unconditional version that no longer ties eligibility to employment. The subsidy continues to be means-tested but removes the work requirement. The generosity of the subsidy is kept at 75%, implying that recipients continue to pay the remaining 25% of childcare expenses, as in the baseline. This design draws

Table 9: Model Fit for P's Employment

	Full-time		Part-time	
	Empirical	Simulated	Empirical	Simulated
P's edu = HS or less				
$t = 1$	0.33	0.25	0.16	0.23
$t = 2$	0.46	0.49	0.17	0.17
$t = 3$	0.44	0.41	0.13	0.08
P's edu = Some college				
$t = 1$	0.44	0.49	0.21	0.14
$t = 2$	0.55	0.54	0.20	0.19
$t = 3$	0.56	0.51	0.15	0.09
P's edu = College +				
$t = 1$	0.49	0.65	0.19	0.17
$t = 2$	0.57	0.54	0.20	0.17
$t = 3$	0.66	0.62	0.14	0.10

on evidence from Guner et al. [2020], who show that unconditional transfers can enhance welfare despite their negative impact on labor supply, and reflects a policy orientation that emphasizes better access and child development rather than employment incentives. Our contribution would lie in examining how this reform targeted at the childcare sector spills over to the LTC sector. The required tax rate to finance this reform is 0.68%, and the same rate is used to finance all subsequent counterfactual policies to ensure fiscal comparability.

The second policy (C2) retains the work requirement but relaxes income eligibility. Specifically, under the same 0.68% income tax rate used to finance the reform, the income threshold for subsidy eligibility increases by 65%, while the copayment rate remains at 25% as in the baseline.

The third policy (M1) operates through the LTC sector by rewarding unpaid grandparental childcare. Under this scenario, the Medicaid consumption floor for grandparents (G) increases by up to 146%, proportionally to the hours of childcare they provided in $t = 1$.[20] Although the policy requires dynamic verification of unpaid childcare, such monitoring appears feasible. Several European governments already track and record unpaid caregiving for future elderly social insurance benefits. For instance, the U.K.'s Specified Adult Childcare Credits program grants pension credits to grandparents who provide regular childcare.

Table 10 reports the effects of the counterfactual policy experiments. Panel A summarizes the impacts on childcare arrangements. Both C1 and C2 shift households toward market-based childcare, increasing formal care use and reducing reliance on grandparents. These responses are

[20] Specifically, if they provided full-time childcare (40 hours per week), the consumption floor increases by 146%. If they provided part-time childcare (12 hours per week), the consumption floor increases by $146\% \times \frac{12}{40} = 43.8\%$.

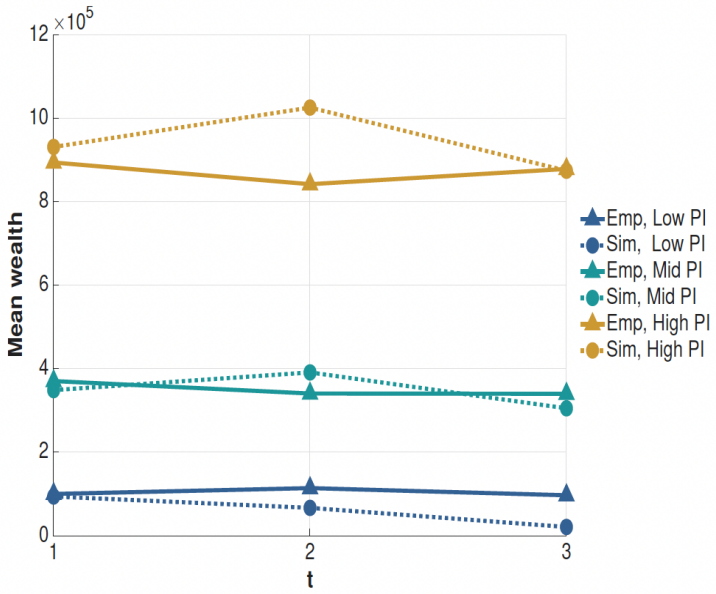


Figure 1: G's Wealth Evolution by Permanent Income (PI)

especially pronounced among parents with lower education levels, reflecting the means-tested nature of the subsidies. The results are qualitatively consistent with the descriptive evidence based on CCDF variation presented in Section 2.[21] In contrast, M1 increases grandparental childcare, as grandparents are more incentivized to provide care in order to secure access to more generous social insurance later in life.

Panel B in Table 10 reports the effects on parental labor supply in $t = 1$. The unconditional subsidy C1 leads to a substantial reduction in work hours across all education groups, consistent with the findings in Guner et al. [2020]. Under C2, low-education parents increase labor supply because they can earn additional income while remaining eligible for benefits. By contrast, higher-education parents who are closer to the eligibility threshold reduce work hours to qualify under the expanded threshold. The Medicaid-based reward M1 has a modest positive effect on labor supply among low- and middle-educated parents. Labor supply responses in $t = 2$ and $t = 3$ are minimal and are therefore reported in the Online Appendix.

Panel C presents the effects on parents' LTC hours in $t = 3$ when grandparents are severely disabled. Under C1 and C2, parents provide fewer LTC hours: as grandparent-provided childcare declines, so does parents' perceived obligation to provide care later in life. This pattern is again

[21] A direct quantitative comparison with the CCDF descriptive results is infeasible because the program generosity index used in the descriptive analysis aggregates multiple policy dimensions to ensure sufficient variation over the sample period.

Table 10: Counterfactual Care Policy Impacts (% change relative to the baseline)

	(C1) Uncond. CC subsidy	(C2) Higher CC threshold	(M1) Medicaid exp. for G childcare
Panel A: Childcare arrangements			
Grandparental childcare share			
P's edu = HS or less	-31.13	-10.11	59.66
P's edu = Some college	-23.76	-16.84	22.10
P's edu = College +	-10.80	-12.02	8.38
Formal childcare share			
P's edu = HS or less	69.07	97.86	0.91
P's edu = Some college	33.92	52.14	5.27
P's edu = College +	2.75	14.28	3.75
Panel B: P's work hours in $t = 1$			
P's edu = HS or less	-37.86	43.47	5.55
P's edu = Some college	-26.84	-7.53	3.24
P's edu = College +	-11.42	-6.40	-0.12
Panel C: P's LTC hours in $t = 3$			
P's edu = HS or less	-10.93	-3.25	19.59
P's edu = Some college	-12.66	-9.31	11.73
P's edu = College +	-6.22	-6.36	4.65
Panel D: Program recipiency rates			
Medicaid rate	4.55	2.78	73.44
Childcare subsidy rate	439.25	334.31	-8.95
Panel E: Low-income G's savings			
$t = 1$	-0.02	-0.00	-1.12
$t = 2$	-0.28	-0.19	-10.73
$t = 3$	-1.10	-0.80	-20.48

Notes: All values represent percent changes relative to the baseline economy. C1 replaces the existing means-tested childcare subsidy with an unconditional subsidy that removes the work requirement while keeping the copayment rate at 25%. C2 retains the work requirement and increases the income eligibility threshold by 65%, with the copayment rate fixed at 25%. M1 increases grandparents' Medicaid consumption floor in proportion to childcare hours provided in $t = 1$, up to a maximum increase of 146% for full-time childcare. All policies are financed by a proportional income tax of 0.68% levied on the P generation. For Panel C, the sample is restricted to Gs who are severely disabled. For Panel D, the baseline Medicaid recipiency rate is 12%, and baseline childcare subsidy recipiency rate is 5%.

consistent with the descriptive evidence in Section 2, which shows that greater affordability of formal childcare reduces family caregiving not only in the childcare sector but also in the LTC sector. In contrast, M1 strengthens intergenerational reciprocity, leading parents to provide more LTC hours after receiving greater childcare support from grandparents.

Panel D reports the impacts on welfare program recipiency rates in both care sectors. As expected, C1 and C2 substantially increase childcare subsidy recipiency. Notably, they also raise Medicaid recipiency rates, reflecting a weakening of family-based insurance and a shift toward formal care in both sectors. In contrast, M1 reduces reliance on means-tested childcare subsidies as both grandparental care and parental employment increase. Although family-provided LTC rises under M1, both Medicaid recipiency and spending increase.

Panel E shows the effects on savings among low-income grandparents.[22] Under M1, low-income grandparents substantially reduce savings across periods, consistent with weaker precautionary saving motives when Medicaid provides stronger consumption insurance. By contrast, the childcare-sector policies C1 and C2 have negligible effects on elderly savings.

Taken together, these counterfactual experiments underscore how childcare and LTC policies are linked through intergenerational family dynamics. Subsidies that expand access to market-based childcare weaken informal care networks and increase reliance on social insurance programs, while policies that reward unpaid care strengthen intergenerational transfers and reduce reliance on means-tested subsidies.

7 Conclusion

This paper studies an extended family's dynamic interactions over childcare and LTC decisions across the life cycle in the U.S. context, where time-intensive care transfers across generations are substantial. Descriptive analysis reveals that policy-induced reductions in grandparent-provided childcare weaken expectations of future informal LTC provided by their adult children, suggesting an implicit family contract in which early childcare help is reciprocated with later elderly care. Our estimated structural model accounts for different motives underlying bi-directional time transfers and shows that strategic motives play a central role in explaining the positive correlation between the two care transfers over the life cycle. Consequently, counterfactual policy simulations reveal substantial spillover effects across the two care sectors. For instance, expansions of childcare sub-

[22] The effects on higher-income grandparents' savings are negligible and are reported in the Online Appendix.

sidies crowd out grandparent-provided care and weaken reciprocal incentives, leading to greater reliance on formal LTC and old-age social insurance programs. In contrast, policies that explicitly recognize and reward intergenerational care provision can strengthen family reciprocity and reduce reliance on public support. Taken together, our findings highlight that policies aimed at one care sector can generate sizable spillovers in the other through dynamic family interactions, underscoring the importance of designing childcare and LTC policies with an integrated, life-cycle perspective.

References

J. D. Angrist and W. N. Evans. Children and their parents' labor supply: Evidence from exogenous variation in family size. *American Economic Review*, 88(3):450–477, 1998.

G. Anstreicher and J. Venator. To grandmother's house we go: Informal childcare and female labor mobility. Unpublished, April 2024.

D. Barczyk and M. Kredler. Evaluating long-term-care policy options, taking the family seriously. *Review of Economic Studies*, 85:766–809, 2018.

G. S. Becker. A theory of social interactions. *Journal of Political Economy*, 82(6):1063–1093, 1974. doi: 10.1086/260265.

G. S. Becker. The economic way of looking at life. *Journal of Political Economy*, 101(3):385–409, 1993. doi: 10.1086/261880.

G. S. Becker, K. M. Murphy, and J. L. Spenkuch. The manipulation of children's preferences, old-age support, and investment in children's human capital. *Journal of Labor Economics*, 34 (S2):S3–S30, 2016. doi: 10.1086/687483.

R. Bernal and M. P. Keane. Child care choices and children's cognitive achievement: The case of single mothers. *Journal of Labor Economics*, 29(3):459–512, July 2011. doi: 10.1086/659343. URL https://www.jstor.org/stable/10.1086/659343.

B. Bernheim, A. Shleifer, and L. Summers. The strategic bequest motive. *Journal of Political Economy*, 93(6):1045–1076, 1985.

A. Bick. The quantitative role of child care for female labor force participation and fertility. *Journal of the European Economic Association*, 14:639–668, 2016.

S. Bonhomme, T. Lamadon, and E. Manresa. Discretizing unobserved heterogeneity. *Econometrica*, 90(2):625–643, 2022. doi: 10.3982/ECTA18218.

J. R. Brown and A. Finkelstein. The interaction of public and private insurance: Medicaid and the long-term care insurance market. *American Economic Review*, 98(3):1083–1102, 2008.

M. Brown. Informal care and the division of end-of-life transfers. *Journal of Human Resources*, 41 (1):191–219, 2006.

E. Cardia and S. Ng. Intergenerational time transfers and childcare. *Review of Economic Dynamics*, 6:431–454, 2003.

M. Chang and A. Ko. Intrahousehold inequality and savings in retirement. Working paper, January 2026.

G. Cil and Z. E. Tuncbilek. The effect of parental health shocks on female labor supply. *Journal of Human Resources*, 53(4):1118–1153, 2018. doi: 10.3368/jhr.53.4.0816-8160R1.

J. Compton and R. A. Pollak. Proximity and coresidence of adult children and their parents: Description and correlates. Working Paper 17120, National Bureau of Economic Research, 2011.

M. De Nardi, E. French, J. B. Jones, and R. McGee. Why do couples and singles save during retirement? household heterogeneity and its aggregate implications. *Journal of Political Economy*, 133(3):750–792, mar 2025. doi: 10.1086/733421.

S. Flood, J. McMurry, A. Sojourner, and M. Wiswall. Inequality in early care experienced by us children. *Journal of Economic Perspectives*, 36(2):199–222, Spring 2022. doi: 10.1257/jep.36.2.199. URL https://doi.org/10.1257/jep.36.2.199.

E. García-Morán and Z. Kuehn. With strings attached: Grandparent-provided child care and female labor market outcomes. *Review of Economic Dynamics*, 23:80–98, 2017.

M. Groneck. Bequests and informal long-term care: Evidence from the hrs exit-interviews. *Journal of Human Resources*, 52:531–572, 2017.

N. Guner, R. Kaygusuz, and G. Ventura. Child-related transfers, household labour supply, and welfare. *Review of Economics Studies*, 87(5):2290–2321, 2020.

C. Ho. Welfare-to-work reform and intergenerational support: Grandmothers' response to the 1996 prwora. *Journal of Marriage and Family*, pages 407–423, 2015.

H. Kleven, C. Landais, and J. E. Søgaard. Children and gender inequality: Evidence from Denmark. *American Economic Journal: Applied Economics*, 11(4):181–209, 2019. doi: 10.1257/app.20180010.

A. Ko. An Equilibrium Analysis of the Long-Term Care Insurance Market. *Review of Economic Studies*, 89(4):1993–2025, 2022.

C. Mommaerts. Long-Term Care Insurance and the Family. *Journal of Political Economy*, 133(1): 1–52, 2025.

M. Skira. Dynamic wage and employment effects of elder parent care. *International Economic Review*, 56(1):63–93, 2015.