Preference Heterogeneity versus Economic Incentives: What Determines the Choice to Give Care?

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Abstract

Family is a primary source of care, yet significant variations in care arrangements exist both across families and countries. We explore the factors contributing to these variations by estimating a discrete-choice model derived from a parsimonious structural model of the family. Parents and children bargain over care arrangements, choosing between child-provided and formal care. Children, heterogeneous in attributes such as labor income and geographical proximity, collectively decide on the potential caregiver. We find that although economic incentives matter, unobserved preference heterogeneity substantially reduces the elasticity of informal care in response to policy changes compared to a model in which only economic motivations for the care choice are included. This suggests that including preference heterogeneity is essential when it comes to policy analysis.

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1 Introduction

Aging populations, combined with shifts in family structure – such as fewer children, higher female labor-force participation, and rising divorce rates – pose significant challenges for governments as demand for elderly care increases.[1] Adult children, traditionally one of the primary sources of care, are under increasing strain due to these demographic shifts, while governments face mounting fiscal pressure to expand formal care provision. The growing imbalance between care needs and family resources underscores the need for governments to pursue long-term care reforms to ensure adequate and sustainable support.

A central question in long-term care policy is the extent to which families adjust their informal caregiving when policies alter the effective cost of formal care. Understanding this elasticity is crucial, since care arrangements differ widely across families and countries. While existing models (e.g., Barczyk & Kredler, 2018) emphasize economic factors such as labor-market opportunity costs and subsidies, caregiving preferences are likely to vary substantially across families. For some, caregiving is a moral obligation; for others, it is not. Because families do not respond uniformly to policy reforms, a better understanding of caregiving preferences is essential for designing effective long-term care policy.

This paper examines how monetary costs and caregiving preferences shape caregiving arrangements and policy evaluation using a simple structural model that incorporates multiple children and heterogeneous preferences. We estimate the model with detailed data on European families caregiving choices and monetary costs of care options, and apply it to study the effects of long-term care policies and demographic shifts. Our analysis underscores the importance of accounting for preference heterogeneity when assessing the elasticity of caregiving responses to policy reforms.

Specifically, we develop a simple static model where parents and children bargain on care arrangements, including the choice between formal and informal care and the selection of primary caregiver among adult children. This model

[1]For example, the share of the oldest-old (80 and over) in the population is projected to double over the next few decades, leading to a rise in long-term care expenditures. As a percentage of GDP, these expenditures are projected to increase by 168% in Germany and 149% in Spain between 2000 and 2050 (Comas-Herrera et al. 2003).

incorporates both idiosyncratic care preferences and those related to observable characteristics across families with varying numbers of children. In addition, it allows children's opportunity costs to depend on the severity of parents care needs, consistent with the wide variation observed in required care intensity. Theoretical results from our model enable empirical estimation of preference parameters within a discrete choice framework.

We estimate the model using several data sources on caregiving in Europe, exploiting variation across families and cross-country policy differences. Our primary dataset is the Survey of Health, Ageing, and Retirement in Europe (SHARE), a nationally representative survey that provides detailed demographic and health information on elderly individuals and their families, as well as their caregiving arrangements. For child opportunity costs in the labor market, we use Eurostat's Structure of Earnings Survey (SES), and for nursing home prices, we rely on OECD data on out-of-pocket costs for institutional care for the elderly.

Our parameter estimates indicate that both observable characteristics and unobservable preferences play a significant role in families' caregiving arrangements. We find that the utility cost of formal care relative to informal care is substantial, particularly in countries with high formal care costs. Additionally, our estimates reveal that being a daughter significantly lowers the utility cost of informal care, while childrens utility costs increase when they have partners. We also find that unobserved preference variation plays a significant role in explaining observed caregiving arrangements, with a one standard deviation preference shock equivalent to an increase of approximately 13,000 Euros in monetary costs.

We use the parameter estimates from the discrete choice model to conduct three sets of counterfactual exercises. First, we compare the elasticity of formal care with respect to formal care prices between the model that incorporates both economic costs and heterogeneous caregiving preferences and the model that considers only economic costs. We find that neglecting preference heterogeneity results in an elasticity 2.5 times higher than in the model that accounts for preference heterogeneity. This underscores the importance of including preference heterogeneity in policy simulations. Second, we simulate formal care usage under the assumption that affordability levels for formal care are transplanted across country groups. We find that if the low-cost country group's affordability level were applied, formal care usage would increase by 37.8% in the middle-cost country group, and by 76.2% in the high-cost country group, relative to their current levels. Finally, we examine how caregiving arrangements are projected to respond to various demographic shifts, including the declining ratio of elderly to adult children, the closing gender wage gap, rising divorce rates, increased mobility, and changes in formal care prices. We find that the declining ratio of elderly to adult children would be the primary driver of increased formal care demand, with formal care policies playing a relatively smaller role compared to demographic shifts.

We contribute to the following strands of literature. First, we contribute to the literature that structurally estimates how caregiving arrangements respond to government policies. Most existing models in this literature (e.g. Barczyk & Kredler, 2018; Braun et al., 2017) account for the economic costs of care but abstract from heterogeneity in caregiving preferences across children and family. Moreover, many models only consider one representative child, overlooking the within-family decision process when multiple children are potential caregivers (Barczyk & Kredler, 2018; Ko, 2022; Mommaerts, 2025). Our paper contributes by estimating the elasticity of formal care use to its price, while explicitly modeling preferences heterogeneities for families with multiple children as decision makers. Our results highlight the importance of accounting for preference heterogeneities when evaluating government policies that alter formal care prices.

Second, our paper contributes to the literature on family decision-making in caregiving choices that involve multiple children. Prior studies on this topic differ in their treatment of choice sets, monetary costs, and care needs. Some papers examine only the choice of a primary informal caregiver among children without considering formal care (Checkovich & Stern, 2002; Fontaine et al., 2008; Knoef & Kooreman, 2011; Bergeot, 2024), while others include formal care as an option but abstract from its monetary costs (Stern, 1995; Hiedemann & Stern, 1999; Engers & Stern, 2002). Byrne et al. (2009) estimate a rich model that accounts for both informal caregiving among children and formal home care,[2] while also accounting for the monetary costs of care, but does not capture the interaction between parental care needs and childrens opportunity costs. Since care needs vary substantially across the elderly, accounting for this interaction is essential: when parents' needs are low, for instance, children may be able to provide care without fully withdrawing from work. Our contribution is to model both formal and informal care choices, explicitly include their monetary costs, and incorporate the interaction between parental care needs and childrens opportunity costs.

The organization of this paper is as follows. Section 2 describes data and documents descriptive statistics regarding formal care and informal care using our estimation sample. Section 3 presents our theoretical model of family caregiving arrangement. Section 5 describes the estimation procedures for the discrete choice model and presents the estimates. Section 7 performs counterfactual analyses. Section 8 concludes.

2 Empirical facts

We begin by documenting key facts about care arrangements and the characteristics of child caregivers in European countries. Additional details on data and our empirical analyses can be found in the Appendix A.1.

2.1 Data

SHARE. The primary data source used to document long-term care is the Survey of Health, Ageing, and Retirement in Europe (SHARE). SHARE is nationally representative of the European population aged 50 and above, and the survey has been conducted every two years since 2004. This dataset provides extensive information on the demographic and socioeconomic characteristics of the senior population and their children, household caregiving arrangements, and respondents' functional limitations and other health-related information. Hence, given its rich information, SHARE is well-suited for analyzing long-term care patterns and the role of children in providing care.

[2]However, Byrne et al. (2009) leaves aside nursing-home care.

We select the analysis sample using several criteria, summarized below. A detailed description of the sample selection procedures is provided in Appendix A.1. First, we restrict the sample to households with a parent aged 65 or older and without a spouse. We exclude elderly individuals living with a spouse to focus on the informal care provided by children and abstract from spousal care. Second, we include only households with at least one working-age child (defined as being between 20 and 60 years old) to examine the impact of labor market opportunity costs. Third, to focus our attention on the elderly with care needs, we limit our focus to households where the parent receives either formal care (nursing home) or intensive care from a child caregiver.[3] Lastly, due to data issues detailed in Appendix A.1, we only use baseline samples from Waves 1, 2, 4, 5, and 6.

After imposing the above sample selection criteria, we have a final sample of 1,887 households with 4,089 parent-child pairs. Appendix Table A4 reports how sample size changes after imposing each of the sample selection criteria.

Formal Care Costs. We focus on nursing home care as the primary form of formal care, as it is more widely used than formal home care in Europe, as documented in Barczyk & Kredler (2019).[4] To estimate the out-of-pocket costs for the long-term formal care faced by each SHARE household, we combine two data sources. First, we use OECD data on out-of-pocket institutional care costs for each country and income group[5], which are reported as a share of old-age disposable income for each income group. Second, we interact the OECD's shares with old-age disposable income for each country, year, and income group, as reported by Eurostat based on the European Union Statistics on Income and Living Conditions (EU-SILC).

Eurostat's Structure of Earnings Survey. SHARE does not provide income

[3]Since this paper focuses on caregiving among children, we do not consider care provided by spouses. For details on spousal care, see Barczyk & Kredler (2019). Additionally, we exclude households with multiple child caregivers to simplify the estimation of the discrete choice model in Section 5.

[4]Specifically, (Barczyk & Kredler 2019) reports that nursing home care for the elderly is used more than twice as often as formal home care across Europe.

[5]Income groups are categorized as: (i) below the 20th percentile, (ii) median, and (iii) above the 80th percentile

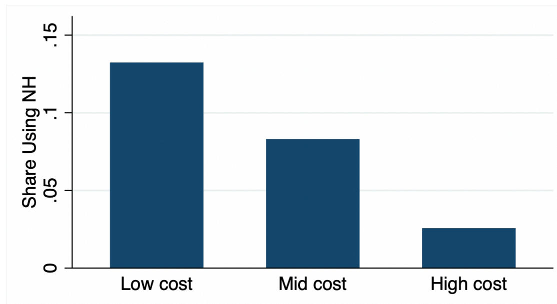
information on respondents' children. However, even if such data were available, it would not reflect the *potential* income of the children since observed income can be influenced by caregiving choices. For instance, a caregiving child might have a low observed income despite having a high potential income based on her education and abilities. To address these issues, we construct the potential income for each child based on their gender and education, as well as country and year, using Eurostat's Structure of Earnings Survey (SES). More details about potential wage construction is documented in Appendix A.2.

2.2 Long-Term Care (LTC) Arrangements

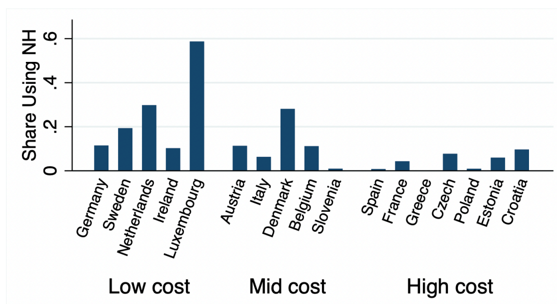
We first show that, among parent households receiving intense care, the vast majority use informal care as a main source of long-term care. Only 10.9% of our sample uses nursing home (NH) care, while the rest receive care from a caregiving child.

However, this proportion may mask differences in nursing home use across European countries, where out-of-pocket costs for formal care vary widely, as shown in OECD (2024). To explore the role of formal care cost in care arrangement, we classify countries based on the relative costliness of nursing home care for a median-income elderly individual: (1) low cost (11∼60% of old-age median income), (2) medium cost (65∼85%), and (3) high cost (90∼136%). Additional information on our classification is provided in Appendix Section A.3.

Figure 1: Nursing Home (NH) Probability by Country



(a) By country group based on FC cost



(b) By country

Note: This figure reports the proportion of households that are permanently using nursing home for sick parents for each country group (Panel (a)) and country (Panel (b)), using our estimation sample. Details on how the estimation sample is selected are provided in Section 2.1. In panel (a), "Low cost" group has FC cost as 11∼60% of old-age median income in each country; "Mid cost" group has FC cost as 65∼85% of old-age median income; "High cost" group has FC cost as 90∼136% of old-age median income. For more details on the grouping of countries, refer to Section A.3.

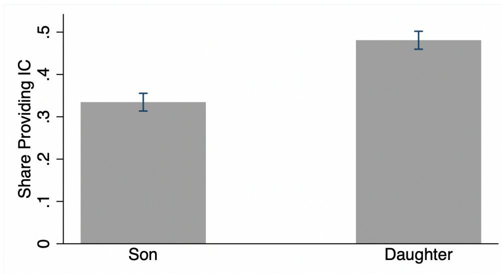
Figure 1 illustrates the significant variation in nursing home usage across countries. Higher formal care costs are associated with a higher likelihood of nursing home usage in our sample. Specifically, Panel (a) shows that 20.4% of households from countries with low formal care costs utilize nursing home in our sample, compared to just 5.6% in countries with high formal care costs. Panel (b) also reveals that countries in the low FC cost group generally have a higher fraction of households using nursing homes than other groups. However, note that the country-level statistics in Panel (b) should be interpreted with caution, because many countries have small sample sizes in our sample.

2.3 Characteristics of Caregiving Children

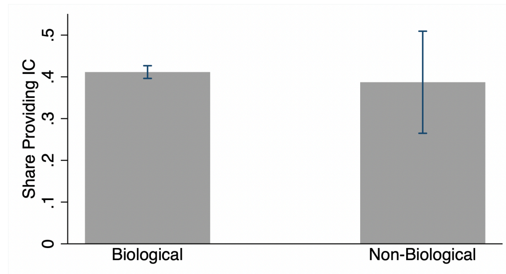
We now examine who the caregiving children are and how they differ from non-caregiving children. Figure 2 reports the fraction of children providing informal care (IC) conditional on each observed characteristic in SHARE. Below, we document several facts.

First, daughters are more likely to provide care than sons do. Panel (a) shows that 48.9% of daughters in our sample provide IC, whereas it is 32% of sons. Second, there is no clear relationship between biological child status and IC probability as shown in Panel (b). Note that this may be partly driven by the small sample size for non-biological children (only 70 cases in our sample). Third, there is a strong negative relationship between the distance between children and their parents and the likelihood of children providing IC. Approximately 80.6% of children who live with their sick parent provide IC, and this fraction decreases as the distance increases.[6] Fourth, there is no clear relationship between a child's education and IC probability. If anything, the higher education category is associated with a slightly larger IC probability.

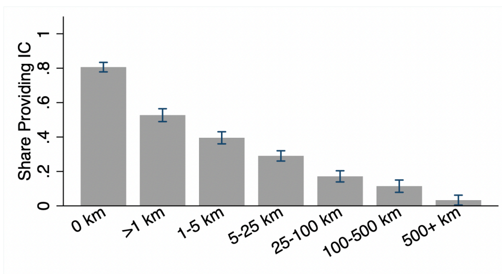
[6]It is important to note that these descriptive statistics do not establish a causal relationship between a child's distance and his or her probability of providing IC. For instance, a child might have moved closer to their parent's home, or the parent might have relocated to the child's home, facilitating the child's ability to provide care after the parent became ill. Conversely, it could be that the physical distance itself causally influences the likelihood of a child providing IC. In future analyses, we aim to better understand this relationship by examining the distances before and after the parent's illness.



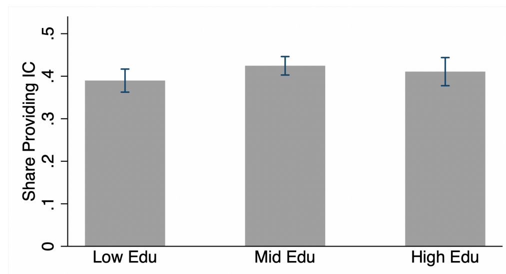
(a) By Gender



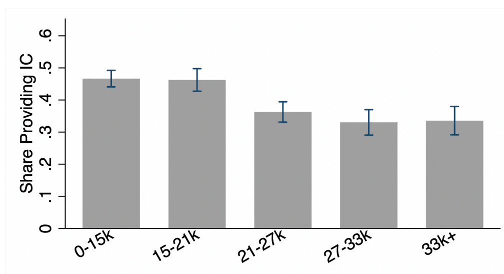
(b) By Biological Child Status



(c) By Distance



(d) By Education



(e) By Potential Income

Figure 2: Informal Care Probability by Child's Characteristics

Note: This figure reports the proportion of children providing IC by each characteristics among our estimation sample. How the estimation sample is selected is documented in Section 2.1. In Panel (b), "Non-biological" children include stepchildren, adopted children, and foster children. In Panel (c), "Distance" is reported as km away from the parent. In Panel (d), "Low Edu" is up to lower-secondary education (middle school), which is ISCED 2011 Levels 0-2. "Mid Edu" is up to high school graduation, which is ISCED 2011 Levels 2-4. "High Edu" is some college education or more, which is ISCED 2011 Levels 5-8. 95% confidence interval is reported.

2.4 Care Needs

Although our analysis sample includes only elderly individuals receiving either informal or formal care, their underlying care needs likely vary. We estimate each SHARE respondents daily care needs using the method developed by (Barczyk & Kredler 2019), which imputes care hours for SHARE respondents based on the observed relationship in the Health and Retirement Study (HRS) between care hours and functional limitations – represented by limitations in activities of daily living (ADLs) and instrumental activities of daily living (IADLs).[7] Linking to HRS is essential, as SHARE does not collect information on care hours, while HRS does for informal care recipients.[8] Appendix A.4 details the procedures for care need estimation.

Table 1 presents summary statistics on the estimated daily hours of care needed among our SHARE analysis sample. Despite restricting the sample to individuals who already receive some form of care, there is substantial variation in care needs. The average daily need is 3.6 hours, but the distribution is highly skewed: the 25th percentile is just 0.2 hours, while the 75th percentile rises to 6 hours, and the maximum reaches 22 hours per day. Similarly, there is wide dispersion in the number of ADL/IADL limitations and mobility limitations reported by respondents. This highlights the considerable heterogeneity in care intensity required even within a relatively high-need population.

[7]Table A10 provides definitions of the ADL/IADL and mobility limitation variables used in SHARE.

[8]For nursing home residents – whose care needs are unobserved in both SHARE and HRS – we apply the Dahl adjustment method (Dahl 2002) to account for potential negative selection.

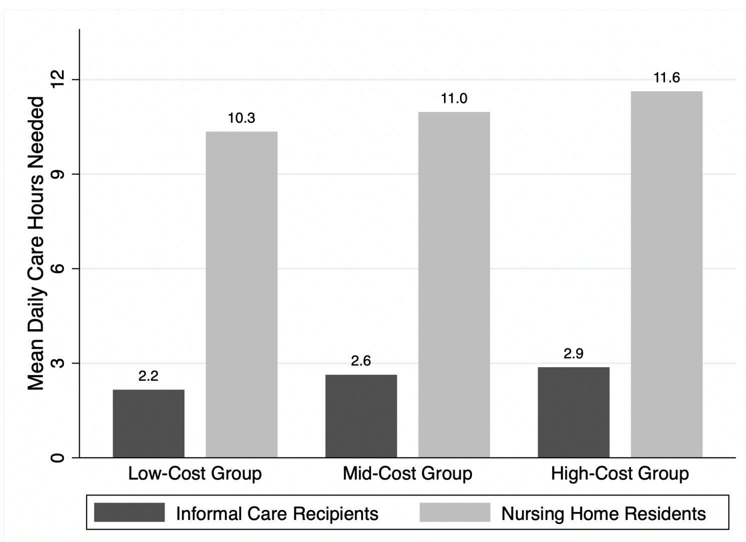
Table 1: Summary statistics: care needs

	# of Obs	Mean	Min	p25	p50	p75	Max
Daily care needs (hrs)	1887	3.6	0.2	0.2	1.7	6.0	22.1
Num. of (I)ADL limitations	1887	3.0	1.0	1.0	2.0	4.0	11.0
Num. of mobility limitations	1886	4.8	0.0	2.0	5.0	7.0	10.0

Notes: SHARE Waves 1-8. The sample is restricted to individuals who (i) are aged 65 or older and do not have a spouse, and (ii) receive either formal care (nursing home) or intensive informal care from a child caregiver. Further details in sample selection are in Section 2.1. Daily care needs are estimated based on individuals' ADL/IADL status and mobility limitations, following the approach in (Barczyk & Kredler 2019). See Appendix A.4 for detailed information on constructing care needs.

Care needs differ markedly by mode of care. As shown in Figure 3, nursing home residents have significantly higher care needs, requiring over 10 hours of daily assistance. In contrast, recipients of informal care require, on average, only 2 to 3 hours of daily care across all country groups.

Figure 3: Mean daily care needs (in hours) by care type and country group



Note: This figure displays the average daily care needs, measured in hours, for informal care recipients and nursing home residents across each country group. Countries are grouped according to the affordability of institutional care for median-income households: (1) low-cost group (11∼60% of old-age income), (2) medium-cost (60∼90%), and (3) high-cost (90∼136%).

The substantial variation in daily care needs has important implications for the opportunity cost faced by adult children providing care. When parents have relatively low care needs, children may be able to provide care without significantly disrupting their labor market participation. In such cases, caregiving may be compatible with full-time or part-time work, resulting in a relatively low opportunity cost. In contrast, for parents with high care needs, the time demands are much greater, potentially requiring children to reduce work hours or exit the labor force altogether. This heterogeneity in care intensity is therefore a key factor in understanding the economic trade-offs involved in informal caregiving. Accordingly, we account for variation in care needs when estimating the opportunity cost of caregiving in our empirical analysis.

3 Family model

There is a large number of families i, each consisting of one elderly parent requiring care and $K = K_i > 0$ adult children.

Care arrangements and costs Care can be provided either through informal care (IC) by one of the children, or through formal care (FC) purchased in the market. If child $j \in \{1, \ldots, K\}$ provides IC, she incurs opportunity cost:

$$OC_j = \big[n_j + t_d(d_j)\big] w_j + c_d(d_j),$$

where n_j denotes hours spent on caregiving, $t_d(d_j)$ represents commuting time over distance d_j, and $c_d(d_j)$ captures the direct travel costs. The parent can provide a financial transfer $Q \geq 0$ to compensate children for IC provision.

Alternatively, if the family chooses FC (indexed by $j = 0$), the parent pays price p_{bc} for basic care services, net of public transfers and costs for room and board.

Individual budget constraints The parent has income y_p, which she can spend on her own consumption c_p, on purchasing FC, and on a transfer to children:

$$c_p + I_{j=0} p_{bc} + Q = y_p \tag{1}$$

where $I_{j=0}$ equals 1 if the parent purchases FC and 0 if she obtains IC instead.

Each child $i \in \{1, \ldots, K\}$ receives full-time labor income y_i, endowment e_i (for example, spousal income), and a portion Q_i of the transfer Q:

$$c_i = y_i + e_i + Q_i - I_{i=j} OC_i, \tag{2}$$

If child i is the designated caregiver $I_{i=j} = 1$, her resources are reduced by OC_i; if $j = 0$ (FC takes place), $I_{i=j} = 0$ for all children.

Preferences Both the parent and the children derive utility from consumption but experience psychic costs from certain care arrangements. These psychic costs are measured in consumption-equivalent units (they effectively reduce the utility derived from consumption). We represent the parent's utility as:

$$u_p(c_p, j) = \begin{cases} u(c_p - \theta_0) & \text{if } \; j = 0 \;\; \text{(FC)} \\ u(c_p) & \text{if } \; j > 0 \;\; \text{(IC)} \end{cases}$$

where $u(\cdot)$ is strictly increasing (assumed to yield $-\infty$ if its argument is ≤ 0). Under FC ($j = 0$), the parent incurs a psychic cost θ_0 relative to IC. In words, when formal care is chosen the parent's effective (i.e. utility-yielding) consumption is her actual consumption c_p minus the amount θ_0.

Each child i experiences a disutility θ_i if they themselves provide care but not otherwise. Thus, child i's utility is:

$$u_i(c_i, j) = \begin{cases} u(c_i - \theta_j) & \text{if } \; i = j \; (i \text{ is the caregiver}) \\ u(c_i) & \text{if } \; i \neq j \; (i \text{ is not the cargiver}) \end{cases}$$

Unitary sibling household We assume that the K siblings act as a single decision-making unit. Preferences of the unitary sibling household over their consumption bundle $\{c_i\}_{i=1}^K$ and care arrangement j are given by:

$$U(\{c_i\}_{i=1}^K, j) = \sum_{i=1}^{K} \mu_i u_i(c_i, j)$$

where μ_i is a fixed weight for child i (reflecting, e.g., relative bargaining power among the children). In the unitary framework μ_i are constants, so the siblings behave as if maximizing a single household utility function.

Siblings distribute among themselves the transfer Q, subject to feasibility, meaning the child-specific transfer amounts Q_i have to sum up to the total transfer: $\sum_{i=1}^K Q_i = Q$.

Income pooling Summing each child's budget constraint (2), yields the siblings' collective budget constraint:

$$\sum_{i=1}^{K} c_i = \sum_{i=1}^{K} (y_i + e_i + Q_i - I_{i=j} OC_i)$$

Let $R = \sum_{i=1}^K (y_i + e_i)$ denote the full-employment resources of siblings. We can then write:

$$\sum_{i=1}^{K} c_i = R + Q - I_{i=j} OC_i, \tag{3}$$

Aggregate consumption of all siblings in the family equals their total income. Substituting the parent's budget constraint (1) into the siblings' budget constraint (3) using Q (assuming an interior solution for Q), yields the family's budget constraint:

$$c_p + \sum_{i=1}^{K} c_i = y_p + R - (I_{i=j} OC_i + I_{j=0} p_{bc}) \tag{4}$$

where the term in parentheses represents the monetary cost of the chosen care arrangement $j \in \{0, 1, \ldots, K\}$ to the family.

Family bargaining problem We model the family's decision-making process as a Nash bargaining game between the parent and the unitary sibling household. We assume that the disagreement (outside) option is that the parent purchases FC. Under this scenario, the parent utility is

$$d_p = u_p(y_p - p_{bc} - \theta_0) \tag{5}$$

The parent optimally chooses to set $Q^* = 0$, consumes $c_p = y_p - p_{bc}$, and incurs the utility penalty θ_0. Siblings' collective disagreement utility is

$$d_k = \max_{\{c_i\}} \sum_{i=1}^{K} \mu_i u(c_i) \quad \text{s.t.} \quad \sum_{i=1}^{K} c_i = R. \tag{6}$$

Children receive their full-employment resources R and allocate them among each other in a way that maximizes their collective utility.

The bargaining problem (if a solution exists) determines the IC allocation (inside option) in the following way:

$$\begin{aligned} \max_{c_p, \{c_i\}_{i=1}^{K}, j \in \{1,\ldots,K\}} & [u_p(c_p) - d_p]^{\mu_p} [\sum_{i=1}^{K} \mu_i u_i(c_i, j) - d_k]^{1-\mu_p} \\ \text{s.t.} \quad & c_p + \sum_{i=1}^{K} c_i = y_p + R - I_{i=j} OC_i, \end{aligned} \tag{7}$$

where $\mu_p \in [0, 1]$ is the parent's bargaining weight. The family chooses the caregiver child and consumption allocation subject to the family budget constraint in order to maximize the Nash bargaining criterion.

A useful property of our preference specification is that we can obtain an equivalent problem by accounting for the psychic costs explicitly in the budget constraints instead of in the utility functions. We define **effective consumption** x for children

$$x_i = c_i - I_{i=j}\theta_i,$$

and for the parent

$$x_p = c_p - I_{j=0}\theta_0.$$

Using these definitions in each child i's budget constraint (2), we obtain their budget constraints in terms of effective consumption:

$$x_i = y_i + e_i + Q_i - I_{i=j}(OC_i + \theta_i) \tag{8}$$

Similarly for the parent:

$$x_p = y_p - I_{j=0}(p_{bc} + \theta_0) - Q \tag{9}$$

The effective budget constraint for the sibling household is:

$$\sum_{i=1}^{K} x_i = R + Q - I_{i=j}(OC_i + \theta_i)$$

Substituting out Q (assuming an interior solution) using the parent's constraint (9) yields the family effective resource constraint:

$$x_p + \sum_{i=1}^{K} x_i = y_p + R - [I_{i=j}(OC_i + \theta_i) + I_{j=0}(p_{bc} + \theta_0)] \tag{10}$$

We can now formulate the Nash program (7) in terms of effective consumption:

$$\max_{x_p, \{x_i\}, j \in \{1,\ldots,K\}} [u_p(x_p) - d_p]^{\mu_p} [\sum_{i=1}^{K} \mu_i u_i(x_i) - d_k]^{1-\mu_p} \tag{11}$$

$$\text{s.t.} \quad x_p + \sum_{i=1}^{K} x_i = y_p + R - I_{i=j}(OC_i + \theta_i),$$

where the disagreement utilities d_p and d_k remain as in equations (5) and (6), respectively.

This formulation makes clear that the optimal caregiver choice – our main focus – can be analyzed separately from the consumption allocation decision.

Specifically, the combination of Pareto efficiency (implied by Nash bargaining) and strict monotonicity of preferences ensures that **the Nash criterion is strictly increasing in effective resources under IC**. Thus, the optimal child caregiver is the child with the least total effective cost (monetary and psychic) of providing IC:

$$j^* = \arg\min_j \{OC_j + \theta_j\}$$

This choice maximizes effective family resources as well as effective resources of the sibling household conditional on IC taking place.

Having determined the designated caregiver child j^*, the family bargains over how family resources between parent and the sibling household are shared by bargaining over the size of the exchange-motivated transfer Q. The Nash bargaining problem (11) over Q, given the optimal caregiver choice j^*, is:

$$\max_{Q \geq 0} [u_p(y_p - Q) - d_p]^{\mu_p} [S_{j^*}(Q) - d_k]^{1-\mu_p} \tag{12}$$

where $S_{j^*}(Q)$ denotes the sibling unit's indirect utility associated with transfer Q:

$$S_{j^*}(Q) = \max_{\{x_i\}} \sum_{i=1}^{K} \mu_i u_i(x_i) \quad \text{s.t.} \quad \sum_{i=1}^{K} x_i = R + Q - (OC_{j^*} + \theta_{j^*}).$$

Children maximize their collective utility subject to their effective resources.[9]

From this bargaining formulation it is straightforward to establish the conditions under which a bargaining solution exists, and hence, IC takes place. Children's surplus from IC is non-negative if and only if Q is such that:

$$S_{j^*}(Q) \geq d_k \quad \Leftrightarrow \quad R + Q - (OC_{j^*} + \theta_{j^*}) \geq R \quad \Rightarrow \quad Q \geq OC_{j^*} + \theta_{j^*} \equiv \underline{Q}$$

[9] We note that the optimal caregiver choice maximizes siblings' indirect utility:

$$j^* = \arg \max_{j \in \{1,\ldots,K\}} S_j(Q)$$

For any given Q, siblings always designate the child with the least total effective cost to be the caregiver which follows again from the logic of separately maximizing available resources.

We only need to compare effective resources between IC and FC since siblings' objective function strictly increases in their effective resources. Children prefer IC if the transfer Q covers at least the smallest effective for the sibling household to provide IC. IC generates surplus for the parent if and only if:

$$u(y_p - \bar{Q}) \geq u(y_p - p_{bc} - \theta_0) \quad \Leftrightarrow \quad Q \leq p_{bc} + \theta_0 \equiv \bar{Q}$$

The transfer can be at most as large as the effective resources under FC. Thus, the feasible set in (12) is $Q \in [\underline{Q}, \bar{Q}]$.

We summarize our central theoretical result in the following Theorem.

Theorem 1 *Let the effective cost of care arrangement $j \in \{0, 1, \ldots, K\}$ be*

$$C_j = \begin{cases} OC_j + \theta_j, & j = 1, \ldots, K, \\ p_{bc} + \theta_0, & j = 0. \end{cases}$$

where OC_j and p_{bc} are monetary costs and θ_j and θ_0 are psychic costs. Then the family chooses

$$j^* = \arg \min_{j \in \{0,1,\ldots,K\}} C_j,$$

where $j^* = 0$ means formal care and $j^* \in \{1, \ldots, K\}$ means child j^* provides informal care. This choice maximizes effective family resources (see equation (10)).

Remark: Exactly how the gains from IC are split is determined by the size of Q in program (12) over the feasible set, $Q^* \in [\underline{Q}, \bar{Q}]$. For our purposes, however, the exact size of this transfer is irrelevant. Also, any other bargaining protocol that satisfies **efficiency** yields the **same care outcome** (e.g. parent makes take-it-or-leave-it offer Q, children bid auction-style, collective model of entire family).

Remark on child consumption: Suppose the bargaining outcome in (12) yields the minimal transfer $Q^* = \underline{Q}$. In this scenario, the effective consumption allocation $\{x_i\}$ is identical to the allocation under the outside option (FC):

$$x_i^{IC} = x_i^{FC} = c_i^{FC}, \quad i \neq j^*$$
$$x_{j^*}^{IC} = x_{j^*}^{FC} + \theta_{j^*} = c_{j^*}^{FC} + \theta_{j^*}$$

Non-caregiving children consume the same level as under FC, while the caregiving child's consumption is increased by exactly her psychic caregiving cost θ_{j^*}. All children receive the exact same utility under IC as under FC.

4 The effect of preference heterogeneity on IC uptake

We examine how informal care (IC) uptake responds to subsidies by measuring the percentage increase in IC per dollar of subsidy (S):

$$\epsilon_{IC} = \frac{\Delta IC/IC}{S}$$

To demonstrate why preference heterogeneity dampens the responsiveness to IC subsidies, we compare two models: one where only economic factors determine IC decisions, and another that additionally incorporates psychic costs. To make these models comparable, we require them to match the same IC uptake rate. Thus, both models can explain the IC prevalence, but they predict different responses to subsidies. The crucial mechanism is that preference heterogeneity reduces the density of families who are close to indifferent between formal and informal care (marginal decision-makers) relative to the purely economic model. These marginal families are exactly those that respond to the subsidy, but since there are fewer of them the response is smaller.

Economic factors only Consider a model where IC decisions are driven solely by economic costs $C_e \sim N(\mu_e, \sigma_e^2)$. Agents provide informal care when their cost falls below a threshold value $\bar{C}$. We require the model to match the observed

IC prevalence $\bar{ic}$ in the data:

$$\bar{ic} = \Pr(C_e < \bar{C}) = \Phi\left(\frac{\bar{C} - \mu_e}{\sigma_e}\right)$$

where $\Phi(\cdot)$ is the CDF of the standard normal distribution. We can now solve for the threshold value $\bar{C}$ that generates the observed IC fraction:

$$\Phi^{-1}(\bar{ic}) = \frac{\bar{C} - \mu_e}{\sigma_e} \quad \Rightarrow \quad \bar{C} = \mu_e + \Phi^{-1}(\bar{ic})\sigma_e$$

The threshold value equals the average economic cost μ_e (in dollars) plus the number of standard deviations $\Phi^{-1}(\bar{ic})$ (unitless) multiplied by σ_e to convert from standard deviation units to dollars. If $\bar{ic} = 50\%$ then $\bar{C} = \mu_e$ since in a normal distribution 50% is the mass below the mean. If $\bar{ic} = 40\%$, we have that $\Phi^{-1}(\bar{ic}) = -0.25$ which means that in the standard normal distribution we need to go 0.25 standard deviations below the mean. To find the threshold in our normal distribution $N(\mu_e, \sigma_e^2)$ we multiply by σ_e to translate standard deviations into dollar values.

Economic factors + psychic costs Now we introduce preference heterogeneity by adding psychic costs $C_p \sim N(\mu_p, \sigma_p^2)$, independent of economic costs. The total cost becomes:

$$C = C_e + C_p \sim N(\mu_c, \sigma_c^2)$$

where $\mu_c = \mu_e + \mu_p$ and $\sigma_c^2 = \sigma_e^2 + \sigma_p^2$. Again, we require this model to match the same IC prevalence $\bar{ic}$:

$$\bar{ic} = \Pr(C < \bar{C}') = \Phi\left(\frac{\bar{C}' - \mu_c}{\sigma_c}\right)$$

This yields a new threshold:

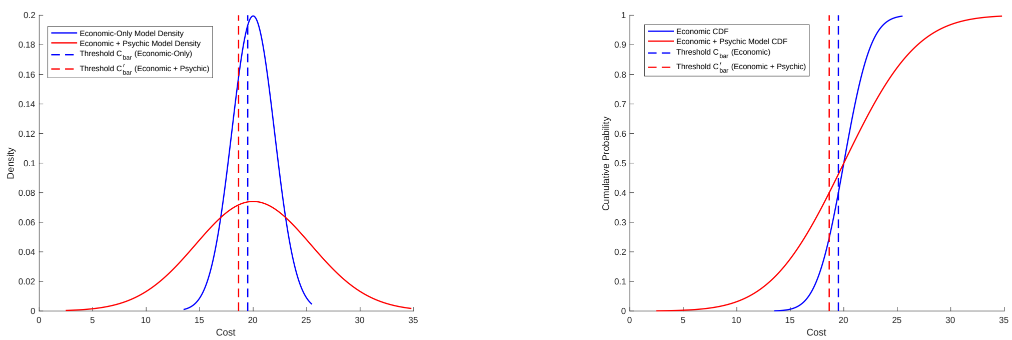
$$\bar{C}' = \mu_c + \Phi^{-1}(\bar{ic})\sigma_c$$

We have threshold values $\bar{C}$ and $\bar{C}'$ at which agents are exactly indifferent between informal and formal care. The densities at these threshold values are given by

$$f_{C_e}(\bar{C}) = \frac{1}{\sqrt{2\pi\sigma_e^2}} \exp\left(-\frac{(\bar{C}-\mu_e)^2}{2\sigma_e^2}\right) = \frac{1}{\sqrt{2\pi\sigma_e^2}} \exp\left(-\frac{[\Phi^{-1}(\bar{ic})]^2}{2}\right)$$

$$f_{C}(\bar{C}') = \frac{1}{\sqrt{2\pi\sigma_c^2}} \exp\left(-\frac{(\bar{C}'-\mu_c)^2}{2\sigma_c^2}\right) = \frac{1}{\sqrt{2\pi\sigma_c^2}} \exp\left(-\frac{[\Phi^{-1}(\bar{ic})]^2}{2}\right)$$

These expressions reveal that the variances σ_e^2 and σ_c^2 fully account for differences in the densities at their threshold value. Clearly, the density at $\bar{C}'$ is **lower** than at $\bar{C}$ since $\sigma_c^2 > \sigma_e^2$. The higher variance flattens the density thereby pushing more mass into the tails, see Figure 4a. Equivalently, this effect means that the slope of the CDF is flatter at the threshold in the model with preference heterogeneity compared to the purely economic model, see Figure 4b.



(a) Density comparison

(b) CDF comparison

Figure 4: Comparing distributions

Note: The fraction of IC equals 40%. The variance of economic costs equals 2, $\sigma_e^2 = 2$, and equals 10, $\sigma_p^2 = 10$, for preference heterogeneity. The average economic cost equals 20, $\mu_e = 20$, preference cost is set to zero, $\mu_p = 0$.

Consider a subsidy S for informal care that reduces the effective cost of providing care to $C_e - S$ and $C - S$, respectively. The fraction of families choosing informal care with the subsidy becomes:

$$\Pr(C_e - S < \bar{C}) = \Pr(C_e < \bar{C} + S) = \Phi\left(\frac{\bar{C} + S - \mu_e}{\sigma_e}\right)$$

in the economics-only model, and

$$\Pr(C - S < \bar{C}') = \Pr(C < \bar{C}' + S) = \Phi\left(\frac{\bar{C}' + S - \mu_c}{\sigma_c}\right)$$

in the model with psychic costs. The subsidy shifts the threshold rightward by S, increasing informal care uptake. We can see the increase in IC by considering Figure 4b. The subsidy pushes the threshold values up by S. The change in the CDF for the economic model when moving from $\bar{C}$ to $\bar{C} + S$ is larger than the change in the CDF for the model with preference heterogeneity because it is steeper which is the driving force behind the reduced elasticity.

The percentage change in informal care uptake per unit of subsidy (elasticity) is respectively:

$$\epsilon^e_{IC} = \frac{\Pr(C_e < \bar{C} + S) - \Pr(C_e < \bar{C})}{\Pr(C_e < \bar{C})} = \frac{\Pr(C_e < \bar{C} + S) - \bar{ic}}{\bar{ic}}$$

and

$$\epsilon^c_{IC} = \frac{\Pr(C < \bar{C}' + S) - \Pr(C < \bar{C}')}{\Pr(C < \bar{C}')} = \frac{\Pr(C < \bar{C}' + S) - \bar{ic}}{\bar{ic}}$$

We have $\epsilon^e_{IC} > \epsilon^c_{IC}$, meaning the model with preference heterogeneity exhibits lower policy elasticity.

This demonstrates why understanding preference heterogeneity is crucial for policy design: seemingly identical populations (same $\bar{ic}$) can have vastly different responses to interventions depending on the underlying variance of preferences.

5 Estimation

This section describes the empirical model used to estimate the preference parameters for caregiving choices. As implied by Theorem 1, the efficient arrangement minimizes total effective caregiving costs – comprising both monetary and psychic components – which motivates our use of a standard discrete choice framework.

Parameterization. We parameterize the utility cost V_{ij} of each caregiving option j for family i as follows:

$$\begin{cases} V_{ij} = \alpha p_i^{bc} + \theta_0 + \boldsymbol{\gamma}_i + \varepsilon_{ij} & \text{if } j = 0 \text{ (Formal care)} \\ V_{ij} = \alpha OC_{ij} + \mathbf{X}_{ij}\boldsymbol{\beta} + \varepsilon_{ij} & \text{if } j \neq 0,\ j \in K_i \text{ (Informal care)} \end{cases} \tag{13}$$

Here, p_i^{bc} denotes the cost of formal care, and OC_{ij} is the opportunity cost of child j. The parameter α captures the marginal effect of monetary cost – whether formal or informal – on the utility cost of caregiving. The parameter θ_0 reflects the average psychic cost of choosing formal care, relative to informal care, with the psychic cost of informal care normalized to zero. $\boldsymbol{\gamma}_i$ are country-group fixed effects that absorb systematic cross-country-group differences in preferences for formal care. The vector $\mathbf{X}_{ij}$ includes child-level characteristics relevant to informal caregiving.[10]

We assume that the idiosyncratic preferences ε_{ij} are distributed as the Extreme Value Type-I distribution with location parameter zero and scale parameter σ. This assumption which yields closed-form choice probabilities and allows for estimation via a multinomial logit model. We estimate the model parameters α, θ_0, $\boldsymbol{\beta}$, and $\boldsymbol{\gamma}_i$ via maximum likelihood using the observed caregiving choices in our SHARE analysis sample. As is standard in the multinomial logit model, each estimated coefficient measures the effect of the corresponding variable relative to the normalized scale of the unobserved preference shocks, σ. See Appendix A.6 for details.

Formal care cost. In practice, we define the formal care cost p_i^{bc} as the out-of-pocket cost of institutional care in each country, income group and year, based on OECD estimates, as detailed in Section 2.1 and Appendix A.3.

Opportunity cost. We specify the opportunity cost OC_{ij} as the product of the parents' care needs and the child's expected full-time wage. Weighting by care needs is essential, as parents in our sample require varying levels of care – from as little as two hours to more than twelve hours per day as shown in

[10] Specifically, $\mathbf{X}ij$ includes indicators for whether the child is female, a non-biological child, lives at a distance from the parent, has a partner, is the first-born, and the number of children the child has.

Section 2.4. For parents with low care needs, it may not be realistic to assume that a child fully exits the labor market to provide care. Specifically, the care needs weight are defined as:

$$Care\,needs\,weight = \frac{Daily\,care\,needs + Commuting\,time}{12\,hours}$$

where we assume that a child has up to 12 hours per day available for market work, and daily care needs are capped at a maximum of 12 hours. Here, we also incorporate daily commuting time from the childs residence to the parents residence using reported distance information. This ensures that the opportunity cost reflects the time burden implied by the parent's care needs.

Finally, we incorporate into the opportunity cost the predicted annual commuting costs to the parents' home, derived from reported distance. Appendix Tables A11 and A12 document the assignment of travel time and monetary travel costs by distance category, respectively.

6 Results

Main Results: Table 2 reports the estimated parameters from the multinomial logit model. All coefficients are normalized such that a positive value corresponds to a higher utility cost (i.e., lower utility) of choosing a given caregiving arrangement. For each parameter, we also report its monetary equivalent, which represents the implied cost of a one-unit change in the corresponding attribute.

Table 2: Parameter Estimates

Parameter	Estimate	Units	Euro Equiv.
θ_0: utility cost of FC	2.738***	utils	28131.2
	(0.380)		
α: monetary cost	0.973***	10K Euro/year	
	(0.191)		
β: daughter	-0.646***	dummy	-6637.5
	(0.126)		
β: non-biological	-0.184	dummy	-1885.6
	(0.405)		
β: has partner	0.396**	dummy	4067.9
	(0.165)		
β: first-born	-0.073	dummy	-746.3
	(0.122)		
β: num of children	0.086	1 child	887.0
	(0.057)		
γ: Mid-cost group $\times$ FC	-0.387	utils	-3974.8
	(0.433)		
γ: High-cost group $\times$ FC	0.890	utils	9142.9
	(0.547)		

Notes: This table presents parameter estimates from Model 13 based on SHARE data. The sample selection criteria are detailed in Section 2.1. Estimates are scaled such that a positive value corresponds to a higher utility cost (i.e., lower utility) of choosing a given caregiving arrangement. The "Euro Equiv." column reports the monetary equivalent of each parameter, obtained by dividing the parameter by the marginal utility of income (i.e., the parameter on the monetary cost variable) and multiplying by 10,000 Euros, so that values are expressed in annual euros based on 2015 Purchasing Power Standard (PPS). Household weights are applied. Standard errors are reported in parentheses. *** Significant at 1% level, **: Significant at 5% level, *: Significant at 10% level.

The estimated utility cost of formal care, relative to informal care, is substantial and statistically significant, especially in the high-cost country group. This reflects strong disutility or stigma associated with institutional care, consistent with its relatively low prevalence in the data. Monetary costs is also positively associated with utility costs of caregiving, which is statistically significant at 1% level. As expected, this indicates that both formal and informal care decisions are sensitive to financial considerations.

Among child characteristics, daughters are significantly more likely to provide care: being a daughter reduces the utility cost by 0.65 units, significant at the 1% level. Having a partner increases the utility cost of caregiving, significant at the 5% level, possibly reflecting competing responsibilities that limit informal care to ones own parents. Other characteristics, including non-biological status, birth order, and the number of ones own children, are estimated imprecisely.

Our estimates also imply that idiosyncratic preference heterogeneity is substantial in shaping caregiving choices. A one-standard deviation preference shock ($1.28 \equiv \sqrt{\pi^2/6}$) exerts about twice the effect of being a daughter and is equivalent to approximately 13,000 Euro in monetary costs.

Overall, the results highlight the importance of both economic incentives and family structure in caregiving decisions. While monetary cost is an important factor, child's gender and partner status remain strong predictors of informal care provision.

Sensitivity Checks to Distance: A potential concern in our setting is that the distance between parents and children may be endogenous to caregiving decisions. Families might strategically choose residential locations based on anticipated care needs, and children may relocate in response to emerging parental health shocks. Moreover, in some cases the direction of causality may be reversed: a child may move into the parental household, or close by, precisely because caregiving is already required.

To assess the extent of this concern, we report sensitivity checks that vary how distance enters the model. In Table 3, Column (1) excludes distance entirely, both from the utility specification and from the construction of children's opportunity costs. Column (2) includes distance as a direct covariate in the informal-care utility specification, while leaving the definition of opportunity costs unchanged. Column (3) instead excludes distance as a separate regressor, but incorporates travel time into the opportunity cost of informal care, thereby treating distance as part of the effective labor-market time cost of providing care.

Across the three specifications, the estimated coefficients on our main covariates of interest – such as the being a daughter, child having a partner, and the monetary cost parameter – remain highly stable in sign, magnitude, and statistical significance. For example, the daughter effect is consistently negative and of similar magnitude across Columns (1)-(3), while the monetary cost parameter remains positive and significant. This robustness suggests that any endogeneity in children's location choices does not meaningfully bias the estimated effects of other child characteristics on caregiving decisions.

Table 3: Sensitivity Checks Regarding Distance

Parameter	(1) No Distance	(2) Distance as Control	(3) Distance in Monetary Cost	Units
θ_0: utility cost of FC	2.577***	2.998***	2.738***	utils
	(0.288)	(0.328)	(0.380)	
α: monetary cost	1.286***	1.264***	0.973***	10K Euro/year
	(0.173)	(0.189)	(0.191)	
β: daughter	-0.571***	-0.607***	-0.646***	dummy
	(0.120)	(0.127)	(0.126)	
β: non-biological	-0.414	-0.189	-0.184	dummy
	(0.492)	(0.447)	(0.405)	
β: distance		1.217***		100 km
		(0.262)		
β: has partner	0.381***	0.395**	0.396**	dummy
	(0.148)	(0.165)	(0.165)	
β: first-born	-0.067	-0.064	-0.073	dummy
	(0.113)	(0.123)	(0.122)	
β: num of children	0.090	0.089	0.086	1 child
	(0.056)	(0.057)	(0.057)	
γ: Mid-cost group $\times$ FC	-0.590*	-0.618	-0.387	utils
	(0.354)	(0.422)	(0.433)	
γ: High-cost group $\times$ FC	0.543	0.669	0.890	utils
	(0.394)	(0.486)	(0.547)	

Notes: This table presents parameter estimates from Model 13 based on SHARE data. The sample selection criteria are detailed in Section 2.1. Estimates are scaled such that a positive value corresponds to a higher utility cost (i.e., lower utility) of choosing a given caregiving arrangement. Household weights are applied. Standard errors are reported in parentheses. *** Significant at 1% level, **: Significant at 5% level, *: Significant at 10% level.

We select Column (3) as our preferred specification. Conceptually, incorporating distance into opportunity costs more directly reflects the time-labor trade-off faced by children: time spent traveling to parents reduces available time for market work, just as hours of caregiving do. At the same time, treating distance in this way avoids interpreting geographic proximity as a direct preference shifter, which could be more susceptible to endogeneity. By embedding distance in the opportunity cost measure, we account for its economic implications while minimizing the risk of biased estimates for other parameters.

7 Counterfactuals

In this section, we describe how we carry out counterfactuals and present their results.

Methodology We follow closely the methodology from the literature on discrete-choice models, making adjustments only where needed. In general, we treat the estimated coefficients β as deep, policy-invariant preference parameters and leave them unchanged in the counterfactuals. However, we make changes to the distribution of right-hand-side variables (specifically of the variables p_{bc}, y_{ij}, $dist_{ij}$, $step_{ij}$ and to the numer of children, K, thereby creating matrices $\tilde{\mathbf{X}} \neq \mathbf{X}$).[11] The counterfactuals thus answer the question: How would care choices change if economic and demographic conditions ($\mathbf{X}$) changed, but the preferences underlying choices (β) stay unchanged? Specifically, denote by $\tilde{\mathbf{X}}_{ij}$ the vector of the counterfactual characteristics. We then compute the probability of care outcome $j \in \{0, 1, \ldots, K_i\}$ in family i in the counterfactual as

$$\tilde{P}_{ij} = \frac{\exp(\tilde{\mathbf{X}}'_{ij}\beta)}{\sum_{j=0}^{K} \exp(\tilde{\mathbf{X}}'_{ij}\beta)}. \tag{14}$$

We then aggregate these probabilities over all families. Concretely, to compute the prevalence of option $j = 0$ (formal care) in the population, for example, we

[11] Essentially, in this step we use the observed joint distribution over $\mathbf{X}$ in the baseline as a non-parametric estimate of the joint cdf of regressors. An alternative approach would be to estimate the joint distribution of the regressors parametrically and then to make changes to this distribution, however, this would require to make parametric assumptions on the distribution, which we avoid here.

compute the weighted sum using the household weights, ω_i:[12]

$$FC = \sum_{i=1}^{N_{fam}} \omega_i \tilde{P}_{i0}, \tag{15}$$

where N_{fam} is the number of families in our data.[13] For the counterfactuals that involve only changes to p_{bc}, y_{ij} and $dist_{ij}$, this completely describes our algorithm.

For the remaining counterfactuals (in which K or *step* or both of them change), however, we do resort to simulation. For these counterfactuals, we run $N_{sim} = 1,000$ simulations in which we randomly change K and/or *dist*, but maintaining all *other* variables unchanged. Specifically, we proceed as follows:

K: We delete each child in the sample with probability p_K, where p_K is set such that we obtain the projected number of children in the future (see below).

step: We change each biological child to a step child with probability p_{step} in order to match the prevalence of non-biological children in the future.

For each simulation $n \in \{1, \ldots, N_{sim}\}$, we then calculate the population change in the FC probability as

$$\Delta FC(\Delta, n) = \frac{1}{N_{fam}} \big[\sum_{i=1}^{N_{fam}} \hat{P}_{i0}(\Delta, n) - P_{i0} \big], \tag{16}$$

where P_{i0} is the predicted FC probability of family i in the baseline estimation and where $\hat{P}_{i0}(\Delta, n)$ is the FC prob. of i in counterfactual Δ in simulation n, which we calculate using (14). Finally, to obtain the predicted change in FC

[12] In practice, household weight ω_i is obtained by normalizing the raw weight w_i: $\omega_i = \frac{w_i}{\sum_{m=1}^{N_{fam}} w_m}$.

[13] Note here that this prediction is preferable to drawing preference shocks for all children, since the logit formula (14) removes sampling noise. Indeed, $\tilde{P}_{i0}$ is the frequency with which family i would choose formal care if we drew an infinite amount of shocks.

from counterfactual Δ, we average over the N_{sim} simulations to obtain

$$\Delta FC(\Delta) = \frac{1}{N_{sim}} \sum_{n=1}^{N_{sim}} \Delta FC(\Delta, n). \tag{17}$$

7.1 Transplanting LTC systems

We begin by running a set of policy counterfactuals to examine how caregiving arrangements would change under more or less generous government provision of formal care. We base our analysis on the country classification by affordability of formal care for median-income households, as documented in Section 2.1 and Appendix A.3. Specifically, the groups are defined as follows:

- Low-FC-cost: Sweden, Germany, Ireland, Netherlands, Luxembourg
- Middle-FC-cost: Denmark, Slovenia, Belgium, Austria, Italy
- High-FC-cost: Spain, Czechia, Croatia, Estonia, France, Greece, Poland

For each country group, we assign counterfactual formal care prices. Recall that the "share" (ρ) of out-of-pocket formal care costs relative to old-age disposable income varies across countries and income groups (below the 20th percentile, between the 20th and 80th percentiles, and above the 80th percentile). For tractability, we take the midpoint value of ρ for each country–income group pair to construct the counterfactual shares. These assignments are reported in Table 4. We denote by $\boldsymbol{\rho}_{low}$ the vector of midpoint share values in the low-FC-cost regime, $\boldsymbol{\rho}_{middle}$ in the middle-FC-cost regime, and $\boldsymbol{\rho}_{high}$ in the high-FC-cost regime.

Table 4: Summary of income-dependent counterfactual shares for FC costs

	ρ by income percentiles		
Group	Below p20	p20-p80	Above p80
Low-FC-cost	0.4	0.36	0.34
Middle-FC-cost	0.73	0.76	0.66
High-FC-cost	1.14	1.14	0.80

Notes: This table reports the midpoint value of the share (ρ) of out-of-pocket formal care costs relative to old-age disposable income, by country group and income group. The midpoint is defined as the average of the minimum and maximum shares within each country group and income group. “Below p20” refers to households below the 20th percentile of old-age disposable income in each country. “p20–p80” refers to households between the 20th and 80th percentiles. “Above p80” refers to households above the 80th percentile.

In the counterfactuals, we explore the impact of applying the ratio $\{\boldsymbol{\rho}_i\}$ of each country group $i \in \{Low, Middle, High\}$ to all other country groups, essentially "transplanting" LTC systems across groups. Table 5 summarizes the results.

Table 5: Formal-care usage when transplanting LTC systems

	Policy		
Region	$\boldsymbol{\rho}_{low}$	$\boldsymbol{\rho}_{middle}$	$\boldsymbol{\rho}_{high}$
Low-FC-cost	12.0%	8.9%	6.8%
Middle-FC-cost	11.3%	8.2%	6.2%
High-FC-cost	3.7%	2.7%	2.1%

Notes: Generosity of LTC system (ρ varies by column. Rows show formal-care usage for each region under the three policies.

We highlight here the left column, i.e. the formal-care usage that our model would predict if countries adopted the policies in the most generous countries (Low-FC-cost). We then compare this counterfactual to the status quo (the numbers on the diagonal). The model predicts that formal-care use would increase by 37.8% (=(11.3-8.2)/8.2) in the Middle-FC-cost countries, while it would increase by 76.2% (=(3.7-2.1)/2.1) in the High-FC-cost countries. This would require a substantial increase in the supply of nursing homes and/or formal home care, underscoring the critical role of formal care subsidies in driving formal care utilization.

It is interesting to ask here how much the inclusion of preference heterogeneity matters for the response of formal-care use (i.e. the price elasticity of FC) that we identify. To do so, we also estimate a *no-heterogeneity* (or "pure-economics") version of our model in which we shut down preference heterogeneity (both idiosyncratic shocks and the systematic variation in psychic informal-care costs in observables); in this alternative model, families only decide based on the effective cost of care (p_{bc}) and the opportunity costs that children face (y_{ij}), facing a *uniform* (non-idiosyncratic) disutility from formal care that we estimate to match observed FC rates. Table 6 reports the elasticity of FC use in the two models. As the point of departure, we choose $\rho_{low} = 0.49$ such that both models feature realistic levels of FC usage; we then increment the effective nursing-home costs by 20% to $\rho_{high} = 1.2\rho_{low}$. The elasticity in the no-heterogeneity model is more than twice as large as in the baseline model, indicating that accounting for preference heterogeneity in caregiving is essential for obtaining realistic elasticity estimates.

Table 6: Elasticity of formal-care usage: baseline vs. no-heterogeneity model

Model	$\rho_{low} = 0.49$	$\rho_{high} = (1 + 0.2)\rho_{low}$	**elasticity**
baseline	7.66%	7.05%	**-0.45**
no heter.	7.66%	6.25%	**-1.12**

7.2 Forecasting counterfactual: Europe in 2050

In a second set of counterfactuals, we ask how demographic and societal changes will affect care choices in the long run. Based on available forecasts for 2050, we model four broad trends:

- **Population aging** (K) will lead to a lower number of potential child caregivers. To simulate this change, we delete each child in the sample with prob. $p_K = (K - \hat{K})/K$, where $K = 2.24$ is the avg. number of potential caregivers per elderly in 2010 and $\hat{K} = 1.25$ is the number of potential caregivers per elderly forecasted for 2050. We obtain these numbers as the ratio of 45-to-65-year-olds over 70-to-90-year-olds in the EU27 from Eurostat.

- **Changes in female labor-force attachment** (y_{ij}) will increase children's opportunity cost of caregiving and thus increase formal-care use. For the gender-wage gap, Eurostat data for the year 2010(?) tell us that the gender-wage gap in the EU27(?) was 14.3%. In our SHARE data, the gap is 17.4%. Averaging the two, we obtain a gender-wage gap of 16%. For the counterfactual, we make the optimistic assumption that this gap closes by 2050 and increment all female wages to $\tilde{y}_{ij} = 1.16y_{ij}$, which we see as an upper bound on effects through this channel.

- **Changing family structures** (*step*) will lead to a lower supply of informal caregivers. To reflect this change, we convert each biological child in the baseline to a step child with probability $p_{step} = 1.1$.[14]

- **Higher mobility** (*dist*) of children will decrease informal-care supply. Again, it is hard to find forecasts for mobility of children. To identify a quantitatively reasonable factor by which the distance of children to parents may increase, we use SHARE data to estimate how the distance child-parent currently varies between low- and high-mobility countries. We obtain a factor 1.8 between Northern and Southern countries and thus set $\tilde{dist}_{ij} = 1.8dist_{ij}$ in the counterfactual.[15]

Table 7 shows how formal-care usage increases when introducing the four changes sequentially. Comparing first the column "total" with "baseline", we see that the model predicts a very large increase in FC: about three-fold in the North, four-fold in the Middle, and five-fold in the East. When looking at the separate contributions of the distinct changes in the environment, we

[14]We could not obtain direct measures on the number of non-biological children in European families. Eurostat reports that the number of single-parent families increased by 3.6% in the period 2005-2030 (Eurostat). Extrapolating to 2050 we use the factor 10%, which we see as an upper bound.

[15]Specifically, in SHARE's Wave 2, we observe that 80% (60%) of children lived $\leq$25km ($\leq$50km) away from parents in Southern countries, while these numbers were 50% (30%) in Northern countries. Averaging over the two (and assuming that Northerners' distances are a multiple of Southerner's across the distribution), we obtain a ratio North-South of $1.8 = (80/50 + 60/30)/2$.

see that the decrease in the number of children is essentially the sole driver of this result (this result is independent of the order in which introduce the four changes). The change in female wages and in family structures play relatively minor roles, and the change in family structures has almost nil effects. Finally, the last column shows how much higher FC use would be if, additionally, all countries implemented Northern policies, showing a modest increase compared. This exercise thus suggests that the raw demographic forces at play will have stronger effects on care choices than policy changes. These results are still preliminary at this stage and should be interpreted with caution.

Table 7: Formal-care use in counterfactual *Europe in 2050*

Region	baseline	#kids↓	$y_{fem}\uparrow$	step↑	distance↑ **(total)**	$+\rho_{low}$
Low-cost	13.2%	38.8%	39.8%	39.6%	43.3%	42.3%
Middle-cost	8.3%	33.4%	34.0%	33.8%	37.2%	39.9%
High-cost	2.6%	27.4%	27.8%	27.8%	31.0%	32.9%

Table presents % of families opting for formal care, switching on changes to environment sequentially (i.e.#kids changes only number of children with respect to baseline, column $y_{fem}\uparrow$ shows counterfactual with a change in number of children and change in female wage etc.) Column in bold (with "total") shows counterfactual with our forecast for 2050, where all four changes are swtiched on. Last column additionally sets $\rho = \rho_{North}$ for all countries.

8 Conclusion

In this paper, we study how families' caregiving arrangements for elderly parents would change in response to policy changes and demographic shifts. Importantly, we account for preference heterogeneity in providing care that differs across families. To this end, we build a model where parents and children bargain on care choices, incorporating both preference heterogeneity in caregiving mode and differences in formal care policies across countries. Our model enables us to estimate how children's characteristics affect their psychic cost of providing informal care and to predict how families' caregiving arrangements respond to various policy counterfactuals and predicted demographic shifts.

Our findings highlight that accounting for preference heterogeneity is crucial for better understanding families' caregiving decisions and for making realistic prediction about future caregiving arrangements. We show that there exists substantial heterogeneity in caregiving preferences, based on child's gender, distance from parents, and unobserved factors that cannot be explained by economic incentives. Our counterfactual exercises show that if we do not account for this preference heterogeneity, we would substantially overestimate the elasticity of formal care usage in response to policy changes. Furthermore, our model predicts that demographic changes, particularly the declining number of children due to decreasing fertility rates and marriage rates, would play a bigger role in increasing the demand for formal care compared to the impact of more generous subsidies for formal care. However, we emphasize that our current results are preliminary, as we currently do not have detailed measures of formal care costs due to a lack of available data.

We conclude by discussing the future steps for our paper. First, we plan to construct better measures for formal care costs by country and by care needs. Second, we aim to construct more granular measures of the potential wage for each SHARE child by using Eurostat microdata. We also plan to examine how measurement errors in potential wages affect our estimates. Third, we will include the non-baseline sample of SHARE survey in our estimation, after addressing data issues documented in Section 2.1. Finally, we plan to embed the cooperative siblings model into the multi-generational life-cycle model that would allow us to better predict the evolution of caregiving arrangements in an aging population.

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A Appendix

A.1 Additional information on SHARE

A.1.1 SHARE waves

For the current analyses, we only use the *baseline* surveys due to several issues with the non-baseline surveys. Note that baseline sample includes households that participated in SHARE for the first time in each wave.

The first issue regarding non-baseline surveys is about the distance between the child and the parent. Although the distance is reported for baseline surveys, it is updated in later surveys *only if* the child moves. Distance is *not* updated when the parent moves, making it difficult to capture the correct distance information in non-baseline surveys. The second issue is regarding tracking the same child over time. Child's index does not remain the same across different waves, especially when the respondent for the child module changes over time.

Furthermore, we do not use Waves 3, 4, and 7 in the current analyses for the following reasons. Waves 3 and 7 differ from other waves in that they are retrospective: they focus on respondents' life histories, not respondents' current life circumstances. Wave 4 is omitted because we cannot identify *which* child provided informal care. This is different from other waves where it is possible to identify the identities of the child caregivers through explicit questions in the Social Support (SP) module. In contrast, in Wave 4, the SP module only asks whether any child provided care, without specifying which one, thus preventing accurate identification of the caregiving child.[16]

For the record, Appendix Table A1 compares the sample size between the full sample and baseline sample for each wave. Note that these counts are before

[16] One way to infer the identity of the child caregiver in Wave 4 is to use the social network (SN) module. In Wave 4, the SP module asks whether parents received informal care from "social network" person, which is defined in the SN module. This "social network" person can be one of the respondent's children. Specifically, SN module documents (i) whether the social network person is a child, (ii) gender of the social network person, and (iii) distance between the respondent and the social network person. However, the caveat is that even the SN module in Wave 4 does not tell us *which* child is reported as a social network person. We can only infer his/her identity by matching the gender and distance information to children's information. Note that this may lead to imprecise matching if the household has multiple children of same gender and distance.

applying any of our sample selection criteria. Further note that the reported sample sizes are not at the household level; it includes both respondents and their spouses.

Table A1: # of Respondents and Spouses, Full sample vs. baseline sample, SHARE

Wave	**Full**	**Baseline**	**Note**
1	30,419	30,419	
2	37,143	14,405	
3	28,463		Retrospective survey
4	58,000	36,717	No variable regarding the identity of child caregiver
5	66,065	21,356	
6	68,085	10,769	
7	77,202		Retrospective survey
8	46,733	9,349	Baseline sample was added in Wave 7 (retrospective survey), but these respondents participated in the regular survey for the first time in Wave 8
Total	383,647	123,015	

Note: This table reports sample size for respondents and spouses for each wave in SHARE. "Full" column shows the sample size for *all* respondents and their spouses. "Baseline" column shows the sample size for respondents and spouses who participated in SHARE for the first time in the corresponding wave. These are raw counts before applying any sample selection criterion.

A.1.2 Defining care needs and types of care using SHARE

We describe how we define care needs, formal care, and intense informal care. In the current analyses, the elderly with "care needs" are defined using a question in the Physical Health (PH) module that asks how many mobility limitations each respondent has (**ph048***). We characterize "need for care" if the respondent reports having at least one mobility limitation.

In the current analyses, formal care is defined as permanently staying in a nursing home (NH). We exclude temporary nursing home care. In future analyses, we plan to include formal home care (FHC) – which is care provided by paid helpers in the elderly's home. Barczyk & Kredler (2019) report that a larger portion of formal care in Europe is provided as NH than as FHC.

Intense informal care (IC) by children is defined using the frequency of informal care. SHARE differentiates between informal care from outside the household (OIC), e.g. from adult children living elsewhere, and informal care from inside the household (IIC), e.g. from the spouse or co-residing children. How OIC and IIC are reported and the associated care frequencies differ across waves, as summarized in Table A2.

Table A2: Overview of Informal care (IC) variables in SHARE

	Informal care from outside hh. (OIC)	Informal care from inside hh. (IIC)
Wave 1	*Level:* Couple *Frequency:* 4 categories *Type:* Specified	*Level:* Individual *Frequency:* Defined as daily
Wave 2	*Level:* Couple *Frequency:* 4 categories *Type:* Specified	*Level:* Individual *Frequency:* Defined as daily
Wave 5	*Level:* Couple *Frequency:* 4 categories *Type:* NOT specified	*Level:* Individual *Frequency:* Defined as daily
Wave 6	*Level:* Individual *Frequency:* 4 categories *Type:* Specified	*Level:* Individual *Frequency:* Defined as daily
Wave 8	*Level:* Individual *Frequency:* 4 categories *Type:* Specified	*Level:* Individual *Frequency:* Defined as daily

Note: This table reports which information on informal care is available in SHARE for each wave and type of informal care. *Level:* whether the IC is reported at the couple level or at the individual level. *Frequency:* How the frequency of specified care is reported. 4 categories refer to (i) about daily, (ii) about every week, (iii) about every month, and (iv) less often. *Type:* refers to the types of OIC care provided, which has 3 categories (personal care, practical household help, and help with paperwork). Note that Waves 3, 4, 7 are not reported because Waves 3 and 7 are retrospective surveys and Wave 4 does not report the identity of child caregiver.

There are a few challenges in defining intense IC consistently across waves. First, in the earlier waves, OIC is reported at the couple level, not at the individual level; in other words, we only know if the respondent *and/or* the spouse received OIC, but not *who* received OIC. In the current analyses, the care need and care is defined at the *couple* level, so this does not pose a problem.[17] However, if we want to do future analyses at the individual parent level, then we would need to identify which of the parents received OIC. Second, the type of OIC (personal care, practical household help, and help with paperwork) is not reported in Wave 5. While this information is useful in determining intense IC, we decide not to distinguish among the types of OIC for consistency across waves.[18] Lastly, only about 21% of OIC by child occurs "about daily," as shown in Appendix Table A3. To increase the sample size, we define both "about daily" and "about every week" OIC as intense informal care. Additionally, we classify all IIC as intense informal care, since by definition in the SHARE survey, IIC occurs on an almost daily basis.

Table A3: Distribution of OIC and IIC intensity, Sick elderly aged 65+ with child aged 20-60, Baseline SHARE

Outside-HH IC		Inside-HH IC	
Intensity	Frequency	Status	Frequency
None	43,120	No	48,461
Daily	1,206	Yes	465
Weekly	2,043		
Monthly	1,232		
Less Often	1,124		
Total	48,725	Total	48,926

Note: This table reports the distribution of the intensity for outside-household informal care (OIC) by children, and inside-household informal care (IIC) status. The sample includes paren-child observations where parent has at least one mobility limitation and is aged 65+ and child is aged 20-60. Note that IIC is defined to happen almost daily by definition.

[17] Specifically, our definition of child caregiver is the child who provided IC to any of the parents.

[18] Only about 10% of caregivers only provided help with paperwork, which can be considered as a light care. Hence, the majority of reported OIC can be considered as substantial care (personal care, household help).

A.1.3 SHARE sample selection

Table A4: Number of parent-child pairs after applying selection criteria, Baseline SHARE only

		After applying each sample selection criterion, subsequently					
	None	1. Sick elderly aged 65+	2. Has child(ren) aged 20-60	3. Either NH or one IC child	4. Matched with FC and wage	5. No missing X vars	6. Convert to (hh, child)-level
Count	194,860	55,255	49,013	6,465	5,262	4,684	4,120

Table A4 shows how the sample size changes after applying each of the sample selection criteria. Note that these counts are at the parent-child level, not at the household level. Column “1. Sick elderly aged 65+" shows that the sample size substantially decreases after limiting to respondents and their spouses who report having at least one mobility limitation and are aged 65+. Column “3. Either NH or one IC child" reports sample size after limiting to elderly who either (i) are in nursing home care or (ii) have one caregiving child. This selection criteria further reduces the sample size by a large margin.

In fact, Table A5 shows that most parents with at least one mobility limitation does not get formal care or is cared by any of their children. Specifically, 84% of parents aged 65+ with at least one mobility limitation are not cared for by any of their children, and 99% of such parents are not in nursing home care. In future analyses, we will examine whether these individuals are cared for by their spouses or if altering the definition of "care need" affects the frequencies of informal and formal care.

After imposing additional sample criteria as shown in Table A4, we have a final sample size of 4,120 household-child pairs and 1,829 households.

Table A5: Distribution of IC and FC for parent-child pairs, Sick elderly aged 65+ with child aged 20-60, Baseline SHARE

Informal Care		Formal Care	
Number of IC children	Frequency	NH status	Frequency
0	41,236	No	48,533
1	5,640	Yes	480
2	1,638		
3	478		
4	21		
Total	49,013	Total	49,013

Note: This table reports the distribution of number of caregiving children and formal care. The sample includes parent-child observations where parent has at least one mobility limitation and is aged 65+ and child is aged 20-60. Informal care by child is defined to be either within-household IC or outside-household IC that happens at least weekly.

A.1.4 Notes on Children (CH) module

In this section, we outline the details of the Children (CH) module of SHARE that complicate the data cleaning process.

1. Only one spouse answers questions in the CH module
As a result, children's information is missing for non-responding spouses in each wave. We need to import children's information for non-responding spouses from the responses of the responding spouses. The respondent for the CH module can change over the panel.

2. Many questions are not asked again from one wave to another if the responses are the same
Information including the child's distance from parent and education are not asked again in the subsequent waves if the responses have not changed. Child's distance is recorded again if child moves, but not when parent moves. This complicates measuring the current distance between parents and children in non-baseline surveys.

3. Children may not have same index across different waves.
For instance, Child 1 in wave 1 may be listed as Child 3 in wave 4. This complicates the data cleaning process, especially since many questions are not repeated in subsequent waves. To track the same child across waves, we need to rely on the child's gender and year of birth. However, in cases involving twins, accurately tracking the same child over time may not be possible.

4. In waves 1 and 2, some information are only recorded up to 4 children
Characteristics like child's education, stepchild status, and employment are recorded only up to 4 children in waves 1 and 2. For subsequent waves, these characteristics are recorded for all children. Hence, for waves 1 and 2, we have missing information for children for households with more than 4 children. Furthermore, these 4 children are not necessarily child indexed 1, 2, 3, 4. Hence, it is crucial to carefully check which child's information is being recorded in waves 1 and 2.

The above four points are the main challenges regarding the CH module. In addition to these points, there are minor challenges including the reported number of children being different from the number of children's characteristics, etc. It is crucial to check each variable carefully in the data cleaning process.

A.1.5 Notes on Social Support (SP) module

In this section, we outline the details of the Social Support (SP) module of SHARE that complicate the data cleaning process.

1. The questions about informal care differ across waves
Waves 1, 2, and 5 share a similar format of questions regarding informal care, while waves 6 and 8 also follow a similar format. Unlike other waves, wave 4 does not have any questions that identify *which* child provided informal care.

2. There are different sets of questions for caregiver within the household and outside the household
See Table A2 to check which questions are available for each wave.

3. Some families do not correctly report OIC and IIC caregiving children.
For example, some families report the same child for different OIC caregivers (which can be reported up to 3 caregivers). Furthermore, some families report same child as being both OIC and IIC caregiver.

A.2 Potential income

We construct the potential income for each child based on their demographic characteristics and the local labor market conditions. Specifically, we assign the potential annual income to each child based on the child's gender, education, and country of residence for each survey year. Income data is sourced from Eurostat's Structure of Earnings Survey for the years 2006, 2010, 2014, and 2018. Specifically, we use "mean hourly earnings by economic activity, sex, education attainment level" and "number of employees by economic activity, sex, educational attainment level." We exclude 2002 Eurostat data due to its lack of information for many countries in SHARE, primarily because many of the current EU countries joined the EU after 2004. To address differing prices across countries, we use the Purchasing Power Standard (PPS) instead of Euro. PPS is a common currency that adjusts national account aggregates for price level differences using Purchasing Power Parities (PPPs). We convert the hourly earnings to potential annual incomes by multiplying them by 40 hours per week and 52 weeks per year.

We construct two versions of potential wages. The first version does not consider the labor force participation rates of different social groups, while the second version incorporates these participation rates. The rationale behind incorporating participation rates in the second version is to address the overestimation of potential income, particularly for social groups with lower labor force participation, such as women. If individuals in these groups are unlikely to participate in the labor force even when not providing informal care, it is crucial to account for this in their potential income estimates.

Specifically, we adjust the first version of potential wage to account for the labor force participation as follows. Let $PotentialWage_{gecy}$ denote the first version potential wage for gender g, education e, country c, and year y. The second version of potential wage is constructed as follows:

$$\begin{aligned} PotentialWage_{gecy}^{Adjusted} &= LFPR_{gcy} * PotentialWage_{gecy} \\ &+ (1 - LFPR_{gcy}) * \frac{1}{2}(MinimumWage_{gcy}) \end{aligned}$$

where $LFPR_{gcy}$ is the labor force participation rate of gender g in country c in year y, and $MinimumWage_{gcy}$ is the minimum wage for gender g in country c in year y. The idea is to weight the potential wage by the labor force participation rate. We assume that for individuals participating in the labor force, the potential wage is the full amount derived in the first version. For those not in the labor force, we assume that their potential wage is the half of the country's minimum wage.

For the current analysis, $LFPR_{gcy}$ is based on the labor force participation rate of people aged 45-65 in each gender and country group for each year. The reason why we chose this age range is because approximately 75% of caregiving children in our SHARE sample are over age 45, as shown in Appendix Figure **??**. Due to the limitations of the available data, we currently cannot further refine potential wages by age group or differentiate labor force participation rates by education level.[19] We plan to update our potential wage estimates once we gain access to the Eurostat microdata.

Appendix A.2.1 documents imputation strategies for potential wage construction. These strategies address several challenges, including (a) missing wage information for some years in Eurostat, (b) changes in educational classifications over time in Eurostat, and (c) differing survey years between SHARE and Eurostat.

A.2.1 Additional details on potential wage construction

Recall that our goal is to construct the potential income for each SHARE child based on country, gender, education, and year. To this end, we need imputation strategies to address several challenges. Below, we describe the challenges and the strategies to address them.

1. Dealing with inconsistent education categories: First, education categories differ across survey years in Eurostat, as shown in Table A6. For consistency, we need to construct synchronized educational categories that are consistent across years.

[19] The public version of Eurostat data does not provide labor-related statistics categorized by age, education, gender, and country.

Table A6: Education Categories, Eurostat's Structure of Earnings Survey

Survey Year	Classification	Education Categories
2006	ISCED 1997	Levels 0-1, Level 2, Level 3-4, Level 5A, Level 5B, Level 6
2010	ISCED 1997	Levels 0-1, Level 2, Level 3-4, Level 5A, Level 5B, Level 6
2014	ISCED 2011	Levels 0-2, Levels 3-4, Levels 5-6, Levels 7-8
2018	ISCED 2011	Levels 0-2, Levels 3-4, Levels 5-8

Note: This table reports educational categories in Eurostat's structure of earnings survey for each year. For more information about what each category means and how to map between ISCED 1997 and ISCED 2011, click [ILO link].

We construct the potential income for synchronized education categories based on the broadest education categorization – which is in survey year 2018. Specifically, the synchronized education categories have 3 levels: (1) ISCED 2011 Levels 0-2: Less than lower secondary education, (2) ISCED 2011 Levels 3-4: Upper secondary and post-secondary non-tertiary education, (3) ISCED 2011 Levels 5-8: College education or more. The mapping between ISCED 1997 and 2011 is done using the ILO classification [ILO link].

To construct wages based on the synchronized education categories, we calculate weighted averages of multiple sub-categories as needed. As a demonstration, consider the survey year 2014. We need to combine gender wages for Levels 5-6 and Levels 7-8 to create the gender wages for the synchronized category Levels 5-8. How we combine is by taking the weighted average, where the weights are the share of workers in each education category relative to the total number of workers for the combined categories. Specifically, for each gender g and country c, the weighted average for education levels 5-8 in year 2014 is calculated as follows:

$$\begin{aligned} Wage_{g,\ c,\ year=2014,\ edu=5-8} = {} & \underbrace{\left(\frac{NumEmployees_{g,\ c,\ year=2014,\ edu=5-6}}{NumEmployees_{g,\ c,\ year=2014,\ edu=5-8}}\right)}_{\text{Weight for level 5-6}} Wage_{g,\ c,\ year=2014,\ edu=5-6} \\ & + \underbrace{\left(\frac{NumEmployees_{g,\ c,\ year=2014,\ edu=7-8}}{NumEmployees_{g,\ c,\ year=2014,\ edu=5-8}}\right)}_{\text{Weight for level 7-8}} Wage_{g,\ c,\ year=2014,\ edu=7-8} \end{aligned}$$

The synchronization procedure is similarly applied to other education categories and survey years.

2. Dealing with missing wages: To apply the synchronization procedure above, ideally, the data should have full information about wages for each gender, education category, country, and year. However, Eurostat data lacks wage information for some cells in year 2006 and 2010. For years 2014 and 2018, we have full information on wages. We document our imputation strategies for the missing wages for several cases:

- **Case 1:** Only one of female or male wages is missing for country c, education e, and year y

  To demonstrate, consider a scenario where only the female wage is missing. In this case, we impute the female wage using the male wage and the total wage. We assume that the total wage is the weighted average of male wage and female wage:

  $$\begin{aligned} TotalWage_{c,y,e} = &\left(\frac{MaleEmployees_{c,y,e}}{TotalEmployees_{c,y,e}}\right) MaleWage_{c,y,e} \\ &+ \left(\frac{FemaleEmployees_{c,y,e}}{TotalEmployees_{c,y,e}}\right) FemaleWage_{c,y,e} \end{aligned}$$

  When $FemaleEmployees_{c,y,e}$ is missing, we impute this using the following assumption:

  $MaleEmployees_{c,y,e} + FemaleEmployees_{c,y,e} = TotalEmployees_{c,y,e}$.

  Once we impute $FemaleEmployees_{c,y,e}$, we can impute $FemaleWage_{c,y,e}$ using the above formula. Imputation for cases where only the male wage is missing is performed similarly.

- **Case 2:** Both female and male wages are missing for country c, education e, and year y

  In these cases, we impute missing wages using information on other years. For example, let's consider that country c has missing gender wages for education e for the year 2010, but not for the year 2006. We impute the missing wages in 2010 using the following formula:

$$\underbrace{GenderWage_{c,y=2010,e}}_{Imputed} = GrowthGenderWage_{c=EU,e}^{2006-2010} \underbrace{GenderWage_{c,y=2006,e}}_{Observed} \tag{18}$$

where $GrowthGenderWage_{c=EU,e}^{2006-2010}$ is the gender wage growth rate between 2006 and 2010 for education e at the EU-level. Note that there is no wage information at the EU-level.

The cases where only wages for 2006 are missing, but not for year 2010, imputation is done similarly. For the cases where both wages for 2006 and 2010 are missing, we address the issue in the next step.

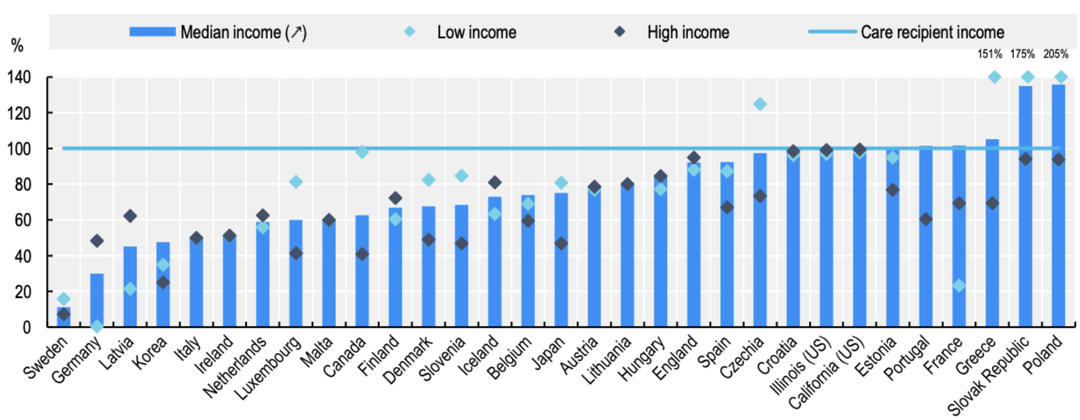
3. Dealing with non-existing years in Eurostat: For missing years in Eurostat, we linearly interpolate and extrapolate potential wages for each gender g, education e, and country c to fill wage information for all years between 2004 and 2018. Note that for cases where gender wages are missing for both 2006 and 2010, the interpolation/extrapolation procedures also fill these gaps using wage information from 2014 and 2018, which are available for all cases.

A.3 Details on formal care cost construction

We construct formal care costs that each SHARE household faces. Out-of-pocket formal care costs vary widely depending on country, household income level, and the severity of care needs. We aim to incorporate these factors when assigning the formal care costs to each SHARE household.

We assign out-of-pocket formal care costs based on OECD statistics on institutional (nursing home) care costs (OECD 2024). Specifically, we use their report on "Out-of-pocket costs of long-term care after having received public support as a share of income at each income level" as shown in Appendix Figure A1.

Figure A1: Out-of-pocket costs of long-term institutional care as a share of old-age disposable income after public support



Source: Figure 3.4 of (OECD 2024). OECD analyses based on the Long-Term Care Social Protection questionnaire, the *OECD Income Distribution Database*, and the *OECD Wealth Distribution Database*. Low, median, and high incomes mean the bottom 20th, 50th, and 80th percentiles of net disposable income among individuals aged 65 years and over, respectively. Estimates for Italy is based on the South Tyrol region, which provides more generous support for institutional care.

To construct formal care costs, we follow a three-step procedure. First, we take the out-of-pocket cost shares for institutional care – as a percentage of old-age disposable income – for each SHARE country and income group, as reported in Figure A1. Second, we apply these shares to the 20th, 50th, and

80th percentiles of net disposable income among individuals aged 65 and over, using EU-SILC data by country and year. This yields estimated out-of-pocket nursing home costs for each income group across countries and years. Finally, we assign these estimated costs to SHARE households based on their income group, country, and year. Note that formal care cost data are not available for Switzerland, Bulgaria, Cyprus, and Romania. In addition, because Italys cost share is based on the South Tyrol region – which provides more generous institutional care support – we increase the share by 20% to approximate out-of-pocket costs for the broader Italian population.

Because the SHARE sample size is not large enough to perform country-level analyses, we group SHARE countries into three groups based on the affordability of formal care for median-income households. The country groups are (1) low-cost group (11∼60% of old-age income), (2) medium-cost (60∼90% of old-age income), and (3) high-cost (90∼136% of old-age income). The grouping of countries is as follows:

- Group 1 (Low FC cost): Sweden, Germany, Ireland, Netherlands, Luxembourg
- Group 2 (Medium FC cost): Denmark, Slovenia, Iceland, Belgium, Austria, Italy
- Group 3 (High FC cost): Spain, Czechia, Croatia, Estonia, France, Greece, Poland

A.4 Calculating care needs

A.4.1 Procedures

We estimate each SHARE respondents care needs in terms of daily hours following the approach in (Barczyk & Kredler 2019). A key limitation of SHARE is that most survey waves do not collect information on the number of care hours provided. To address this, we combine data from SHARE and the Health and Retirement Study (HRS), which has a similar structure but differs in that it records the number of care hours associated with each limitation in activities of daily living (ADLs) and instrumental activities of daily living (IADLs) for community residents. This allows us to impute care hours for SHARE respondents based on their reported functional limitations.

Below, we outline the procedures for constructing care needs.

Step 1: *Predict care hours for SHARE respondents using regression estimates from HRS.*

We begin by estimating a regression of care hours on ADL and IADL limitation dummies using data from the 2000-2012 Health and Retirement Study (HRS), which reports care hours for each limitation among community residents receiving informal care. In this regression, we also incorporate data from SHARE Waves 1 and 2 for outside-household informal care (OIC) recipients, the only SHARE respondents for whom care hours are recorded. The estimates are reported in Table A7.

Using the estimated coefficients from this regression, we predict daily care needs (in hours) for all SHARE respondents. This approach relies on the assumption that the relationship between functional limitations and care intensity is comparable across the two surveys. For SHARE community residents who receive informal care but report no ADL/IADL limitations, we assume they have at least one unreported limitation and assign them the minimum observed value of care hours among community residents.

For nursing home residents, care hours are not observed in either SHARE or HRS. As a result, we take additional steps to impute their care needs, as described in Step 2 below.

Table A7: Regression Estimates of Daily Care Hours on ADL/IADL Limitations

	(1) Daily care hours b/se
Dress	0.6314***
	(0.1063)
Walk across a room	0.8542***
	(0.1212)
Bath or shower	1.0251***
	(0.1142)
Eat	1.1331***
	(0.1444)
Get in/out of bed	0.7313***
	(0.1370)
Use the toilet	0.1776
	(0.1374)
Prepare a hot meal	2.1033***
	(0.1169)
Shop for groceries	1.0805***
	(0.0938)
Telephone calls	1.4671***
	(0.1251)
Take medications	2.0236***
	(0.1420)
Manage money	1.3419***
	(0.1071)
Observations	10371

Note: This table presents regression estimates of observed daily care hours on individual ADL/IADL limitations. Each row corresponds to a specific activity for which a limitation is reported. The estimation sample includes community residents with at least one ADL/IADL limitation in the 2000-2012 HRS and outside-household informal care (OIC) recipients in SHARE Waves 1 and 2. Household weights are applied.

Step 2: *Adjust care hours for nursing home residents.*

Because the care needs imputation in Step 1 is based on informal care recipients, the care needs may be underestimated for nursing home residents – who likely have more severe care needs. (Barczyk & Kredler 2019) note that there is negative selection of nursing home residents in terms of health, both in terms of observables (e.g. (I)ADL limitations) and unobservables. This implies that even among individuals with the same observed limitation profile, those with more severe – yet unmeasured – needs are more likely to reside in nursing homes. As a result, controlling for observables alone is insufficient to address this selection problem.

To address the potential negative selection, we use the (Dahl 2002) correction method to adjust care needs for nursing home residents. This method exploits cross-country variation in nursing home usage to account for selection into institutional care. To illustrate, consider the case where the probability of entering a nursing home, $P(NH|\mathbf{X}_{it})$, is relatively low in Italy for individuals with a given level of disability. This likely reflects higher out-of-pocket costs or limited access, meaning that only individuals with the most severe conditions enter nursing homes. As a result, nursing home residents in Italy are more negatively selected on unobserved health than in countries with higher usage rates. Consequently, the adjustment for care needs should be larger in Italy than in other European countries.

To implement the Dahl correction method, we first define an (I)ADL count index (from 0 to 11) that counts the number of (I)ADL limitations. Then, let h_{it} be the care needs of individual i at time t and $\mathbf{X}_{it}$ the vector of eleven dummies that indicate to which of the eleven dependence categories defined by the index a respondent pertains. The correction equation for nursing home hours is:

$$h_{it} = \mathbf{X}_{it}\boldsymbol{\beta} + \mu(P_{it}) + \epsilon_{it} \tag{19}$$

where P_{it} is the probability that individual i is in a nursing home at t (given their IADL count and the region they live in) and $\mu(\cdot)$ is a correction function, which is defined such that $\mu(0) = 0$. Following (Barczyk & Kredler 2019), we opt for linear specification $\mu(P_{it}) = \delta P_{it}$.

To estimate Equation 19, we use the following assumption as used in (Dahl 2002) and (Barczyk & Kredler 2019):

$$E[\epsilon_{it} \mid \mathbf{X}_{it}, \mathbf{Z}_{it}] = 0 \tag{20}$$

where $\mathbf{Z}_{it}$ is a vector of country dummies for Europe (for SHARE) and five regional dummies for the U.S. (for HRS). This assumption states that given a fixed profile of (I)ADL limitation, the population care hours h_{it} have the same mean in all countries (and all regions of the U.S.). This assumption leads to the following identity:

$$
\begin{aligned}
E[\epsilon_{it} \mid \mathbf{X}_{it}, \mathbf{Z}_{it}] &= P(NH \mid \mathbf{X}_{it}, \mathbf{Z}_{it})\, E[\epsilon_{it} \mid \mathbf{X}_{it}, \mathbf{Z}_{it}, NH] \\
&\quad + P(C \mid \mathbf{X}_{it}, \mathbf{Z}_{it})\, E[\epsilon_{it} \mid \mathbf{X}_{it}, \mathbf{Z}_{it}, C] \\
&= 0
\end{aligned} \tag{21}
$$

where C stands for being in the community, and NH being in the nursing home.

Applying Equation 21 to Equation 19 leads to the following specification, which we use to correct care need for nursing home residents in SHARE:

$$\hat{h}_{it}^{NH} = \mathbf{X}_{it}\hat{\beta} - \frac{1-\hat{P}_{it}}{\hat{P}_{it}}\hat{\mu}(\hat{P}_{it}) \tag{22}$$

In practice, we take the following procedures to estimate Equation 22:

- First, we estimate P_{it}, the probability of residing in a nursing home using a probit model:

  $$P(NH_{it} = 1|\mathbf{X}_{it}, \mathbf{Z}_{it}) = \phi(\mathbf{X}_{it}\boldsymbol{\beta} + \mathbf{Z}_{it}\boldsymbol{\gamma})$$

  This yields $\hat{P}_{it}$, the predicted probability of nursing home residence, based on the (I)ADL count index and the region of residence. We estimate this model separately for the HRS and SHARE samples.

- Second, to obtain $\hat{\boldsymbol{\beta}}$ and $\hat{\delta}$, we estimate the following regression using the community residents in HRS, which are the group with complete care hour information:

  $$h_{it} = \mathbf{X}_{it}\boldsymbol{\beta} + \delta\hat{P}_{it} + \varepsilon_{it}$$

  The estimates are reported in Table A8.

- Lastly, using the estimated $\hat{\boldsymbol{\beta}}$ and $\hat{\delta}$ from the previous step, we estimate Equation 22 for nursing home residents in SHARE.

Table A8: Regression estimates of daily care hours (among community residents) on predicted NH probability and the number of ADL/IADL limitations

	(1) Daily care hours b/se
Predicted NH Probability	-4.616
	(3.773)
2 ADL/IADL Limitations	0.716***
	(0.142)
3 ADL/IADL Limitations	1.525***
	(0.184)
4 ADL/IADL Limitations	2.931***
	(0.311)
5 ADL/IADL Limitations	4.129***
	(0.463)
6 ADL/IADL Limitations	5.558***
	(0.553)
7 ADL/IADL Limitations	6.911***
	(0.872)
8 ADL/IADL Limitations	9.089***
	(1.227)
9 ADL/IADL Limitations	10.543***
	(1.444)
10 ADL/IADL Limitations	13.681***
	(1.960)
11 ADL/IADL Limitations	16.209***
	(2.349)
Constant	1.740***
	(0.090)
Observations	8646

Note: This table reports regression estimates of observed daily care hours as a function of the predicted probability of nursing home residence and indicator variables for each level of ADL/IADL limitations. The estimation sample includes community residents with at least one ADL/IADL limitation in the 2000-2012 HRS and outside-household informal care (OIC) recipients in SHARE Waves 1 and 2. Household weights are applied.

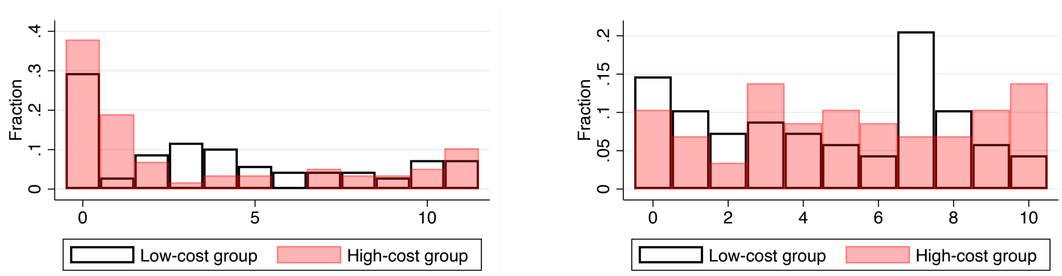
Due to potential data issues in SHAREs ADL/IADL variables, we rely on predicted ADL/IADL measures to estimate care needs for nursing home residents. The procedure is detailed in the following subsection.

A.4.2 Handling data issues in SHARE's ADL/IADL variables

In this section, we discuss anomalies in the ADL/IADL variables for nursing home residents in SHARE and describe the adjustments we make to these variables to predict care needs, as outlined in Section A.4.1.

Figure A2, Panel (a), shows the distribution of ADL/IADL limitations among nursing home residents in our SHARE estimation sample. Notably, there is a spike at zero reported limitations in both the low and high formal care cost country groups, as well as a disproportionately high share of individuals reporting only one limitation in the high-cost group. In contrast, we do not observe spikes in 0 or 1 limitation for mobility limitation variables.

Figure A2: Distribution of health variables among nursing home residents, SHARE estimation sample



(a) ADL/IADL Limitations

(b) Mobility Limitations

Note: This figure presents the distribution of the number of ADL/IADL limitations (Panel (a)) and mobility limitations (Panel (b)) reported by nursing home residents in our SHARE estimation sample. The sample selection criteria are described in Section 2.1. "Low-cost group" refers to the country group with low formal care costs. "High-cost group" refers to the country group with high formal care costs. Table A10 provides definitions of the ADL/IADL and mobility limitation variables used in SHARE.

The disproportionate spikes in reports of 0 or 1 ADL/IADL limitation among nursing home residents in SHARE raise concerns about potential survey errors. This issue becomes more apparent when compared to data from the Health and Retirement Study (HRS). As shown in Table A9, only 3.96% of nursing home residents in HRS report having no ADL/IADL limitations, and just 1.69% report having one. In contrast, the corresponding shares in SHARE

are substantially higher – 31.55% and 9.71%, respectively – suggesting possible underreporting or misclassification in the SHARE data.

Table A9: ADL/IADL distribution, HRS vs SHARE

Num of (I)ADLs	HRS	SHARE
0	3.96%	31.55%
1	1.69%	9.71%
2	2.02%	6.80%
3	2.54%	7.28%
4	4.52%	8.25%
5	6.26%	4.37%
6	5.97%	4.37%
7	7.62%	4.37%
8	8.80%	5.83%
9	10.96%	3.40%
10	17.07%	5.83%
11	28.69%	8.25%
Obs	2126	206

Note: This table reports the percentage of nursing home residents by the number of ADL/IADL limitations reported in HRS and SHARE, respectively. For HRS, we use data from the 2000-2012 survey waves. For SHARE, the tabulation is based on our estimation sample. The sample selection criteria for SHARE are described in Section 2.1.

To address anomalies in SHAREs ADL/IADL variables, we implement a method that predicts each ADL/IADL limitation based on mobility limitations and other health-related variables for nursing home residents who report having 0 or 1 ADL/IADL limitation. Specifically, For each ADL/IADL variable, we estimate a logistic regression model where the binary outcome is whether the individual has the given IADL/IADL limitation. The predictors include (i) indicator for age 75 or older, (ii) indicator for reporting poor health, and (iii) a set of mobility limitation variables. This logistic regression model is estimated only on the SHARE nursing home residents who report at least 2 ADL/IADL problems. The estimates from the logistic regressions are used to predict the probability of having each ADL/IADL condition for nursing home residents who reported 0 or 1 condition – the cases where the original data may be misreported or incomplete.

Table A10: Descriptions of ADL/IADL and Mobility Limitation Variables in SHARE

ADL/IADL		Mobility Limitation	
Variable	Difficulty in:	Variable	Difficulty in:
`ph049d1`	Dressing	`ph048d1`	Walking 100 metres
`ph049d2`	Walking across a room	`ph048d2`	Sitting for about two hours
`ph049d3`	Bathing or showering	`ph048d3`	Getting up from a chair
`ph049d4`	Eating	`ph048d4`	Climbing several flights of stairs
`ph049d5`	Getting in/out of bed	`ph048d5`	Climbing one flight of stairs
`ph049d6`	Using a toilet	`ph048d6`	Stooping, kneeling, or crouching
`ph049d8`	Preparing a hot meal	`ph048d7`	Extending arms above shoulder
`ph049d9`	Shopping for groceries	`ph048d8`	Pulling or pushing large objects
`ph049d10`	Making telephone calls	`ph048d9`	Lifting or carrying weights (10+ pounds)
`ph049d11`	Taking medications	`ph048d10`	Picking up a small coin
`ph049d13`	Managing money		

Note: This table describes the variables related to ADL/IADL and mobility limitations in SHARE. Each item is recorded as a binary response: “Yes" or “No."

A.5 Calculating Commuting Costs

In this section, we describe how we specify the commuting costs of children. As introduced in Section 3, the opportunity cost of each child j in family i is given by:

$$OC_{ij} = \Big[n_i + t_d(d_{ij})\Big]w_{ij} + c_d(d_{ij})$$

where n_i denotes hours needed spent on caregiving for parents, d_{ij} is the distance between child j and her parent, $t_d(d_{ij})$ represents commuting time over distance d_{ij}, $c_d(d_{ij})$ captures the direct travel costs for distance d_{ij}, and w_{ij} is the hourly wage rate.

The assignment of daily commuting time (one-way) by distance category is reported in Table A11. We assume car travel for all distances except those exceeding 500 km, for which we assume air travel. To compute the daily commuting time $t_d(d_{ij})$, we take the midpoint of the one-way travel time for each distance category and multiply it by two, assuming that the child commutes to the parent's residence daily.

The assignment of daily direct travel costs (one-way) is reported in Table A12. The daily monetary cost of travel, $c_d(d_{ij})$, is calculated by doubling the approximate one-way travel cost.

Although OC_{ij} is defined in terms of hourly wages w_{ij}, we only observe the annual potential wage for each child j. We therefore express OC_{ij} in annual terms. Specifically, we use y_{ij}, the child's annual potential wage, and weight it by the *time weight*, which combines daily care hours needed and commuting time:

$$\text{Time weight} = \frac{(\text{care hours needed}) + t_d(d_{ij})}{12 \text{ hours}}$$

For direct travel costs, we similarly convert to an annual measure by multiplying $c_d(d_{ij})$ by 365, under the assumption that the informal care provider commutes to the parent's residence daily.

Table A11: Approximate travel time by distance category in Europe

Distance Range	**Approx. Travel Time (one-way)**	**Notes**
$<$ 1 km	3–5 minutes (car)	Urban traffic, stoplights, parking time dominate
1–5 km	5–15 minutes (car)	City traffic can vary, $\sim$20–30 km/h average speed
5–25 km	15–35 minutes (car)	Suburban/rural roads or urban highways ($\sim$40–60 km/h average)
25–100 km	30 minutes – 1.5 hours (car)	Mostly highway or rural roads ($\sim$70–100 km/h average)
100–500 km	1.5 – 6 hours (car)	Highways; traffic and tolls add variation ($\sim$80–110 km/h average)
$>$ 500 km (by car)	6–10+ hours (car)	Depends on country and traffic; overnight or rest stops likely needed
$>$ 500 km (by air)	1–3 hours (flight) + 2–3 hours prep	Short-haul EU flights; includes check-in, boarding, and airport travel

Table A12: Approximate (one-way) monetary travel costs by distance category in 2015 Euros

Distance Range	**Travel Mode**	**Approximate Cost**	**Notes**
$<$ 1 km	Car	0	No cost due to short distance.
1–5 km	Car	0	No cost due to short distance.
5–25 km	Car	EUR 2.25	Urban/suburban driving conditions.
25–100 km	Car	EUR 9.02	Longer trips; potential for better fuel efficiency on highways.
100–500 km	Car	EUR 45.08	Significant travel; consider rest stops.
$>$ 500 km (by car)	Car	EUR 90.16	Long-distance driving; fatigue and accommodation costs may arise.
$>$ 500 km (by air)	Airplane	EUR 20.69 – 80+ (Assumed to be 80 Euro)	Low-cost carriers offer competitive rates; prices vary by route and timing.

A.6 Estimation: Details

In a deterministic setting family i chooses $j^* = \arg\min_{j \in \mathcal{C}_i} C_{ij}$, where the choice set is $\mathcal{C}_i = \{0, 1, 2, \ldots, K_i\}$. Each alternative has deterministic total cost:

$$C_{ij} = \begin{cases} p_i^{bc} + \theta_0, & \text{if } j = 0 \text{ (Formal care)} \\ OC_{ij} + \mathbf{X}_{ij}\boldsymbol{\beta}, & \text{if } j \neq 0,\ j \in K_i \text{ (Informal care)} \end{cases}$$

We specify systematic (observable) heterogeneity in psychic costs among children by $\mathbf{X}_{ij}\boldsymbol{\beta}$, where $\mathbf{X}_{ij}$ are observable attributes of child j in family i (e.g., gender, distance, step-child status) that plausibly correlate with the propensity to provide care.[20]

To account for unobserved preference variation we embed our theoretical implications in a random-utility model. Specifically, parents differ in their psychic cost of receiving FC due to unobservable preference shocks ε_{i0}; each child has an idiosyncratic preference shock ε_{ij} of providing IC – hence, observably identical families make potentially different choices. We assume that the unobservable shocks ε_{ij} are i.i.d. Gumbel (location parameter 0 and scale parameter σ). Furthermore, we define utility from a care option as:

$$U_{ij} = \underbrace{-C_{ij}}_{\equiv V_{ij}} + \epsilon_{ij} = V_{ij} + \epsilon_{ij}, \quad \epsilon_{ij} \sim \text{Gumbel}(0, \sigma), \quad Var(\eta_{ij}) = \sigma^2\pi^2/6$$

Since discrete-choice models are scale-invariant – only the ratio V_{ij}/σ matters for the outcome, so σ itself cannot be identified (the scale is not identified) – we normalize by σ:

$$\frac{U_{ij}}{\sigma} = \frac{V_{ij}}{\sigma} + \underbrace{\frac{\varepsilon_{ij}}{\sigma}}_{\equiv \eta_{ij}}, \quad \eta_{ij} \sim \text{Gumbel(0,1)}, \quad Var(\eta_{ij}) = \pi^2/6.$$

[20] Also, the labelling of children, $1, \ldots, K$, in our setting has no meaning so that the constant θ^*_{IC} is the same for all children. In principle there is also a common parameter θ_{IC} in the child-specific cost specification but it is impossible to identify both θ_{IC} and θ_{FC}. Thus, we have set $\theta_{IC} = 0$ so that θ_{FC} is interpreted as the extra disutility of FC relative to IC.

Family i implements care arrangement $j = j^*$ if and only if:

$$\frac{U_{ij^*}}{\sigma} = \frac{V_{ij^*}}{\sigma} + \eta_{ij^*} \geq \frac{V_{ij}}{\sigma} + \eta_{ij} = \frac{U_{ij}}{\sigma}, \quad \forall j \in \mathcal{C}_i,\ j \neq j^*$$

Given our distributional assumption, the probability that family i chooses option j is

$$P_{ij} = \frac{\exp\left(V_{ij}/\sigma\right)}{\sum_{k=0}^{K_i} \exp\left(V_{ik}/\sigma\right)}$$

where

$$V_{ij} = \begin{cases} -(p_i^{bc} + \theta_{FC}), & \text{if } j = 0 \text{ (Formal care)} \\ -(OC_{ij} + \mathbf{X}_{ij}\boldsymbol{\beta}), & \text{if } j \neq 0,\ j \in K_i \text{ (Informal care)} \end{cases}$$

When σ becomes very large ($\sigma \to \infty$), every $V_{ij}/\sigma \to 0$, and so each term $\exp(V_{ij}/\sigma)$ goes towards 1 – the model assigns equal probability $P_{ij} = 1/(1 + K_i)\ \forall j \in \mathcal{C}_i$ to each alternative. Unobserved idiosyncratic preference heterogeneity swamps observable costs (monetary costs and factors that correlate with psychic costs) making each alternative look equally good. To the contrary, when σ becomes very small ($\sigma \to 0$) we recover the deterministic rule that family i chooses $j^* = \arg\max_{j \in \mathcal{C}_i} V_{ij}$, i.e., $P_{ij^*} = 1$ and $P_{ik} = 0\ \forall k \neq j^*$.[21]

[21]Let j^* be the care arrangement with the highest systematic utility V_{ij^*} with probability:

$$P_{ij^*} = \frac{1}{1 + \sum_{k \neq j^*} \exp(V_{ik}/\sigma)/\exp(V_{ij^*}/\sigma)} = \frac{1}{1 + \sum_{k \neq j^*} \exp(\frac{V_{ik} - V_{ij^*}}{\sigma})}$$

where

$$\Delta_{i,k} = V_{ik} - V_{ij^*} < 0 \quad \forall k \neq j^*.$$

As $\sigma \to 0$ each $\Delta_{i,k}/\sigma \to -\infty$ so that each $\exp(\Delta_{i,k}/\sigma) \to 0$ and $P_{ij^*} \to 1$; for all other alternatives the probability goes to 0.

The scaled utility benefit is given by:

$$\tilde{V}_{ij} = \begin{cases} -\frac{1}{\sigma}p_i^{bc} - \frac{\theta_0}{\sigma} & \text{if } j = 0 \\ -\frac{1}{\sigma}OC_{ij} - (\mathbf{X}_{ij}\frac{\boldsymbol{\beta}}{\sigma}) & \text{if } j > 0 \end{cases} \tag{23}$$

$$= (-1) * \begin{cases} \tilde{\alpha}p_i^{bc} + \tilde{\theta}_0 & \text{if } j = 0 \\ \tilde{\alpha}_0 OC_{ij} + \mathbf{X}_{ij}\frac{\tilde{\boldsymbol{\beta}}}{\sigma} & \text{if } j > 0 \end{cases} \tag{24}$$

Here, we can see that the estimated coefficients capture the true effect of a variable (structural parameter) relative to the size of the variation in the unobserved factors.

To estimate the unknown coefficients, we maximize the likelihood (or log-likelihood) of observing the actual choices made in the data, i.e. coefficient estimates that best explain the observed choices given the assumptions of the model. Our log-likelihood function is the following:

$$\begin{aligned} LL(\boldsymbol{\beta}) &= \sum_{i=1}^{N} \sum_{j \in C_i} 1\{d_{ij} = 1\} \ln(P_{ij}) \\ &= \sum_{i=1}^{N} \sum_{j \in C_i} 1\{d_{ij} = 1\} \ln\left(\frac{e^{\tilde{V}_{ij}}}{\sum_{j \in C_i} e^{\tilde{V}_{ij}}} \right) \\ &= \sum_{i=1}^{N} \sum_{j \in C_i} 1\{d_{ij} = 1\} \left(\tilde{V}_{ij} - \ln\left(\sum_{j \in C_i} e^{\tilde{V}_{ij}} \right) \right) \end{aligned}$$

Using a standard maximum likelihood estimation (MLE) approach, we estimate the parameters in Equation 24: $\{\theta^{FC}, \alpha, \boldsymbol{\beta}\}$. In practice, we multiply all constants and explanatory variables by -1 so that the interpretation of each coefficient becomes the effect of each characteristic on the utility “cost" of caregiving.