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

Daniel Barczyk — McGill University and CIREQ

Yu Kyung Koh — McGill University

Matthias Kredler — Universidad Carlos III de Madrid

November 2, 2025

Abstract

Family is a primary source of care, yet significant variations in care arrangements exist both across families and countries. To understand why, we develop a tractable static model in which parents and children bargain over care arrangements, accounting for both financial incentives and heterogeneous caregiving preferences. Our structural model directly implies a discrete-choice estimation equation that we implement on European data. We find that non-monetary preferences significantly shape care decisions: omitting preference heterogeneity overstates the price elasticity of formal care by a factor of 2.5. Counterfactuals show that implementing formal-care subsidies as in the most generous low-cost countries leads to a 38-76% increase in nursing-home uptake in the remainder of Europe; cross-country preference heterogeneity is an equally important determinant for the low-cost versus high-cost country gradient in formal-care use. Our model forecasts a three- to thirteen-fold rise in future formal care demand by 2050, driven mainly by a declining ratio of adult children to elderly parents.

Contact information: Daniel Barczyk (daniel.barczyk@mcgill.ca): McGill University, Department of Economics, Leacock Building, Room 321b, 855 Sherbrooke Street West, Montreal, QC, H3A 2T7. Yu Kyung Koh (yu.koh@mcgill.ca): McGill University, Department of Economics. Matthias Kredler (matthias.kredler@uc3m.es): Universidad Carlos III de Madrid, Departamento de Economía, C. Madrid, 126, 28903 Getafe.

1 Introduction

Aging populations and evolving family structures place significant pressures on governments to reform long-term care systems. As the demand for elderly care rises, public subsidies now account for a substantial and growing share of government budgets (Gruber & McGarry, 2023). Care is delivered through two primary channels: formally, through paid services, or informally, by family and friends. The reliance on these forms of care varies dramatically across countries, as do public policies (Barczyk & Kredler, 2019).

A central, yet largely unanswered, question for designing effective policy is understanding how family care arrangements respond to financial incentives. Existing structural models (e.g., Skira, 2015, Barczyk & Kredler, 2018, Mommaerts, 2025) primarily emphasize economic trade-offs – such as labor-market opportunity costs of adult children and caregiving subsidies. However, this work largely abstracts from the role of caregiving preferences. In reality, families differ not only in their economic circumstances but also in their intrinsic attitudes toward various care arrangements. These preferences can be complex, involving the adult child's sense of duty or burden as well as the parent's preference for receiving care from family versus a formal institution. For some children, providing care is seen as a moral obligation or a display of affection; for others, it is an undesirable burden.

The interplay between economic factors and preference heterogeneity raises a fundamental question: To what extent are caregiving decisions shaped by financial incentives as opposed to non-monetary (psychic) factors? The answer has critical policy implications. If decisions are primarily driven by monetary considerations, financial tools like subsidies are likely effective at influencing behavior. If, however, preference heterogeneity dominates, such policies will have limited impact on behavior and be mainly re-distributive.

To disentangle the roles of financial and non-monetary factors in caregiving decisions, we develop a tractable static bargaining model of the family. Parents and children bargain over informal care and which child becomes the primary caregiver if care is informal. The parent can make a transfer in exchange for informal care; the outside option is formal nursing-home care, paid for by the parent. Siblings are modeled as a collective household, with each member having distinct preferences over caregiving and facing idiosyncratic financial costs. These include labor-market opportunity costs through foregone work hours, which depend positively on the parent's care needs, and commuting costs, that depend on geographical distance to the parent.

A key feature of our framework is that it allows us to transform this complex bargaining problem into two separate problems: the determination of the optimal care arrangement – our main focus – and how the surplus from informal care is divided between the parent and children through the the exchange-motivated transfer. The central theoretical result is that the family selects the care arrangement – formal care or informal care provided by a specific child – that minimizes the family's total *effective cost*, defined as the sum of monetary and psychic costs. This characterization gives rise to a simple discrete-choice estimation equation derived directly from our structural theory of the family.

The advantage of a structural approach is twofold. First, it allows us to use observed choices to identify the underlying preference and economic parameters. Second, with the estimated parameters, we can use the model to conduct policy counterfactuals, simulating how families would respond to new policies, changes in family structure, or shifts in the broader economic environment, such as rising female labor-force attachment.

We estimate the model using rich data from Europe, which serves as an ideal laboratory due to the large cross-country variation in the generosity of public long-term care. This variation in the effective price of formal care, combined with differences in care needs and children's opportunity costs, allows us to identify how families trade off economic incentives against their preferences. 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, their families, and their caregiving arrangements. We supplement this with labor market data using Eurostat's Structure of Earnings Survey (SES) to estimate potential income for adult children to proxy their labor-market opportunity costs. We rely on OECD data on out-of-pocket costs for institutional care for the elderly. Our data allows us to exploit variation across families and cross-country policy differences.

Our estimates indicate that both observable characteristics and unobservable preferences play a substantial role in shaping caregiving arrangements. We find that parent's utility cost of formal care is high: Parents require 28,131 Euros higher annual consumption in a nursing home to be indifferent to receiving informal care. Caregiving costs also vary systematically with child characteristics: being a daughter significantly lowers the utility cost of informal care, while having a partner increases it. Importantly, unobserved preference heterogeneity explains a large share of the variation in observed care choices. A one-standard-deviation shock to preferences is equivalent to an increase of approximately 13,000 Euros in annual monetary costs of care.

We conduct four counterfactual exercises. First, we show that omitting preference heterogeneity leads to an overestimation of the price elasticity of formal care by a factor of 2.5, highlighting how non-economic factors dampen the impact of financial incentives. Second, we simulate a policy that substantially reduces formal care costs by "transplanting" the lower nursing-home costs of Nordic countries to other regions. This policy would increase formal care use by 38% in the middle-cost countries and by 76% in high-cost countries. Third, we simulate scenarios in which all country groups share identical preferences for formal care and face the same formal care costs. We find that differences in formal care prices and preferences each explain approximately half of the observed gap in formal care usage between the low-cost and high-cost country groups, underscoring the importance of both factors. However, even after equalizing both, formal care usage in the low-cost country group remains notably higher, suggesting that other factors – such as children's characteristics and opportunity costs – play an important role. Fourth, we forecast the impact of future socio-demographic shifts. Our model predicts a three- to thirteen-fold increase in formal care demand by 2050, driven primarily by the declining ratio of adult children to elderly parents. Changes in formal care policies and child mobility play a modest role, while changes in the gender-wage gap and rising divorce rates have the least impact.

Our paper makes four primary contributions to the literature. First, we advance the literature that structurally estimates how caregiving arrangements respond to government policies. Existing models (e.g. Barczyk & Kredler, 2018; Braun et al., 2017) typically account for the economic costs of care but abstract from heterogeneity in caregiving preferences across children and families. Moreover, these frameworks typically assume a representative child, thereby overlooking the intra-family decision process when multiple children are potential caregivers (Barczyk & Kredler, 2018; Ko, 2022; Mommaerts, 2025). Our contribution is to estimate the elasticity of formal care utilization while explicitly modeling preference heterogeneity in families with multiple decision-making children. Our results demonstrate that accounting for such heterogeneity is critical for evaluating policy interventions that alter relative care prices.

Second, our work is closely related to recent structural approaches to long-term care decisions, notably Montesinos (2025) and Kesternich et al. (2025). While Kesternich et al. (2025) emphasize *patient-side* preference heterogeneity in choosing among care arrangements, our framework shifts the focus to heterogeneity in *caregiver* preferences of adult children and examines care arrangements as an outcome of intra-family bargaining. Montesinos (2025) aligns more closely with our approach but diverges in two important aspects. First, we explicitly model the monetary costs of formal care, thereby introducing a clear mechanism that motivates informal care: an exchange-motivated transfer from the parent. The compensation obtained in exchange for care reflects a growing body of literature that demonstrates that caregiving by adult children leads to higher compensation such as in the form of higher bequests, made possible by slowing the spend-down on costly care services (Brown, 2006; Groneck, 2017; Barczyk et al., 2023). Second, we take into account that parental care needs vary substantially and model the interaction between these needs and a child's opportunity costs, arguing that this interaction is essential for understanding caregiving choices.

Third, we contribute to a large literature on family decision-making in caregiving choices involving multiple children. Prior studies differ markedly in their treatment of choice sets, monetary costs, and care needs. Some examine only the selection 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 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, leaving nursing-home care aside. They incorporate the monetary costs of care, but do not capture the interaction between parental care needs and children's opportunity costs.

Finally, we extend the literature on intra-family transfers and care decisions using a cooperative bargaining framework. Our approach builds on seminal work such as Pezzin & Schone (1999), one of the first papers to develop and estimate a bargaining model for joint labor supply and parental care decisions. Stern (1995) and Engers & Stern (2002) also adopt cooperative frameworks to analyze caregiving among multiple children, yet they abstract from both monetary costs and bargaining with parents. We offer a methodological innovation: a tractable discrete-choice estimation equation derived directly from bargaining theory.

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 4 discusses how preference heterogeneity conceptually influences the price elasticity of formal care usage. Section 5 describes the estimation procedures for the discrete choice model. Section 6 presents the estimation results. Section 7 performs counterfactual analyses. Section 8 concludes.

2 Empirical facts

Our central focus is on understanding the key trade-offs in the determination of care arrangements when an elderly parent may receive informal care from a working-age adult child. This is where the interplay between economic costs and preference heterogeneity is most salient. To sharpen this focus, we restrict attention to families with single elderly parents, excluding partnered households. In such cases, spousal care typically represents the default arrangement, with children playing a more minor role (see Barczyk & Kredler (2019)). In the following, we document key facts – care choices, child characteristics, and care needs – about these families. Further details on the data and empirical analyses are provided in Appendix A.1.

2.1 Data

SHARE. Our primary data source is the Survey of Health, Ageing, and Retirement in Europe (SHARE), a nationally representative panel of the European population aged 50 and over, conducted biennially since 2004. Its extensive information on seniors' health and functional limitations, demographic and socioeconomic characteristics, and family caregiving arrangements makes it well-suited for analyzing long-term care decisions and the role of children in providing care. Due to several data issues outlined in Appendix A.1, we use the baseline samples from SHARE Waves 1, 2, 4, 5, 6, and 8.

Estimation sample. We construct our sample using several restrictions designed to isolate the key trade-offs in the determination of caregiving arrangements.

First, in line with our objective, we restrict the sample to single parents aged 65 or older. To examine the role of children's labor market opportunity costs, we further require that they have at least one child aged 20 to 60, dropping children outside of this age range.

Second, we focus on parents with substantial care needs – those receiving either formal care in a nursing facility or intensive care from a child caregiver, defined as care provided at least weekly. Households receiving both formal home care and intensive informal care from a child are retained in the sample and classified as informal care households.[1]

Third, among households receiving informal care, we focus on families with an identifiable primary child caregiver. Here the trade-offs are most salient and empirically we document that it is the dominant form of informal caregiving by children: one child typically takes on the lion's share of care, while others play a much smaller role.[2] Households with multiple children providing equal

[1]In our analysis, we treat nursing home care as the primary form of formal care, excluding formal home care as a separate category due to its relatively low intensity in terms of hours provided (see Barczyk & Kredler (2019)).

[2]As shown in Table A5, when intense informal care occurs, roughly 75% of cases involve a

amounts of care are excluded.

Applying these sample selection criteria yields a final sample of 1,887 households, comprising 4,089 unique parent-child pairs. Table A4 provides a detailed breakdown of the sample size at each stage of the selection process.

Formal Care Costs. 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, categorized as: (i) below the 20th percentile, (ii) median, and (iii) above the 80th percentile, 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). Additional details on the construction of formal care costs are provided in Appendix Section A.3.

Eurostat's Structure of Earnings Survey. SHARE does not provide income 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). Details about potential wage construction are reported in Appendix A.2.

2.2 Long-term care arrangements

The first key fact is that the vast majority of elderly individuals in our sample rely on informal care (IC) as their primary source of support – 92.2% receive

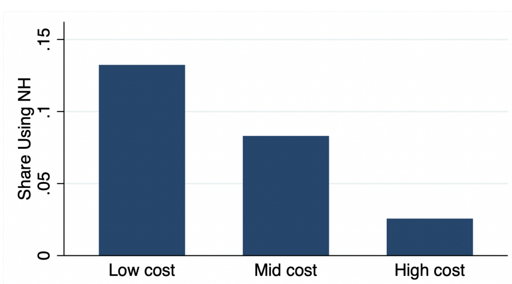
single primary child caregiver. This includes cases with only one child providing informal care, as well as those with multiple caregivers, where we assign the child who provides the largest amount of care as the main caregiver. We identify the main caregiver using the following hierarchy: (i) a child providing daily informal care while living with the parent; (ii) a child providing daily informal care while living apart from the parent; and (iii) a child providing weekly informal care while living apart from the parent.

IC from a child while only 7.8% utilize nursing home (NH) care.

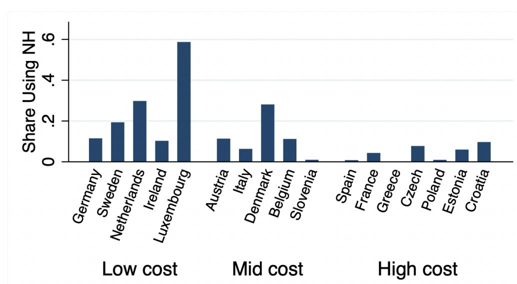
However, this low overall rate of NH use masks substantial cross-country variation across Europe, where out-of-pocket costs for formal care vary widely (see OECD (2024)). To explore the role of formal care cost in shaping care arrangements, we classify countries based on the relative costliness of NH care for a median-income elderly individual, after accounting for government subsidies: (1) low cost (11∼60% of old-age median income), (2) medium cost (65∼85%), and (3) high cost (90∼136%). Additional details on this classification are provided in Appendix Section A.3.

Figure 1 illustrates substantial variation in nursing home usage across countries. In our sample, higher formal care costs are associated with a lower likelihood of nursing home use. Specifically, Panel (a) shows that 13.2% of households in countries with low formal care costs utilize NH care, compared to just 2.6% in countries with high formal care costs. Panel (b) further confirms this pattern: countries in the low-cost group generally exhibit a higher fraction of households using nursing homes than those in the medium- or high-cost groups. We note, however, that the country-level statistics should be interpreted with caution as many countries have small sample sizes in our sample.

Figure 1: Nursing Home Probability by Country



(a) By country group based on FC cost



(b) By country

This figure shows the proportion of households in our estimation sample that permanently use nursing home care for elderly parents, broken down by country group (Panel a) and by individual country (Panel b). Household weights are applied.

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 proportion of children providing IC, conditional on various observed characteristics in SHARE. Several patterns emerge.

First, daughters are significantly more likely to provide care than sons. Panel (a) shows that 48.1% of daughters in our sample provide IC, compared to only 33.5% of sons.

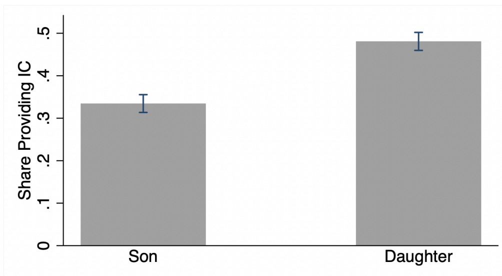
Second, there is no clear relationship between biological child status and the likelihood of providing IC as shown in Panel (b). This result should be interpreted with caution, due to the small number non-biological children (only 62 cases in our sample).

Third, there is a strong negative relationship between the distance between children and their parents and the probability of providing IC. Approximately 80% of children who live with their parent provide IC, and this fraction decreases as the distance increases.[3]

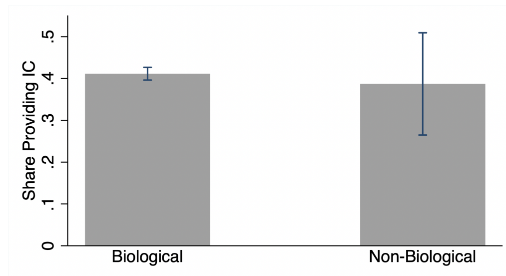
Finally, children with lower potential income are more likely to provide informal care. This pattern suggests that opportunity costs may play a role in caregiving decisions, with higher-income children potentially facing greater trade-offs between labor market participation and caregiving responsibilities.

[3] 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.

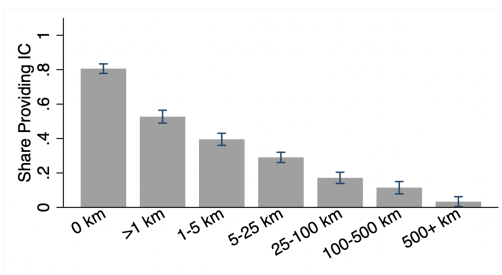
Figure 2: Informal Care Probability by Child's Characteristics



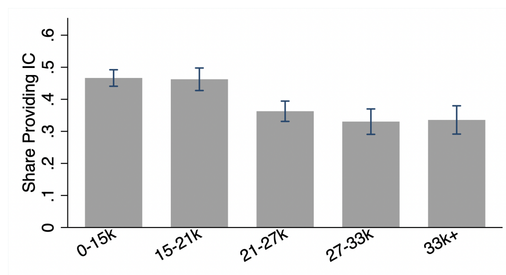
(a) By Gender



(b) By Biological Child Status



(c) By Distance



(d) By Potential Income

This figure reports the proportion of children providing IC across different child characteristics in our estimation sample. 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. Potential income for each child is based on their gender and education, as well as country and year, using Eurostat's Structure of Earnings Survey (SES). 95% confidence interval is reported.

2.4 Care Needs

Although our sample includes only elderly individuals receiving either informal or formal care, their underlying care needs vary substantially. To estimate each respondent's daily care needs, we apply 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 – specifically, limitations in activities of daily living (ADLs) and instrumental activities of daily living (IADLs). Linking to HRS is essential because SHARE does not collect information on care hours, while HRS does for informal care recipients. For nursing home residents – whose care needs are unobserved in both SHARE and HRS – we apply the adjustment method developed by Dahl (2002) to account for negative selection.

Table 1 presents summary statistics on the estimated daily hours of care needed among individuals in our sample and their number of functional limitations. There is substantial variation in care needs. The average estimated need is 3.6 hours per day, 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. These patterns highlight the considerable heterogeneity in care intensity required even within a population selected for relatively high care needs.

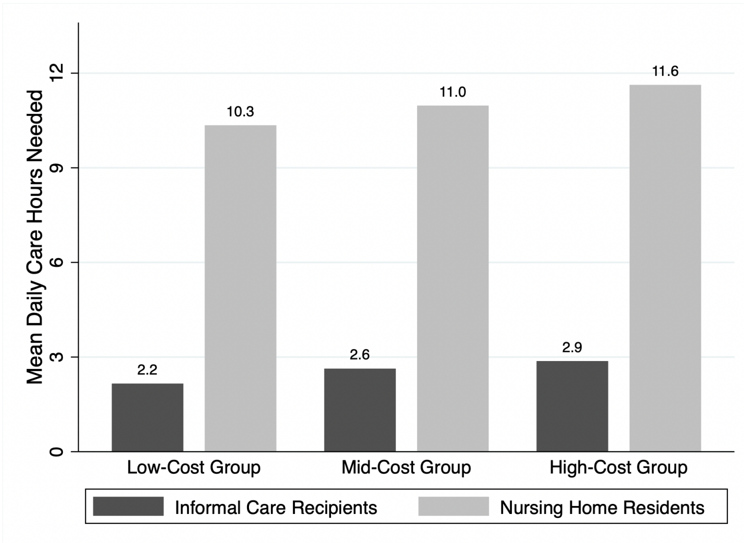
Table 1: Care needs

	# 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

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 the care need estimation procedure. Table A11 provides definitions of the ADL/IADL and mobility limitation variables used in SHARE.

Care needs also differ markedly by mode of care. Figure 3 shows that NH residents have significantly higher care needs, requiring over 10 hours of assistance per day on average. In contrast, individuals receiving IC typically require far less supposrt – between 2 and 3 hours per day on average across all country groups.

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



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 costs faced by adult children providing care. When a parent's care needs are relatively low, caregiving may be compatible with full-time or part-time employment, resulting in minimal disruption to the child's labor market participation and a relatively low opportunity cost. In contrast, when care needs are high, the time demands can be substantial, potentially requiring the child 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, our empirical analysis accounts for variation in care needs when estimating the opportunity cost of caregiving.

3 Family model

We now develop a formal framework for how care arrangements are determined within families. The central predictions concern which type of care is chosen – informal care or institutional care in a nursing home– and, conditional on informal care being selected, which child becomes the designated caregiver.

There is a large number of families, each consisting of one elderly parent in need of care and $K > 0$ adult children, where K may vary across families.

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 (and 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:

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

Collective sibling household We assume that the K siblings act collectively, always attaining a Pareto-efficient allocation (among themselves) and that the point on the Pareto frontier selected is determined by fixed bargaining weights.[4]

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 over all children's budget constraints (2), yields the

[4]We will show that the care choice is independent of the bargaining weights. In general, the care choices we derive obtain under any decision-making process among siblings that attains efficiency.

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:

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

i.e. 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 yields the family's budget constraint:

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

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

Family bargaining problem We model the family's decision-making process as a (generalized) 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

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

i.e. the parent 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:

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

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

Characterization 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 and parents as

$$x_i = c_i - I_{i=j}\theta_i, \qquad\qquad x_p = c_p - I_{j=0}\theta_0.$$

Using these definitions, we obtain the following *effective budget constraints* for the parent

$$x_p = y_p - I_{j=0}(p_{bc} + \theta_0) - Q \tag{8}$$

and for the collective sibling household:

$$\sum_{i=1}^K x_i = R + Q - \sum_{i=1}^K I_{i=j}(OC_i + \theta_i). \tag{9}$$

Substituting out using the parent's constraint (8) yields the family effective resource constraint:

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

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

$$\max_{x_p, \{x_i\}_{j \in \{1,\ldots,K\}}} [u_p(x_p) - d_p]^{\mu_p} [\sum_{i=1}^{K} \mu_i u_i(x_i) - d_k]^{1-\mu_p} \tag{11}$$
$$\text{s.t.} \quad x_p + \sum_{i=1}^{K} x_i = y_p + R - \sum_{i=1}^{K} I_{i=j}(OC_i + \theta_i),$$

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

This formulation immediately implies 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 non-satiation (i.e. strict monotonicity of utility) 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:

$$j^* = \arg \min_{j \in \{1,\ldots,K\}} \{OC_j + \theta_j\}$$

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:

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

Here, children maximize their collective utility subject to their effective resources.[5]

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

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

That is, 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 lowest effective cost of the members of the sibling household to provide IC, $\underline{Q}$, which we may call the "willingness-to-sell" IC for the child household.

As for the parent, IC generates a surplus if and only if

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

where $\bar{Q}$ is the parent's "willingness-to-pay" for IC, which equals the parent's loss of effective resources under FC. Thus, the choice set for transfers in (12) that yield non-negative surplus to both bargaining parties is $Q \in [\underline{Q}, \bar{Q}]$ and the family opts for IC if and only if this set is non-empty, i.e. iff $\underline{Q} \leq \bar{Q}$.

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

[5] 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.

the family chooses

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

where $j^* = 0$ *means formal care and* $j^* \in \{1, \dots, K\}$ *means child* j^* *provides informal care. This choice is efficient and 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), which is governed by the bargaining weight μ_p. For the purpose of determining the care choice, however, the bargaining weight and the size of this transfer is irrelevant. Crucially, we note that any other bargaining protocol that satisfies **efficiency** yields the **same care outcome** j^* (e.g. parent makes take-it-or-leave-it offer Q, children bid auction-style to provide Q, a collective model for the entire family, etc).

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):

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

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 How does preference heterogeneity affect elasticities?

To gain insight into how preference heterogeneity modulates responsiveness to subsidies, we compare two stylized models, both calibrated to the same baseline share of care arrangements. The first "economics-only" model features only monetary factors, while the second adds heterogeneous psychic costs. We compare the elasticity of formal care (FC) uptake with respect to a price-reducing subsidy ($\Delta S > 0$):

$$|\epsilon_{FC}| = \left| \frac{\Delta FC/FC}{\Delta p_{fc}/p_{fc}} \right|,$$

where $\Delta p_{fc} = -\Delta S$. We denote the baseline FC share by $\hat{FC}_0$.

Economic factors only The care decision depends solely on the net monetary cost of IC over FC, $C_e \sim N(\mu_e, \sigma_e^2)$.[6] In order for the model to generate $\hat{FC}_0$, we introduce a uniform psychic FC cost for the parent, denoted by θ_0^e, such that FC is chosen if $C_e > \theta_0^e$. The threshold θ_0^e is calibrated to match the observed FC share:

$$\hat{FC}_0 = \Pr(C_e > \theta_0^e) = 1 - F_e(\theta_0^e)$$

where F_e is the CDF of C_e. A subsidy ΔS for formal care is equivalent to shifting the decision threshold to $\theta_0^e - \Delta S$. The new FC share is $\hat{FC}_S = 1 - F_e(\theta_0^e - \Delta S)$, and the change in uptake is $\Delta FC = \hat{FC}_S - \hat{FC}_0 = F_e(\theta_0^e) - F_e(\theta_0^e - \Delta S)$. Using a first-order Taylor approximation, denoting the PDF of C_e by f_e,

$$F_e(\theta_0^e - \Delta S) \simeq F_e(\theta_0^e) - f_e(\theta_0^e)\Delta S \quad \Rightarrow \quad \Delta FC \simeq f_e(\theta_0^e)\Delta S$$

allows us to approximate the elasticity by:

$$|\epsilon_{FC}^e| \simeq \left| \frac{f_e(\theta_0^e)\Delta S/\hat{FC}_0}{(-\Delta S)/p_{fc}} \right| = \frac{f_e(\theta_0^e)}{\hat{FC}} p_{fc}$$

Thus, the elasticity is proportional to the density of marginal families at the threshold θ_0^e.

Economic factors + psychic costs In this model we add heterogeneous psychic caregiver costs, $C_p \sim N(0, \sigma_p^2)$, which are independent of economic costs C_e. We normalize the mean of C_p to zero; the parent again incurs a uniform

[6] In terms of our model specification C_e corresponds to $\min_j OC_j - p_{bc}$, the difference between the lowest possible opportunity cost and the FC price. We restrict attention to normally-distributed costs for analytical convenience, but the mechanism carries through to more general distributions. In practice, μ_e and σ_e can be calibrated using data on care expenditures and wages.

utility cost from FC, denoted by θ_0^c.[7] The total net cost of IC is $C = C_e + C_p$ which is also normal, $C \sim N(\mu_c, \sigma_c^2)$, where $\mu_c = \mu_e$ and $\sigma_c^2 = \sigma_e^2 + \sigma_p^2$.[8] The key insight is that introducing preference heterogeneity (via σ_p^2) strictly increases the total variance of the net cost.[9]

Denote by F_c and f_c the CDF and PDF of C. This model is calibrated with a new threshold θ_0^c to match the same baseline share $\hat{FC}_0 = 1 - F_c(\theta_0^c)$. Following the same derivation as before, the elasticity is again proportional to the density at this new threshold:

$$|\epsilon_{FC}^c| \simeq \left| \frac{f_c(\theta_0^c)\Delta S/\hat{FC}_0}{(-\Delta S)/p_{fc}} \right| = \frac{f_c(\theta_0^c)}{\hat{FC}} p_{fc}$$

Comparing elasticities Since both models are calibrated to the same baseline share of care arrangements – $\hat{FC}_0$ or equivalently $\hat{IC}_0 = 1 - \hat{FC}_0$ – their standardized decision thresholds are identical:

$$\begin{aligned}
\hat{IC}_0 &= \Pr(C_e < \theta_0^e) = \Phi\left(\frac{\theta_0^e - \mu_e}{\sigma_e}\right) \quad &\Rightarrow \quad \Phi^{-1}(\hat{IC}_0) = \frac{\theta_0^e - \mu_e}{\sigma_e} \\
\hat{IC}_0 &= \Pr(C < \theta_0^c) = \Phi\left(\frac{\theta_0^c - \mu_c}{\sigma_c}\right) \quad &\Rightarrow \quad \Phi^{-1}(\hat{IC}_0) = \frac{\theta_0^c - \mu_c}{\sigma_c}
\end{aligned}$$

Let $z_0 = \Phi^{-1}(\hat{IC}_0)$ denote this common standardized threshold. The densities f_e and f_c at its threshold can be written in terms of the standard normal PDF, ϕ,

$$f_e(\theta_0^e) = \frac{1}{\sigma_e}\phi(z_0), \quad f_c(\theta_0^c) = \frac{1}{\sigma_c}\phi(z_0).$$

showing that the density of marginal families at the decision threshold differs if $\sigma_e \neq \sigma_c$.

[7] To separately identify average psychic costs for parent and child, data from care choices alone are insufficient. Identification would require data on consumption allocations combined with an assumption on bargaining weights.

[8] In our model specification C corresponds to $(OC_{j^*} - p_{bc}) + \theta_{j^*}$, where j^* denotes the child with the lowest opportunity cost, and θ_{j^*} is the utility cost for this child when providing IC.

[9] Our argument goes through under a weaker assumption, namely $\sigma_c^2 > \sigma_e^2$. Under a joint normal distribution for C_e and C_c, this is true if and only if the correlation between the two costs satisfies $\rho_{cp} > -\sigma_p/\sigma_e$.

Preference heterogeneity dampens the FC elasticity. Because $\sigma_c^2 > \sigma_e^2$, it follows that $f_c(\theta_0^c) < f_e(\theta_0^e)$, and so $|\epsilon_{FC}^e| > |\epsilon_{FC}^c|$. Intuitively, introducing heterogeneous psychic costs increases the overall dispersion of net costs. This "thins out" the density of families at the margin, reducing the number who switch to FC in response to a subsidy and dampening the policy's effectiveness.

5 Estimation

We now present the empirical model used to estimate preference parameters governing caregiving choices. As established in Theorem 1, the efficient caregiving arrangement minimizes total effective costs – comprising both monetary and psychic components – naturally leading to a standard discrete choice framework.

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

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

where ε_{ij} captures idiosyncratic preference shocks. Here, p_i^{bc} denotes the out-of-pocket cost of basic formal care services, and OC_{ij} is the opportunity cost of child j. Our model imposes the restriction that monetary costs enter with the same coefficient in all choices. Thus, the parameter α captures the marginal effect of monetary cost on the utility cost whether formal or informal care takes place. The parameter θ_0 reflects the average psychic cost of choosing formal care relative to informal care, with the latter normalized to zero. $\boldsymbol{\gamma}_i$ are country-group fixed effects that absorb systematic cross-country-group differences in preferences for formal care.[10] The vector $\mathbf{X}_{ij}$ includes child-level characteristics relevant to informal caregiving (e.g., is female, has a partner).

We assume that the idiosyncratic preferences ε_{ij} are distributed independently and identically as the Extreme Value Type-I distribution with location

[10] We omit the indicator for the low-FC-cost country group, so all other country-group fixed effects are interpreted relative to this group.

parameter zero and scale parameter σ. This assumption 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 estimation sample.

As is standard in the multinomial logit model, we cannot separately identify the scale parameter σ. Consequently, estimated coefficient measure the effect of the corresponding variable relative to this scale (e.g., α/σ, β/σ, etc.). 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 Appendix A.3.

Opportunity cost. We specify the opportunity cost OC_{ij} as the sum of a time cost and a monetary cost: $OC_{ij} = \text{time cost}_{ij} + \text{monetary cost}_{ij}$. The **time cost** represents the value of the child's time spent on care and commuting. We define it as the child's expected full-time wage weighted by the care needs of the parent. This weighting 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 Section 2.4. For parents with low care needs, it is unlikely that a child would fully exit the labor market to provide care, making proportional weighting essential. Specifically, we define this weight as:

$$\text{Care needs weight}_{ij} = \frac{\text{Daily hourly care needs} + \text{Daily commuting time}}{12 \quad \text{hours}}$$

Here, we assume that a child has up to 12 hours per day available for market work, and we cap the daily hourly care needs at 12 hours. The daily commuting time is derived from reported distance to the parent's residence (see Appendix Table A12).

The monetary cost component is the predicted annual commuting cost, which is also derived from the reported distance. Appendix Table A13 documents the assignment of these monetary travel costs by distance category.

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 estimation sample. 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. The monetary equivalence calculation implies that parents would require an additional 28,131 Euro in annual consumption in a nursing home to be indifferent between formal and informal care. Moreover, monetary costs, such as formal care price and children's opportunity costs, are estimated to play a major role in care decisions, statistically significant at the 1% level. As expected, this indicates that the formal-vs-informal care decision is sensitive to financial considerations.

Among child characteristics, in line with previous literature, being a daughter is associated with the most prominent effect: 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 one's own parents. The estimate for non-biological status is noisy, reflecting the low number of stepchildren in our sample, thus our data do not allow us to infer much on this front. Birth order and the number of one's own children are not significant.

Crucially, our estimates imply that idiosyncratic preference heterogeneity is substantial in shaping caregiving choices. A one-standard deviation preference shock (of size $1.28 \equiv \sqrt{\pi^2/6}$) 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 economic incentives, family structure and idiosyncratic motives in caregiving decisions. While monetary cost are 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 we treat distance in our 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 with respect to (1). Column (3) is our baseline specification from Table 2, which 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.

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 estimation sample. 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.

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, and thus how they relate to idiosyncratic preference shocks – remain remarkably 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 close to unity and significant. This robustness suggests that any endogeneity in children's location choices does not meaningfully bias the estimated effects on caregiving decisions.

We select Column (3) as our preferred specification because incorporating distance into opportunity costs 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 simulate counterfactual formal care usage under alternative policy and demographic scenarios. Specifically, we conduct four sets of counterfactual analyses. First, we quantify the role of preference heterogeneity in shaping formal care elasticities by comparing results from an economics-only model with those from a model incorporating preference heterogeneity. Second, we transplant long-term care systems across country groups to examine how formal care usage would change under the formal care prices of each country group. Third, we assess the extent to which cross-country-group differences in formal care usage can be explained by differences in prices and preferences. Finally, we analyze how demographic and societal changes would influence families' care choices.

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 modify the distribution of the right-hand-side variables – specifically, the formal care price (p_{bc}), children's opportunity costs (OC_{ij}), distance between children and parents, stepchild status, and the number of children (K) – thereby generating 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 compute the weighted summation 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 economic costs, such as formal care price or children's opportunity costs, this completely describes our algorithm.

For the remaining counterfactuals – in which the number of children (K), the number of stepchildren (*step*), or both change – we must rely on simulation. For these counterfactuals, we run $N_{sim} = 1,000$ simulations in which we randomly change K and/or *step*, but maintaining all *other* variables unchanged. Specifically, we proceed as follows:

[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.

[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.

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

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 probability of i in counterfactual Δ in simulation n, which we calculate using (14). Finally, to obtain the predicted change in FC 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 Quantifying the effect of preference heterogeneity on elasticities

Our first exercise revisits the theoretical point of Section 4, where our stylized models illustrated that preference heterogeneity dampens policy responses. We now quantify this effect by comparing our full baseline model to an *economics-only* version of our model. In this alternative model, we shut down preference heterogeneity due to both idiosyncratic shocks and the systematic variation in psychic informal-care costs in observables. Families only decide based on the effective cost of care (p_{bc}) and the opportunity costs that children face (OC_{ij}), facing a *uniform* (non-idiosyncratic) disutility from formal care that we estimate to match observed formal care rates.

To implement this comparison, we first set a uniform level of formal care affordability that equalizes aggregate formal care usage across the two models.

Recall that the formal care price for each family is defined as the product of the "share" (ρ) of out-of-pocket formal care costs relative to old-age disposable income for each country-income group and that group's old-age disposable income. We denote by ρ_{low} the affordability level that equalizes formal care usage between the two models. We then raise ρ_{low} by 20% to obtain ρ_{high} and compare how formal care usage responds in each model.

Table 4 reports the FC elasticity in the two models. We find that $\rho_{low} = 0.49$ equalizes formal care usage between the two models in our estimation sample. In the baseline model, which accounts for both economic and preference heterogeneity, we estimate an FC elasticity of -0.45: A 1% increase in effective FC costs leads to a 0.45% decrease in FC use. In contrast, the elasticity in the economics-only model is -1.12. The magnitude of this elasticity is about 2.5 times larger than in the baseline model, indicating that accounting for preference heterogeneity in caregiving is essential for obtaining realistic elasticity estimates.

Table 4: Elasticity of formal-care usage: baseline vs. no-heterogeneity model

Model	$\rho_{low} = 0.49$	$\rho_{high} = 1.2\rho_{low}$	**elasticity**
baseline	7.66%	7.05%	**-0.45**
econ. only	7.66%	6.25%	**-1.12**

Notes: This table compares the elasticity of formal care usage with respect to formal care prices between the model that accounts for preference heterogeneity ("baseline") and the model that includes only monetary costs of care ("economics only").

7.2 Transplanting LTC systems

We now 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 Appendix A.3.

For each country group, we assign counterfactual formal care prices. 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 simplicity, we take the midpoint value of ρ for each country–income group pair to construct the counterfactual shares. These assignments are reported in Table 5. We denote by $\boldsymbol{\rho}_{low}$ the vector of midpoint share values in the low-cost regime, $\boldsymbol{\rho}_{middle}$ in the middle-cost regime, and $\boldsymbol{\rho}_{high}$ in the high-FC-cost regime.

Table 5: Summary of income-dependent counterfactual shares for FC costs

	ρ by income percentiles		
Group	Below p20	p20-p80	Above p80
Low-cost	0.40	0.36	0.34
Middle-cost	0.73	0.76	0.66
High-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 $\{\boldsymbol{\rho}_g\}$ of each country group $g \in \{low, middle, high\}$ to all other country groups, essentially "transplanting" LTC systems across groups. Table 6 summarizes the results. The $\boldsymbol{\rho}_{low}$ column reports predicted formal care usage if all countries adopted the policies of the most generous country group. Comparing $\boldsymbol{\rho}_{low}$ column with the status quo (diagonal elements),[14] the model predicts that formal-care use would increase by 37.8% (=(11.3-8.2)/8.2) in the middle-cost countries, while it would increase by 76.2% (=(3.7-2.1)/2.1) in the high-cost countries. Achieving such levels would require a substantial increase in the supply of nursing homes, underscoring the critical role of formal care subsidies in driving formal care utilization.

[14]Note that the status quo differs from the observed nursing home usage in each country group, as it imposes a uniform set of nursing home affordability levels by income group within each country group, as detailed in Table 5.

Table 6: Formal-care usage when transplanting LTC systems

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

Notes: This table reports formal care usage in each region under the formal care affordability level of each country group. $\boldsymbol{\rho}_{low}$, $\boldsymbol{\rho}_{middle}$, and $\boldsymbol{\rho}_{high}$ denote the vectors of midpoint share values in the low-, middle-, and high-cost regimes, respectively.

7.3 Culture or Economics? Explaining country-group differences

A long-standing question is if the large differences in informal caregiving are driven by a country's family culture or economic incentives. In the following set of counterfactuals, we investigate in how far care allocations across country groups can be explained by economic factors (effective prices of formal care, differences in opportunity costs of children induced by female labor-force participation and wages) and how much is left to country-specific preferences for or against formal care – which subsumes culture or social norms in our setting. Specifically, we examine how formal care usage changes across country groups when (i) formal care prices are equalized across groups, and when (ii) all groups are assumed to share the same preferences for formal care. Formal care affordability level is set to the low-cost country group's level, using midpoint affordability values by income group (see Table 5). Likewise, the preference parameter for the formal care utility cost is set to the value observed in the low-cost country group, effectively shutting down country-group fixed effects.

Table 7 reports how formal-care usage changes across country groups when differences in preferences and affordability are removed. Starting from the baseline observed in the SHARE sample (Column (1)), Column (2) equalizes preferences for formal care across country groups, Column (3) equalizes formal-care affordability levels, and Column (4) applies both equalizations simultaneously.

Equalizing either preferences or costs narrows the cross-country dispersion in formal-care usage, and applying both together reduces the range between low- and high-cost country groups from 10.6 percentage points to 4.8 percentage points. Because the effects of costs and preferences are nonlinear and depend on the order in which they are imposed, we use a Shapley-style decomposition that averages their contributions across both possible sequences – equalizing costs before preferences and equalizing preferences before costs. This decomposition indicates that differences in nursing-home costs account for roughly half (51%) of the explained gap between low-cost and hig-cost groups in formal-care usage, while differences in preferences explain the remaining 49%.[15] For the middle-cost group, the two forces partly offset each other – cost equalization raises formal-care usage, whereas preference equalization lowers it – highlighting that both economic and preference factors jointly shape observed cross-country patterns.

[15] Specifically, when we first equalize FC costs (Column 2) and then equalize preferences (Column 4), the cost factor reduces the FC usage gap between the low-cost and high-cost country groups by 2.3 percentage points (from 10.6 to 8.3), and the preference factor further narrows the gap by 3.5 percentage points (from 8.3 to 4.8). When the order is reversed – equalizing preferences first (Column 3) and then costs (Column 4) – the preference factor reduces the gap by 2.2 percentage points (from 10.6 to 8.4), while the cost factor further reduces it by 3.6 percentage points (from 8.4 to 4.8). Averaging across the two sequences following a Shapley-style approach, differences in FC costs account for roughly 51% ($\approx (2.3+3.6)/(2.3+3.6+2.2+3.5)$) of the total reduction in the cross-country FC usage gap, while differences in preferences account for the remaining 49%.

Table 7: Formal-care use in the absence of country-group differences

Region	(1) Baseline	(2) Same FC cost	(3) Same FC pref.	(4) Both
Low-cost	13.2%	12.0%	13.2%	12.0%
Middle-cost	8.3%	11.3%	6.6%	8.9%
High-cost	2.6%	3.7%	4.8%	7.2%

Notes: This table reports changes in the share of households using formal care among those with elderly members aged 65 or older who require care, under alternative counterfactual scenarios. Column (1) presents the baseline formal-care usage observed in the SHARE estimation sample. Column (2) equalizes only the affordability of formal care ("Same FC Cost"), using the midpoint values of low-cost country group's level as shown in Table 5. Column (3) equalizes only the preferences for formal care across country groups ("Same FC Pref."), using the value observed in the low-cost country group. Column (4) applies both counterfactuals simultaneously, imposing equal costs and preferences across country groups.

Although equalizing formal-care costs and preferences substantially reduces cross-country differences in formal-care usage, the low-cost group continues to display considerably higher usage, suggesting that other factors also play an important role. We can rule out gender wage disparities as the main explanation for the remaining cross-country gap, since the female-to-male wage ratio is lowest in the low-cost country group (Appendix Table A6).[16] Consequently, daughters in low-cost countries do not face higher opportunity costs relative to sons compared with those in other country groups. Characteristics such as the number of children, the share of stepchildren, and the share of children with a partner are also unlikely to be the primary factors, as these variables are similar across country groups, as shown in Appendix Table A6. These patterns point to other factors – such as overall wage levels, geographic distance from parents, and interactions among children's characteristics – as potential drivers of the remaining cross-country differences in formal-care usage.

[16]This pattern is consistent with Eurostat statistics showing that countries such as Germany and Sweden (low-cost group) have higher gender wage gaps than countries like Spain (high-cost group) (Eurostat 2024).

7.4 Forecasting counterfactual: Europe in 2050

In the last 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, alongside a change in formal care costs:

1. Population aging will reduce the number of potential child caregivers (K), thereby lowering the ratio of working-age children to elderly parents. To simulate this demographic change, we randomly remove each child from the sample with probability $p_K = (K - \hat{K})/K$, where $K = 2.24$ represents the average number of potential caregivers per elderly person in 2010 based on Eurostat statistics, and $\hat{K} = 1.25$ is the projected value for 2050. The 2050 projection is derived from Eurostat population statistics, computed as the ratio of individuals aged 45-65 to those aged 70-90 in EU countries, extrapolated from population trends observed over recent decades.

2. Stronger labor-force attachment among women will raise daughters' opportunity cost of providing care and, consequently, increase formal care use. According to Eurostat data, the gender wage gap in the EU was 16.0% in 2010. In our counterfactual, we make an assumption that this gap closes by 2050 and increase all female opportunity costs from the labor market to $\widetilde{OC}_{ij} = 1.16 OC_{ij}$, which we interpret as an upper bound on the effects operating through this channel.

3. Changing family structures due to a rise in divorce would raise the proportion of stepchildren, potentially affecting informal caregiving decisions. To reflect this change, we convert each biological child in the baseline to a step child with probability $p_{step} = 1.1$.[17]

4. Greater geographic mobility of children is likely to reduce the supply of informal care. Since reliable forecasts of future child mobility are scarce, we use current cross-country-group variation in the SHARE data to calibrate a reasonable increase in distance between each child and the parent. Specifically,

[17] 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.

we compare the average distance between children and parents in low-FC-cost and high-FC-cost country groups and obtain a factor of 1.8. Accordingly, in the counterfactual, we set $\tilde{dist}_{ij} = 1.8 dist_{ij}$.[18] Since distance enters into children's opportunity costs, this adjustment effectively increases the opportunity costs by raising both the time and monetary costs associated with commuting, such as fuel expenses.

Table 8 shows how formal-care usage increases when introducing the demographic and policy changes sequentially. Comparing the observed FC usage in Column (1) with the full counterfactual scenario in Column (6), the model predicts a substantial increase in formal care use – approximately threefold in the low-cost country group, fivefold in the middle-cost group, and thirteenfold in the high-cost group. Among the individual drivers, the decline in the number of children (Column (2)) emerges as the dominant factor behind this rise. In contrast, changes in female wages (Column (3)) and family structure (Column (4)) play relatively minor roles, and the increase in step-children has almost no effect. Greater geographic mobility (Column (5)) of children generates somewhat larger impacts than the previous two factors. Finally, when all countries are assumed to adopt the formal care price level of the low-cost group (Column (6)), formal care usage rises modestly. Overall, this exercise suggests that demographic forces – particularly the declining ratio of children to elderly – will have a stronger impact on future caregiving patterns than policy-induced changes in formal care costs.

[18] In SHARE, 80% (60%) of children in high-FC-cost countries lived within 25km (50km) of their parents, compared with 50% (30%) in low-FC-cost countries. Averaging the two ratios – $(80/50 + 60/30)/2$ – yields a distance multiplier of approximately 1.8. We interpret this as a representative difference between high-FC-cost and low-FC-cost country groups.

Table 8: Formal-care use in counterfactual *Europe in 2050*

		Applying each scenario, sequentially				
Region	(1) Baseline	(2) #kids↓	(3) y_{fem} ↑	(4) step↑	(5) distance↑	(6) $+\rho_{low}$
Low-cost	13.2%	38.8%	39.8%	39.6%	43.3%	43.3%
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%

Note: The table reports the percentage of families opting for formal care (FC) as we sequentially introduce changes to the environment. Column (1) shows the baseline FC usage observed in the SHARE estimation sample. Column (2) reports FC usage when the number of children decreases. Column (3) reflects the scenario in which the gender wage gap is closed. Column (4) shows FC usage when the share of stepchildren increases. Column (5) presents results when the average distance between children and parents rises. Finally, Column (6) additionally sets the formal care affordability level to that of the low-cost country group, $\rho = \rho_{\text{low-cost}}$, 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.

Looking ahead, a promising avenue for future research is to extend our framework into a dynamic setting. Such a model would allow us to capture additional long-run channels – such as savings for old age, intergenerational mobility decisions, and geographic relocation of children – that shape the evolution of family care arrangements over time.

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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.

Second, we do not use Waves 3 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.

Third, for Wave 4 baseline respondents, we use information on caregiving arrangements and health status reported in Wave 5. We exclude the corresponding information from Wave 4 because it does not 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.[19]

[19] 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

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 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: Number of Respondents and Spouses: Full Sample vs. Baseline Sample (SHARE, No Sample Restrictions)

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 Details about informal care (IC) in SHARE

We describe further information about informal care (IC) in SHARE. Intense informal care 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

children of same gender and distance.

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.[20] 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

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

waves.[21] Lastly, among elderly individuals aged 65 and older without a spouse, only 23.23% of OIC cases involve care provided âĂIJabout daily,âĂİ 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, Elderly aged 65+ without spouse and with child aged 20-60, Baseline SHARE

Outside-HH IC		Inside-HH IC	
Intensity	Frequency	Status	Frequency
None	26,700	No	30,679
Daily	990	Yes	383
Weekly	1,589		
Monthly	915		
Less Often	768		
Total	30,962	Total	31,062

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 only includes baseline SHARE respondents in Wave 1, 2, 4, 5, 6, and 8, as discussed in Appendix A.1.1. The sample is restricted to parent-child observations where parent is aged 65+, with no spouse, and child is aged 20-60. Note that IIC is defined to happen almost daily by definition. Note that the total sample in this table includes elderly individuals without care needs, which explains the high frequency of cases with no informal care.

[21] 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

		After applying each sample selection criterion, sequentially					
	None	1. Elderly aged 65+	2. No spouse	3. Has child(ren) aged 20-60	4. Either NH or one intense IC child	5. Matched with FC cost and wage	6. No missing X vars
Count	234,885	109,620	38,084	31,412	5,121	4,625	4,089

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. Columns “1. Elderly aged 65+" and “2. No spouse" shows that the sample size substantially decreases after limiting to respondents who are aged 65+ and without spouse. Column “3. Either NH or one intense IC child" reports sample size after limiting to elderly who either (i) are in nursing home care or (ii) have one child who provides most intense informal care among the siblings, as documented in Section 2.1. This selection criteria further reduces the sample size by a large margin.

In fact, Table A5 shows that most parents aged 65+ and without spouse do not get formal care or is cared by any of their children. Specifically, 81.13% of such parents are not cared for by any of their children, and 98.1% of such parents are not in nursing home care.

After imposing additional sample criteria as shown in Table A4, we have a final sample size of 4,089 household-child pairs and 1,887 households.

Table A5: Distribution of informal and formal care among parent-child pairs (aged 65+, single with children aged 20-60), Baseline SHARE

Informal care (at least weekly)		Formal care (nursing home)	
Number of IC children	Frequency	Nursing home status	Frequency
0	25,485	No	30,815
1	4,392	Yes	597
2	1,217		
3	311		
4	7		
Total	31,412	Total	31,412

<u>Note:</u> This table reports the distribution of number of caregiving children, who provide at least weekly informal care, and formal care among baseline SHARE sample from Waves 1, 2, 4, 5, 6, and 8. The sample includes parent-child observations where parent is aged 65+ and has no spouse, and where child is aged 20-60.

A.1.4 Family characteristics by country group

Table A6: Mean family/child characteristics by country group, SHARE estimation sample

	Mean value by country group						
	Number of children	Male child wage	Female child wage	Gender wage ratio	Distance from parents	Share of step-children	Share of children with partner
Low-cost group	2.09	40211.63	26650.18	0.66	64.48	0.03	0.72
Mid-cost group	2.18	26377.10	18725.51	0.71	46.76	0.01	0.75
High-cost group	2.18	21704.75	15353.71	0.71	48.73	0.01	0.71

Note: This table presents mean family/child characteristics by country group in our SHARE estimation sample. The sample selection criteria are detailed in Section 2.1. "Number of children" refers to the number of children aged 20-60 that the SHARE elderly have. Household weights are applied.

A.1.5 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.1.6 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 over-estimation 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.

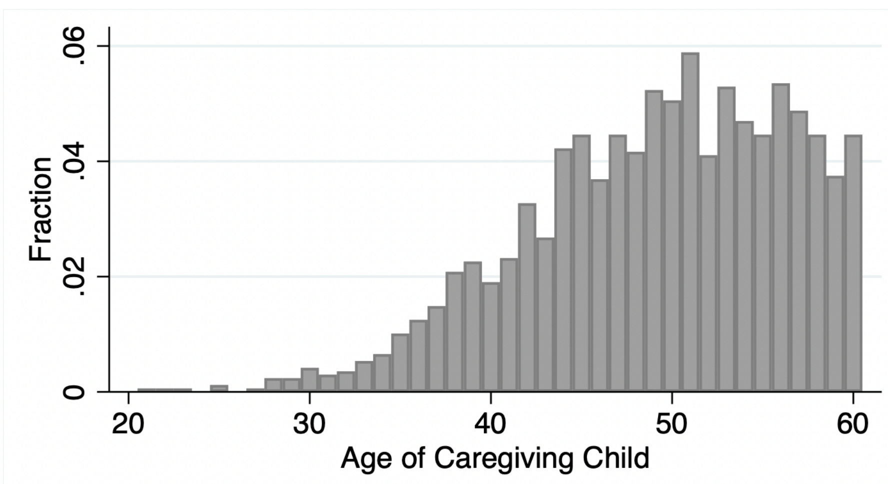
Specifically, we adjust the first version of potential wage to account for the labor force participation as follows. Let $PotentialWage_{gecy}$ denote the first version potential wage for gender g, education e, country c, and year y. The second version of potential wage is constructed as follows:

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

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 A1. 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.[22] We plan to update our potential wage estimates once we gain access to the Eurostat microdata.

Figure A1: Age distribution of caregiving children in the SHARE sample



Note: This figure presents the age distribution of children who provide informal care in the SHARE sample.

Appendix A.2.1 documents imputation strategies for potential wage construction. These strategies address several challenges, including (a) missing

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

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 A7. For consistency, we need to construct synchronized educational categories that are consistent across years.

Table A7: 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.

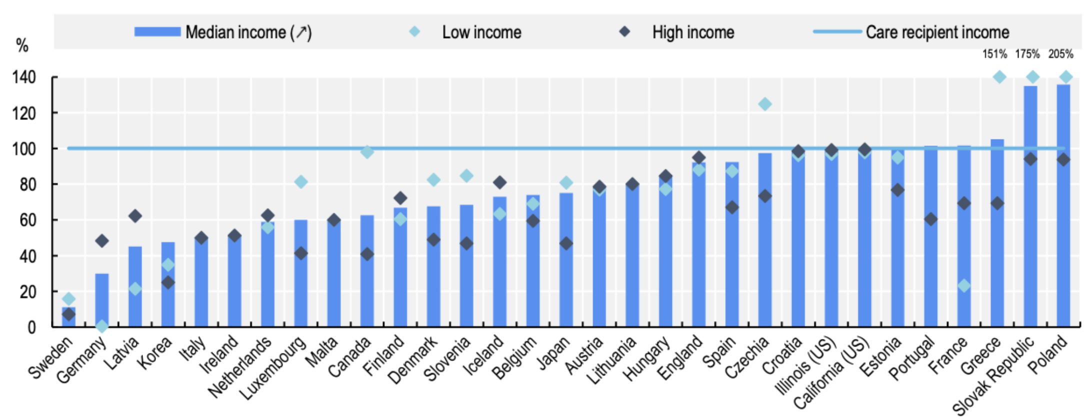
3. Dealing with non-existing years in Eurostat: For missing years in Eurostat, we linearly interpolate and extrapolate potential wages for each gender g, education e, and country c to fill wage information for all years between 2004 and 2018. Note that for cases where gender wages are missing for both 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 A2.

Figure A2: 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 A2. 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 Italy's 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$\sim$60% of old-age income), (2) medium-cost (60$\sim$90% of old-age income), and (3) high-cost (90$\sim$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 respondent's 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 A8.

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 A8: 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:

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

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:

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

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 A9.

- 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 A9: 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.

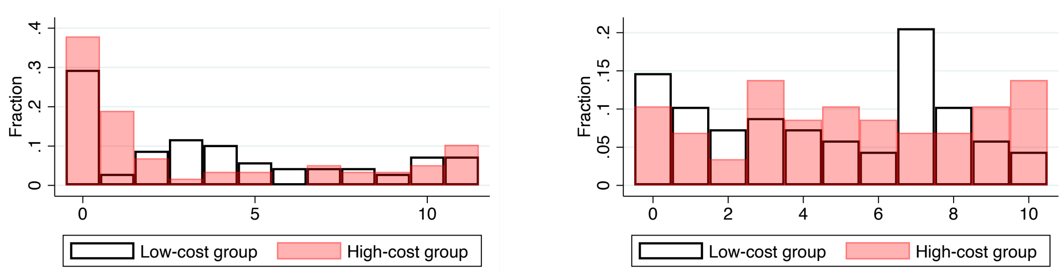
Due to potential data issues in SHARE's ADL/IADL variables, we rely on predicted ADL/IADL measures to estimate care needs for nursing home residents. The procedure is detailed in the following subsection.

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 A3, 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 A3: 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 A11 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 A10, 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 A10: 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 SHAREâĂŹs 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 A11: 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 A12. 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 A13. 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 A12: 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 A13: 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.[23]

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:

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

[23] 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 $P_{ik} = 0\ \forall k \neq j^*$.[24]

[24] 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.