Preference Heterogeneity versus Economic Incentives: What Determines Long-Term Care Arrangements in Europe?

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July 3, 2026

Abstract

Care arrangements vary widely across families and countries. To understand why, we develop a tractable static bargaining model of family long-term-care choices and estimate it using European data. Families choose among child-provided informal care, including which child becomes the caregiver, formal home care, mixed care, and nursing-home care, taking into account both monetary costs and heterogeneous non-monetary preferences over care arrangements. Preference heterogeneity strongly dampens policy responsiveness: without it, a 20% subsidy to nursing-home and formal-home-care costs raises the use of formal care by 7.5%, compared with only 4.0% in the baseline model. Cross-country differences in care arrangements are shaped more by non-monetary factors than by formal-care prices. Looking ahead, the model predicts a substantial increase in demand for formal care by 2050, driven by a declining ratio of adult children to elderly parents, with the largest increases in countries where informal care is currently predominant.

Keywords: Long-term care, informal care, formal home care, family caregiving, preference heterogeneity, Europe
JEL codes: **J14, D13, I18, H31, C35**

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The authors gratefully acknowledge financial support from the European Commission through the Horizon Europe Grant for the project *The Care Wave and The Future of the Baby Boomers and Their Children* (Project number: 101093849).

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 account for a substantial and growing share of government budgets (Gruber & McGarry, 2023). Care is provided either formally, through paid services, or informally, by family and friends. The mix of these arrangements varies strongly across countries, as do the policies that shape their relative costs (Barczyk & Kredler, 2019).

A central, yet largely unanswered, question for policy design is how care arrangements respond to monetary incentives. These decisions reflect not only financial costs, but also non-monetary caregiving considerations.[1] Such considerations operate along two distinct margins: they shape how families value child-provided care relative to formal alternatives, and they generate heterogeneity across siblings within the same family, affecting which child becomes the caregiver. Understanding the relative importance of these margins is central for policy design. If caregiving choices are highly responsive to monetary incentives, subsidies can substantially reshape care arrangements. If non-monetary factors loom large, behavioral responses will be more limited, and much of their impact will take the form of financial relief rather than changes in care provision.

In this paper, we quantify the relative importance of monetary and non-monetary forces, and show that accounting for preference heterogeneity fundamentally alters key policy-relevant objects, most notably the elasticity of formal-care use to prices.

We develop a tractable static bargaining model of the family. Parents and children bargain over the care arrangement and, when care involves a child, over which child becomes the primary caregiver. The parent can make a transfer in exchange for caregiving; if no child participates, the parent falls back on the preferred purely formal arrangement, either formal home care or nursing-home care. Siblings are modeled as a collective household, which provides a parsimonious way to incorporate multiple children with heterogeneous caregiving costs into the model. Each child faces distinct non-monetary and financial caregiving costs, including labor-market opportunity costs that rise with the parent's care needs, and commuting costs that depend on geographic distance. Thus, the framework is not unitary in the sense of imposing identical preferences or identical costs across children. Rather, siblings jointly decide which child is designated as caregiver, taking into account each child's own psychic cost of informal care as well as monetary caregiving costs.

A key feature of our framework is that it allows us to separate this complex bargaining

[1] For example, Gentili et al. (2017) exploit linguistic borders within Switzerland to show that culturally driven differences in family ties generate substantial variation in the use of informal versus formal long-term care, even holding institutions and prices constant.

problem into two parts: the determination of the care arrangement – our main focus – and the division of the surplus from child involvement in care through the exchange-motivated transfer. The central theoretical result is that the family selects the arrangement – informal care provided by a specific child, formal home care, mixed care (formal home care combined with child-provided informal care), or nursing-home care – that minimizes the family's total *effective cost*, defined as the sum of monetary and psychic costs. This characterization yields a simple discrete-choice estimation equation derived directly from our structural theory of the family.[2]

The structural approach is useful for two reasons. First, it allows us to use observed care choices to identify the underlying economic and non-monetary determinants of caregiving arrangements. Second, once those determinants are estimated, the model can be used to evaluate families' responses to formal-care subsidies, demographic change, and cross-country differences in long-term-care systems.

We estimate the model using rich data from Europe, which serves as an ideal laboratory because public long-term-care systems vary widely across countries. 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 non-monetary preferences. Our primary dataset is the Survey of Health, Ageing, and Retirement in Europe (SHARE), a large cross-country panel survey that provides detailed demographic and health information on elderly individuals, their families, and their caregiving arrangements.[3] We also use cross-country data on out-of-pocket costs for both institutional care and formal home care. For formal home care, we construct cost schedules from underlying cross-country home-care out-of-pocket schedules that vary by country, care needs, and income, and assign them at the household level. Finally, we carefully construct children's opportunity costs. Because caregiving can affect children's observed labor-market outcomes, we do not infer opportunity costs from realized child earnings or labor supply. Instead, we use labor-market data from Eurostat's Structure of Earnings Survey (SES) to construct external potential income for adult children. To account for labor-force participation by gender, we combine this with gender-specific labor-force-participation adjustments. With labor-force-participation-adjusted potential income for adult children in hand, we allow their opportunity costs to depend on parental care needs, geographic distance, commuting time and monetary travel costs. All of these factors are important for caregiving decisions.

Our estimates indicate that both non-monetary heterogeneity linked to observable char-

[2]We discuss the implications and limitations of this cooperative structure in Section 3, especially the paragraph *Interpretation of the cooperative benchmark.*

[3]SHARE underrepresents nursing-home residents in some country-wave cells, and so we adjust the household weights accordingly; see Section 2.1.

acteristics and residual latent heterogeneity play substantial roles in shaping caregiving arrangements. On the child side, caregiving costs vary systematically with observable characteristics: being a daughter significantly lowers the utility cost of informal care, while having a partner increases it. Importantly, residual non-monetary heterogeneity explains a large share of the variation in observed care choices. Under the multinomial-logit normalization, a one-standard-deviation shock in this latent term is equivalent to roughly EUR 12,000 in annual monetary care costs. On the formal-care side, the estimated non-monetary utility cost of formal arrangements differs substantially across policy environments: formal care is relatively attractive in more generous long-term-care systems, but much less so in less generous ones, especially for nursing-home care.

Three quantitative findings stand out. First, omitting preference heterogeneity almost doubles the responsiveness of formal-care use to subsidies: in the baseline model, the elasticity of formal-care use to a joint subsidy for nursing home and formal-home care is 0.20 in absolute value, compared with 0.38 in a version of the model without preference heterogeneity. Second, policy responsiveness varies considerably across Europe. The elasticity is merely 0.08 in high-generosity long-term-care systems, compared with 0.44 where formal care remains least affordable. Third, care arrangements are shaped to an important extent by the broader cultural-institutional environment: in our decomposition, equalizing formal-care prices accounts for only about one-fifth of the explained reduction in cross-group formal-care gaps.

We then use the model to predict care arrangements in Europe in 2050. Demographic and social change, especially the decline in the number of children, substantially increase formal-care use: it rises by about 11 percentage points in high-generosity long-term-care systems and by 21 percentage points in low-generosity systems. The 2050 policy variants also deliver a nuanced message for formal home care: targeted expansions of formal home care do more to support aging at home than broad reductions in formal-care costs that also subsidize nursing-home care.

Our paper makes four primary contributions to the literature. First, we advance the structural literature on how caregiving arrangements respond to government policies. Existing models capture key economic trade-offs, such as labor-market opportunity costs and caregiving subsidies, and incorporate non-monetary heterogeneity to match observed differences across individuals and families (e.g., Skira, 2015; Braun et al., 2017; Barczyk & Kredler, 2018; Ko, 2022; Mommaerts, 2025). In this literature, the primary quantitative focus is on economic trade-offs, with non-monetary factors primarily serving to account for heterogeneity in caregiving arrangements. Our contribution is to show that preference heterogeneity is not merely required to match observed behavior, but materially changes the

estimated impact of long-term-care policy on care arrangements.

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 the choice among care arrangements, we focus on intra-family bargaining and heterogeneity in families' non-monetary caregiving preferences. Montesinos (2025) is closer to our approach, but differs in two important respects. First, we explicitly model the monetary costs of alternative formal-care arrangements. When care is provided informally, this gives rise to an exchange-motivated transfer from parent to child, which is consistent with evidence that caregiving may be compensated through inter vivos support or bequests (e.g. Brown, 2006; Groneck, 2017; Barczyk et al., 2023). Second, we allow parental care needs to vary and interact with children's opportunity costs, a margin that is essential for understanding caregiving choices.

Third, we contribute to a large literature on family decision-making in caregiving choices involving multiple children. Existing studies differ along several key dimensions, including the set of care arrangements considered, the role assigned to monetary costs, and the treatment of parental care needs. Some papers examine only the selection of a primary informal caregiver among children, abstracting from formal care altogether (e.g. Checkovich & Stern, 2002; Fontaine et al., 2009; Knoef & Kooreman, 2011; Bergeot, 2024), while others incorporate formal care but abstract from its monetary costs (e.g. Stern, 1995; Hiedemann & Stern, 1999; Engers & Stern, 2002). Byrne et al. (2009) estimate a rich model featuring both informal caregiving and formal home care, but do not consider nursing-home care and abstract from the interaction between parental care needs and children's opportunity costs. Hunt (2026) studies a dynamic sibling-care model with an emphasis on strategic interaction and gender differences in caregiving. Our approach focuses on care-arrangement choice in a setting with multiple children and multiple care options, and on how these choices respond to long-term-care policy.

Finally, we contribute to the literature on intra-family transfers and caregiving decisions within cooperative family models. Our approach builds on seminal work such as Pezzin & Schone (1999), which develops and estimates a bargaining model of joint labor supply and parental care decisions. Stern (1995) and Engers & Stern (2002) also study caregiving among multiple children in cooperative settings, but abstract from both monetary formal-care costs and explicit bargaining between parents and children. Our contribution is methodological: we provide a bargaining framework that yields a tractable discrete-choice estimating equation.

The remainder of the paper is organized as follows. Section 2 describes the data and presents descriptive evidence on formal and informal care in our estimation sample. Section

3 develops the theoretical model of family caregiving arrangements and shows how preference heterogeneity conceptually shapes the price responsiveness of formal-care use. Section 4 describes the estimation of the micro-founded discrete-choice model. Section 5 reports the counterfactual analyses. Section 6 concludes.

2 Empirical facts

In this section, we first describe the data and sample construction, and then document the main empirical facts on care choices, care needs, and child characteristics.

2.1 Data

SHARE. Our primary data source is the Survey of Health, Ageing, and Retirement in Europe (SHARE), a large cross-country 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. A key measurement concern is that SHARE under-represents nursing-home residents in some country-wave cells. We address this by constructing nursing-home-adjusted (NH-adjusted) household weights using information on observed and follow-up-wave institutionalization together with OECD data on nursing-home use from the institutional side, which do not suffer from sampling bias; Appendix Section A.1.2 provides the construction details and shows that the adjustment moves weighted SHARE nursing-home prevalence materially closer to the OECD benchmark. Separately, because later SHARE interviews create measurement problems for parent-child distance and child identity over time – Waves 3 and 7 are retrospective – we use the baseline samples from SHARE Waves 1, 2, 4, 5, 6, and 8; Appendix Section A.1 describes the wave restrictions.

Income measures for children. 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 gender, education, country, and year, using Eurostat's Structure of Earnings Survey (SES). Appendix Section A.2 describes the construction of these potential wages.

Formal-care cost measures. We construct separate out-of-pocket cost measures for nursing-home care and formal home care. Nursing-home costs are based on OECD data on institutional-care costs by country and income group, combined with country-year-income-group data on old-age disposable income from Eurostat's European Union Statistics on Income and Living Conditions (EU-SILC). Formal home-care costs are constructed from the corresponding home-care price schedules and vary additionally with the parent's care needs. Appendix Section A.4 explains how the nursing-home and formal-home-care cost measures are constructed from the OECD and EU-SILC inputs.

Estimation sample. 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). The paper should therefore be read as analyzing the arrangement margin among families in which care is required and a child-caregiving decision is salient, rather than the full extensive-margin care decision for the entire elderly population (which includes milder cases that can go without care).

With this in mind, we construct our sample using several restrictions. We restrict the sample to single parents aged 65 or older with at least one child aged 20 to 60, since this is the population for which children's labor-market opportunity costs are most relevant. Within this group, we focus on parents observed on an intensive care margin. Operationally, this includes parents using nursing-home care, formal home care, mixed formal-home and child-provided care, or child-provided informal care at least weekly. Among households with child involvement in care, we further restrict attention to families with an identifiable primary child caregiver. This again where the relevant trade-offs are most salient, and empirically it is also the dominant form of child caregiving.[4] When multiple children are involved, we assign the primary caregiver based on caregiving intensity and living arrangement. Households with multiple children providing equal amounts of care are excluded. Appendix Section A.3 spells out the caregiver-assignment rules.

Taken together, these restrictions define a sample in which the economically meaningful choice is among intensive care arrangements and, when child care is used, among potential child caregivers. Our final estimation sample includes 2,743 households, comprising 5,971

[4]In the broader baseline SHARE sample of single parents aged 65+ with children aged 20–60, 79.1% of households with at least one child providing intense informal care have exactly one caregiving child, compared with 17.4% with two, 3.5% with three, and 0.1% with four.

parent-child observations. Appendix Section A.1.5 lays out the sample-selection steps.

Country groups by long-term-care generosity. We group countries into three long-term-care (LTC) generosity groups. The primary reason is empirical: country-level analysis would leave many cells too small once we move to narrower samples and more detailed care margins, so we require a grouping that preserves sufficient sample size. To form these groups, we use public LTC spending as it captures broad institutional commonalities in the generosity and scope of formal-care systems, and may also correlate with wider country-level environments shaping care choice. Countries with public LTC spending above 2% of GDP are classified as high generosity (e.g. Sweden), those between 1% and 2% as middle generosity (e.g. France), and those below 1% as low generosity (e.g. Spain).[5] Appendix Table A9 lists the countries in each group together with their household counts in the final estimation sample.

2.2 Cross-country variation in care arrangements

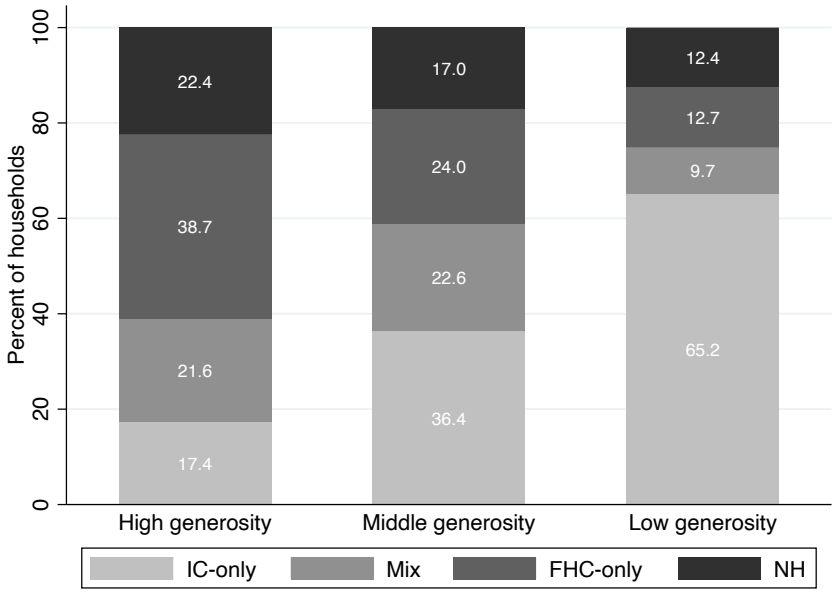
Figure 1 shows that the LTC-generosity groups differ sharply in the composition of care arrangements. In high-generosity systems, only 17.4% of households rely on child-provided informal care, compared with 65.2% in low-generosity systems. The corresponding difference is absorbed not only by nursing-home care, but also by formal home care and mixed arrangements. Thus, the main cross-group contrast is a broad shift away from purely child-provided care and toward both home-based and institutional formal care.

At the same time, substantial heterogeneity remains even among countries facing broadly similar long-term-care policy environments. For example, the IC share ranges from 12.1% in the Netherlands to 52.7% in Finland across high-generosity countries, from 10.4% in Luxembourg to 67.5% in Czechia across middle-generosity countries, and from 38.4% in Lithuania to 92.7% in Poland across low-generosity countries. The formal-care margins vary substantially as well: in the middle-generosity group, FHC ranges from 6.1% in Czechia to 43.1% in France, while NH ranges from 11.8% in France to 31.3% in Luxembourg. This suggests that public support matters, but does not by itself pin down care choices; Appendix Figure A4 shows the country-level care-arrangement shares within each group.

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[5]The spending measure is constructed from OECD long-term-care expenditure data as the sum of the health and social LTC components under government and compulsory schemes (HC3 + HCR1), expressed as a share of GDP (https://data-explorer.oecd.org/).

Figure 1: Care arrangement shares by country group



This figure shows the share of households in each observed care arrangement in the estimation sample, broken down by country group. The four arrangements are nursing-home care (NH), formal home care (FHC), mixed formal-home and child-provided care (Mix), and child-provided informal care (IC). NH-adjusted household weights are applied.

2.3 Care needs across arrangements

Care need is a central input into our model because it determines how costly child involvement in care can be. We measure it using imputed daily care hours following Barczyk & Kredler (2019), who map respondents' limitations in activities of daily living (ADLs), instrumental activities of daily living (IADLs), and mobility into care hours using the Health and Retirement Study (HRS). We therefore do not treat realized informal-care hours in SHARE as the care-needs measure. Doing so would confound how much care the parent needs with how much informal care the family happened to provide. Instead, we predict care needs from respondents' limitation profiles. For nursing-home residents – whose care needs are unobserved in both SHARE and HRS – we then apply the adjustment method developed by Dahl (2002) to account for negative selection, namely that nursing-home residents are disproportionately drawn from the upper tail of the unobserved care-needs distribution. Appendix Section A.5 describes the construction in detail.

Table 1: Estimated daily care hours needed

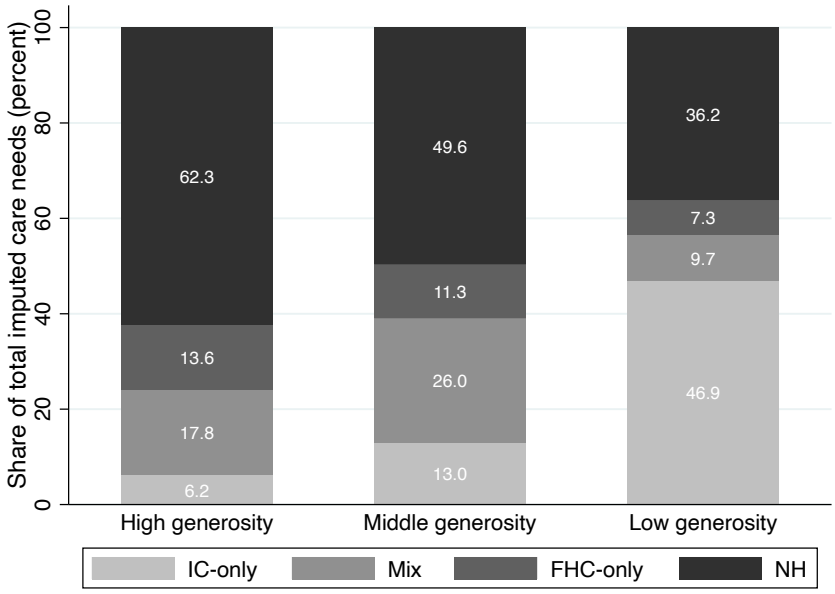
	Mean	Min	p25	Median	p75	Max
Overall distribution	4.2	0.2	0.5	1.8	7.0	22.4
Mean by arrangement						
	IC	Mix	FHC	NH		
	2.5	4.3	1.9	12.0		

The top panel reports the overall distribution of estimated daily care needs in the estimation sample. The bottom panel reports mean estimated daily care needs by arrangement. Summary statistics use NH-adjusted household weights.

Table 1 reports both the overall distribution of these imputed care needs and their mean levels by arrangement in our estimation sample. Care needs vary widely across households. Accounting for this variation is essential for measuring children's opportunity costs accurately: when a parent's care needs are modest, caregiving may be compatible with continued market work; when care needs are high, child involvement can require substantial reductions in work time. This interaction has received relatively little attention in the existing structural caregiving literature.

Figure 2 makes a separate aggregate point. It complements Figure 1 by showing how total care needs, rather than just the number of households, are distributed across arrangements once intensity is taken into account. The most striking result is that child-involving care remains quantitatively important even in high-generosity systems once IC and Mix are combined (24%). At the same time, the aggregate importance of FHC shrinks markedly relative to the case counts presented in Figure 1. By contrast, it is less surprising that nursing-home care absorbs a much larger share of total care needs, because it serves the highest-need households.

Figure 2: Share of total imputed care needs by arrangement and country group



This figure displays the share of total imputed care needs accounted for by each observed care arrangement within each country group. Total care needs are measured as the sum of imputed daily care hours across households. NH-adjusted household weights are applied.

2.4 Child characteristics across arrangements

These arrangement differences line up closely with the family care supply available to parents. Table 2 summarizes household-level child-pool characteristics. The table shows that households relying on informal care have the strongest family-care supply: they are most likely to have a daughter, they have the closest child on average, and they face the lowest child opportunity costs. Mixed-care households sit between informal care and the two fully formal arrangements, while nursing-home households have the weakest family-care supply overall.

Table 2: Child-pool characteristics by parental care arrangement

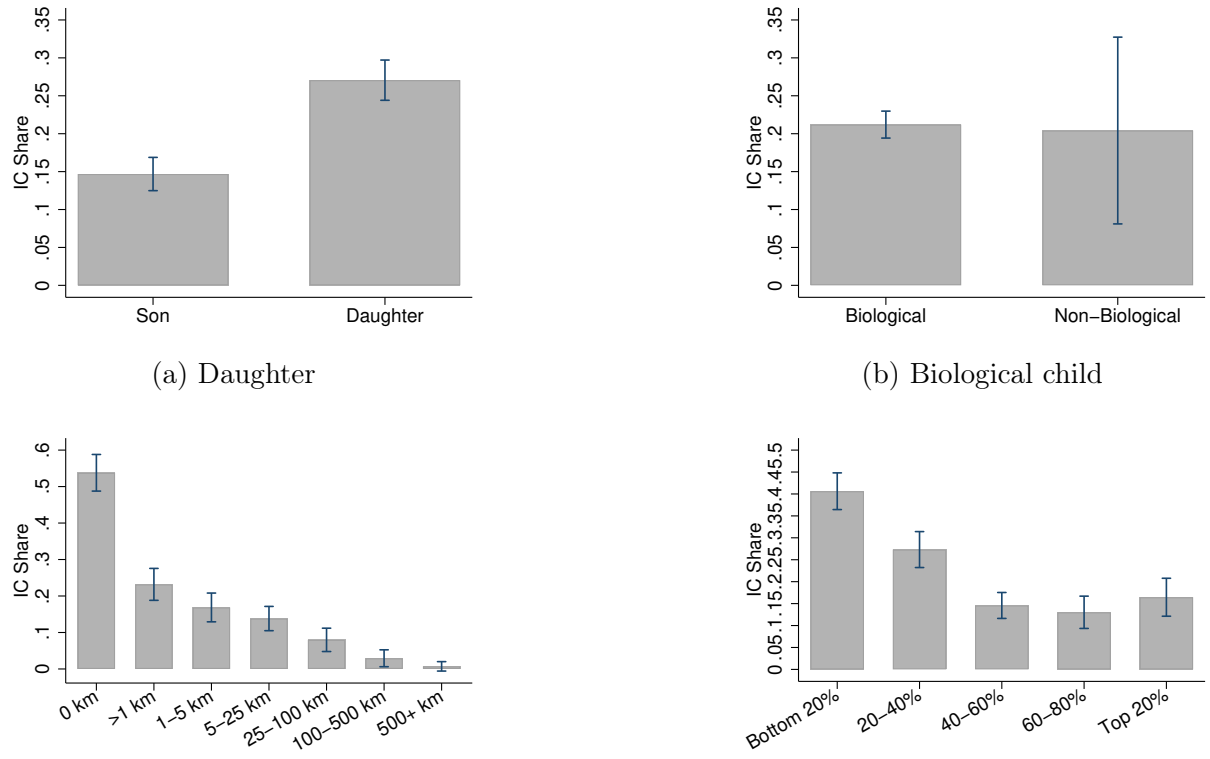
Arrangement	Has daughter	Closest child (km)	Lowest potential income	Number of children
IC-only	81.3%	6.5	20,525	2.21
Mix	78.9%	12.2	24,324	2.09
FHC-only	74.7%	74.5	25,490	2.16
NH	64.0%	57.7	26,558	1.82

Entries are household-level means in the estimation sample, using NH-adjusted household weights. "Has daughter" indicates whether the parent has at least one eligible daughter. "Closest child" is the minimum child-parent distance within the household. "Lowest potential income" is the minimum LFP-adjusted potential income across children. "No. children" is the number of eligible children.

Turning from the child pool to the realized caregiver, we now focus on informal-care households, where the caregiving child can be identified cleanly. Figure 3 shows that informal care is disproportionately provided by daughters, by children who live close to the parent, and by children with lower potential income. Biological-child status is less informative, in part because non-biological children are rare in the estimation sample. These patterns foreshadow key child-side economic margins in the model, especially distance as a determinant of commuting costs and children's labor-market opportunity costs.

Finally, while within families these observable economic margins are powerful, they are not decisive predictors of who becomes the caregiver. In informal-care households, the realized caregiver is the closest child in about 89% of cases and the lowest-potential-income child in about 77% of cases. Thus, distance and opportunity costs matter greatly, but they do not fully determine caregiver choice. Even observationally similar families can make different caregiving assignments, pointing to the importance of non-monetary heterogeneity within families.

Figure 3: Informal-care probability by child's characteristics



(a) Daughter

(b) Biological child

(c) Distance to parent

(d) Potential income

This figure reports the proportion of children providing informal care across different child characteristics in the estimation sample. Non-biological children include stepchildren, adopted children, and foster children. NH-adjusted household weights are applied. 95% confidence intervals are reported.

3 Family model

The empirical patterns above point to two questions: which care arrangement families choose, and, when care involves a child, which child within the family becomes the caregiver. To address these questions, we develop a formal framework in which families choose among informal care, formal home care, mixed care (formal home care combined with child-provided informal care), and nursing-home care, while also selecting the child involved in care when a child-involving arrangement is chosen. The model is designed to capture both the economic margins highlighted in the data, namely formal-care costs, distance, and children's opportunity costs, and the residual preference (i.e. non-monetary) heterogeneity that remains both within and across families.

3.1 Physical environment

In this section, we present the environment and discuss our assumptions where appropriate. Consider a family i consisting of one elderly parent in need of care and $K_i > 0$ adult children, where the number of children may vary across families. We henceforth omit the family subscript i in the economic model to simplify notation. The parent requires n hours of care, where n may vary across families.

Care arrangements The family-specific choice set is

$$\mathcal{A} = \{\text{NH}, \text{FHC}\} \cup \mathcal{A}^C, \quad \text{where} \quad \mathcal{A}^C = \{\text{Mix}_j, \text{IC}_j : j = 1, \ldots, K\}.$$

The family may choose nursing-home care (NH), formal home care (FHC), a mixed arrangement in which formal home care is combined with child j's informal care (Mix_j), or informal care provided by child j (IC_j). We denote a generic element of the choice set by $a \in \mathcal{A}$ and refer to $\mathcal{A}^C$ as the set of *child-involving care arrangements*.

Care costs If the family chooses NH, the parent pays out-of-pocket price p^{NH} for nursing-home care. If the family chooses FHC, the parent pays out-of-pocket price $p^{FHC}(n)$ for formal home care. We interpret p^{NH} and $p^{FHC}(n)$ as annual out-of-pocket care burdens net of public support.[6] If child $j \in \{1, \ldots, K\}$ provides informal care, she incurs (opportunity) cost

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

where n is the number of hours spent on caregiving, $t_d(d_j)$ represents commuting time over distance d_j, and $c_d(d_j)$ captures direct travel costs. Under a mixed arrangement, we assume that a fraction $\lambda \in (0, 1)$ of care is provided formally and the remaining fraction $1 - \lambda$ by child j, so that the parent pays $\lambda p^{FHC}(n)$, while child j incurs informal-care opportunity cost $(1 - \lambda)OC_j$.

Transfers The parent can provide a financial transfer $Q \geq 0$ to children. We interpret Q broadly: it may represent contemporaneous monetary compensation, implicit within-family support such as co-residence or resource sharing, or future transfers such as bequests that are understood by the family but not modeled explicitly here.[7] What matters for our analysis is

[6] Under this specification, the cost of formal home care varies, potentially non-linearly, with care needs, whereas the nursing-home cost does not. In the empirical implementation, both p^{NH} and $p^{FHC}(\cdot)$ also depend on country and family income, so both should be understood as family-specific objects.

[7] This interpretation is consistent with evidence that parents compensate caregiving children through larger transfers or bequests; see, for example, Groneck (2017); Barczyk et al. (2023).

that child involvement in care can be sustained through the redistribution of family resources, not the precise form that this redistribution takes.

Endowments and individual budget constraints The parent has income y_p, which she can spend on her own consumption c_p, on financing the chosen care arrangement, and on a transfer to children. Transfers are feasible under all arrangements, although in equilibrium they only play a role when care involves a child. Thus,

$$c_p = \begin{cases} y_p - p^{NH} - Q, & a = \text{NH}, \\ y_p - p^{FHC} - Q, & a = \text{FHC}, \\ y_p - \lambda p^{FHC} - Q, & a = \text{Mix}_j, \\ y_p - Q, & a = \text{IC}_j. \end{cases}$$

where we omit the dependence of p^{FHC} on n from now on. Here, we interpret y_p as the sum of the parent's income, assets, and savings. Under this interpretation, nursing-home costs need not be paid out of the parent's current income alone. We also assume that the government provides sufficient support such that at least one formal-care option guarantees non-negative consumption to the parent.

Each child $j \in \{1, \ldots, K\}$ receives labor income y_j, endowment e_j (for example, spousal income), and a portion Q_j of the transfer, where $\sum_{j=1}^{K} Q_j = Q$. Their budget constraints under care arrangement a are

$$c_j = \begin{cases} y_j + e_j + Q_j - OC_j, & a = \text{IC}_j, \\ y_j + e_j + Q_j - (1-\lambda)OC_j, & a = \text{Mix}_j, \\ y_j + e_j + Q_j, & \text{otherwise}. \end{cases}$$

Preferences Both the parent and the children derive utility from consumption but may experience psychic costs under different care arrangements.[8] These psychic costs are measured in consumption-equivalent units, so they effectively reduce the utility derived from

[8] Our results also go through for altruistic preferences. The remark after Theorem 1 expands on this statement.

consumption. Specifically, we assume that the parent's utility is

$$u_p(c_p, a) = \begin{cases} u(c_p - \theta^{NH}) & \text{if } a = \text{NH} \\ u(c_p - \theta^{FHC}) & \text{if } a = \text{FHC} \\ u(c_p - \theta_p^{Mix}) & \text{if } a \in \{\text{Mix}_j\} \\ u(c_p) & \text{if } a \in \{\text{IC}_j\} \end{cases}$$

where $u(\cdot)$ is a strictly increasing function.[9] Thus, the parent may dislike NH, FHC, and Mix to different degrees, while the parent-side psychic penalty of IC is normalized to zero.

Each child j experiences a psychic cost only if that child provides care. Child j's utility under care arrangement a is

$$u_k(c_j, a) = \begin{cases} u(c_j - \theta_j^{IC}) & \text{if } a = \text{IC}_j \\ u(c_j - \theta_j^{Mix}) & \text{if } a = \text{Mix}_j \\ u(c_j) & \text{otherwise.} \end{cases}$$

This allows the child's psychic cost to differ between mixed and pure informal care, and it allows these psychic costs to vary across children. While these psychic costs are in principle unrestricted, in the empirical specification we parameterize the child-side psychic cost in pure informal care as

$$\theta_j^{IC} = \theta^{IC}(\mathbf{x}_j) = \mathbf{x}_j^\top \boldsymbol{\beta}.$$

where $\mathbf{x}_j$ is a vector of observable child characteristics. Any remaining unobserved heterogeneity is absorbed by the idiosyncratic preference shock in the empirical discrete-choice model.[10] These child-side psychic costs should be interpreted broadly. They may reflect the child's personal attitudes toward care and the child's relationship to the parent, but they may also capture family- or society-specific norms or altruistic motives toward the parent; the model does not distinguish among these different motivations. Accordingly, the estimated β is best interpreted as reduced-form latent utility costs of providing care rather than as a full structural decomposition of motives. When the empirical analysis finds large child-side non-monetary caregiving margins, these should therefore be read as capturing total non-

[9] Formally, we let $u : \mathbb{R} \to \mathbb{R}$, i.s. the utility function is also defined for negative arguments. Note that $c_p - \theta^{\cdot}$ may be negative due to the psychic-cost shifters, even though consumption c_p itself is non-negative.

[10] For mixed care, we impose a simpler empirical structure to keep estimation feasible. Rather than modeling a full set of child-specific mixed-care alternatives, we use a single mixed-care option and assign to it the child who is most plausibly the caregiver based on observables.

monetary willingness to provide care, rather than a clean separation between burden and altruism.

Collective sibling household We assume that the K siblings act collectively, i.e. they choose an efficient allocation, where the point on the Pareto frontier is determined by fixed Pareto weights $\mu_j \geq 0$. Let

$$R = \sum_{j=1}^{K} (y_j + e_j)$$

denote the total resources of the sibling household before caregiving costs are incurred. For a given care arrangement a, the collective sibling household solves

$$\max_{\{c_j\}_{j=1}^{K}} \sum_{j=1}^{K} \mu_j u_j(c_j, a)$$

subject to the pooled budget constraint

$$\sum_{j=1}^{K} c_j = \begin{cases} R + Q, & a \in \{\text{NH}, \text{FHC}\}, \\ R + Q - (1-\lambda) OC_j, & a = \text{Mix}_j, \\ R + Q - OC_j, & a = \text{IC}_j. \end{cases}$$

Note here that the transfers $\{Q_j\}$ are implicit in the consumption allocation $\{c_j\}$.

Family bargaining problem We model the family's decision-making process as a generalized Nash bargaining game between the parent and the collective sibling household, with bargaining weight $\mu_p \in [0, 1]$ on the parent. As the disagreement (outside) option, no child participates in caregiving and the parent unilaterally chooses her preferred (purely) formal arrangement. The inside options are the child-involving care arrangements $a \in \mathcal{A}^C$, together with an associated parent-to-children transfer Q.

3.2 Characterization

We now characterize the bargaining problem formally. To characterize the feasible set for the family, we first study how the alternative care arrangements affect total family resources.

Family resources across arrangements. Total family resources net of monetary care

costs are

$$\begin{aligned} y_p + R - p^{NH} &\quad \text{under NH}, \\ y_p + R - p^{FHC} &\quad \text{under FHC}, \\ y_p + R - \lambda p^{FHC} - (1-\lambda)OC_j &\quad \text{under Mix}_j, \\ y_p + R - OC_j &\quad \text{under IC}_j. \end{aligned}$$

These expressions show that different care arrangements burden the family in different ways: purely formal arrangements reduce resources through parent-borne formal-care spending, while child-involving arrangements reduce resources through child-borne opportunity costs.

Outside option. Under the disagreement point, the parent chooses

$$a^F = \arg\min\{p^{NH} + \theta^{NH},\, p^{FHC} + \theta^{FHC}\},$$

that is, the preferred purely formal arrangement. The parent's disagreement utility is therefore

$$d_p = \max\{u(y_p - p^{NH} - \theta^{NH}),\, u(y_p - p^{FHC} - \theta^{FHC})\}. \tag{1}$$

Since the children bear neither monetary nor psychic costs under the disagreement point, their collective disagreement utility is

$$d_k = \max_{\{c_j\}_{j=1}^K} \sum_{j=1}^K \mu_j u(c_j) \qquad \text{s.t.} \qquad \sum_{j=1}^K c_j = R. \tag{2}$$

It is important to note here that the parent's choice under the outside option is intra-family efficient, as the children are indifferent between NH and FHC under our assumptions.[11]

Inside option. Bargaining is relevant only for the child-involving arrangements in $\mathcal{A}^C$. For any $a \in \mathcal{A}^C$, let $M_p(a)$ denote the monetary cost borne by the parent, $M_k(a)$ the monetary cost borne by the designated child, $\theta_p(a)$ the parent's psychic cost, and $\theta_k(a)$ the designated caregiver's psychic cost under care option a, where the sub-index k is for *kid*

[11] If children also had a preference over NH and FHC, in order to maintain our approach feasible one would have to assume bargaining over one of the formal-care options as well, with associated transfer Q.

(child). Concretely,

$$\big(M_p(a), M_k(a), \theta_p(a), \theta_k(a)\big) = \begin{cases} \big(\lambda p^{FHC}, (1-\lambda)OC_j, \theta_p^{Mix}, \theta_j^{Mix}\big), & a = \text{Mix}_j, \\ \big(0, OC_j, 0, \theta_j^{IC}\big), & a = \text{IC}_j. \end{cases}$$

The family bargaining problem is then

$$\max_{c_p, \{c_i\}_{i=1}^K,\, a \in \mathcal{A}^C} [u_p(c_p, a) - d_p]^{\mu_p} \left[\sum_{j=1}^K \mu_j u_j(c_j, a) - d_k\right]^{1-\mu_p} \tag{3}$$

$$\text{s.t. } c_p + \sum_{j=1}^K c_j = y_p + R - M_p(a) - M_k(a). \tag{4}$$

In words, the family chooses the child-involving arrangement and the allocation of consumption subject to the family budget constraint to maximize the generalized Nash product.[12]

Effective consumption A useful property of our preference specification is that we can obtain an equivalent problem by accounting for the psychic costs *as if* they were budget items. We define *effective consumption* x for child j and the parent as

$$x_j = c_j - \mathbb{I}_{j=j(a)}\theta_k(a), \qquad\qquad x_p = c_p - \theta_p(a),$$

where $j(a)$ denotes the designated caregiving child under arrangement a and where $\mathbb{I}$ is the indicator function. Using these definitions in 3, we obtain the Nash program in terms of effective consumption:

$$\max_{x_p, \{x_i\}_{i=1}^K, a \in \mathcal{A}^C} [u(x_p) - d_p]^{\mu_p} [\sum_{j=1}^K \mu_j u(x_j) - d_k]^{1-\mu_p} \tag{5}$$

$$\text{s.t. } x_p + \sum_{j=1}^K x_j = \underbrace{y_p + R - \big[\overbrace{M_p(a) + \theta_p(a) + M_k(a) + \theta_k(a)}^{\equiv C_a}\big]}_{\text{family effective resources}}, \tag{6}$$

where the disagreement utilities d_p and d_k remain as in equations (1) and (2) and where we denote by C_a the (total) *effective cost* of option a to the family. Analogously, for the purely formal arrangements $a \in \{NH, FHC\}$, we define effective cost as $C_a = p^a + \theta^a$, recalling that children bear neither monetary nor psychic costs under these arrangements.

[12] Any solution to this problem must also solve the siblings' collective allocation problem under the chosen child-involving arrangement. If there existed a feasible reallocation among siblings that increased their collective utility, the candidate allocation would be dominated in the Nash program. For this reason, we do not state a separate collective-sibling problem for child-involving arrangements here.

This formulation makes it transparent that utility is essentially transferable under our assumptions and that the care choice can be analyzed separately from the consumption-allocation problem. The combination of Pareto efficiency, implied by Nash bargaining, and non-satiation (increasingness of u) ensures that the Nash criterion is strictly increasing in the family's effective resources, or decreasing in C_a. Therefore, the joint problem in (5) can be solved by first selecting the effective-cost-minimizing arrangement and then determining how the resulting surplus is divided. Still, it is important to note that the collective structure does not remove heterogeneity across siblings: the effective cost of a child-involving arrangement depends on which child is involved, through child-specific opportunity costs and non-monetary caregiving costs.

Solving the bargaining problem step by step, among the purely formal arrangements under the outside option, the parent chooses

$$a^F = \arg \min_{a \in \{\text{NH,FHC}\}} C_a.$$

Among the child-involving arrangements, the family chooses

$$a^C = \arg \min_{a \in \mathcal{A}^C} C_a.$$

Now, if a^C is such that it implies lower effective costs to the family than the outside option, i.e. $C_{a^C} \leq C_{a^F}$, there exists a transfer Q that makes both the parent and children better off under the inside option a^C. Conversely, if $C_{a^C} > C_{a^F}$, then no transfer exists that makes both parties better off and the outside option is chosen. As children bear neither monetary nor utility costs under the outside option, the parent's choice under the outside option also maximizes the family's effective resources. It follows that:

Theorem 1 (Care choice) *Under any bargaining solution to (3), the care choice satisfies*

$$a^* = \arg \min_{a \in \mathcal{A}} C_a, \tag{7}$$

where C_a is the effective cost of arrangement $a \in \mathcal{A}$ defined in (6). This choice is efficient and maximizes effective family resources, i.e. the right-hand side of (6). Conditional on a child-involving arrangement being selected, the designated child is the one associated with the lowest relevant effective cost. Furthermore, any family bargaining protocol (or other assignment rule) that satisfies efficiency must imply care choice (7).

Proof: The claim in (7) follows from the discussion before, as well as the claim that $a^C = \arg\min_{a \in a^C} C_a$. The claim on the maximization of effective family resources then

follows immediately from (6). Efficiency of a^* follows from efficiency of generalized Nash bargaining together with the fact that a^F is the (family-)efficient choice under the outside option. The last claim on other efficient protocols follows from the fact that if $C_a < C_{a^*}$ for some $a < a^*$ it follows that there exist transfers that make all family members better off under choice a. ■

Remark. We remark that the theorem goes through also under altruistic preferences, at least of the Becker type. We now argue that under altruistic (non-spiteful) preferences, any bargaining arrangement must satisfy efficiency. Suppose that for a given allocation A with care choice a there exists care choice a' with a lower effective cost than a. Then, starting at the allocation A, one could construct a dominating allocation B with care choice a' as follows. Splitting the gained (effective) esources between all agents, all involved parties must obtain higher payoffs, as preferences are increasing in effective consumption and as preferences are altruistic and non-spiteful. Thus A cannot be a bargaining solution.

Surplus sharing and transfers The transfer Q^* from the bargaining problem above, and hence the division of the gains from child-involving care, depends on the bargaining weight μ_p.[13] We will now derive bounds on Q^* and provide intuition for some benchmark cases.

For the children to be better off under the inside option, it must be that their effective resources $R - C_{a^C} + Q$ are at least as high as under the outside option, where they are given by R. Hence the children's "willingness-to-sell" care is

$$\underline{Q} = C_{a^C} = \begin{cases} OC_j + \theta_j^{IC}, & a^C = \text{IC}_j \\ (1-\lambda)OC_j + \theta_j^{Mix}, & a^C = \text{Mix}_j, \end{cases} \tag{8}$$

That is, children prefer a child-involving arrangement if the transfer Q covers at least the relevant effective child-side cost, which equals the effective cost to the entire family.

As for the parent, to be better off under the inside option it must be that $u(y^p - C^{a^F}) \leq u(y^p - Q)$, from which it follows that the parent's "willingness-to-pay" for care is

$$\bar{Q} = C_{a^F} = \min\{p^{NH} + \theta^{NH}, p^{FHC} + \theta^{FHC}\}. \tag{9}$$

That is, the parent transfer can never exceed its effective cost under the outside option. However, the parent may transfer higher amounts than the formal-care cost, i.e. $Q > \theta^{a^F}$, if it prefers informal care.

[13] The transfers among children $\{Q_j\}$ and thus the division of surplus among them depends on the collective weights $\{\mu_j\}$.

Proposition 1 (Transfer bounds) *Consider the bounds* $\underline{Q}$ *and* $\bar{Q}$ *given in* (8) *and* (9). *We have* $a^* = a^C$ *, i.e. a child-involving care option is chosen, if and only if* $\underline{Q} \leq \bar{Q}$*, the equilibrium transfer satisfying* $Q^* \in [\underline{Q}, \bar{Q}]$*. Furthermore:*

1. *If the parent has all bargaining power (*$\mu_p = 1$*), then:*
   (a) $Q^* = \underline{Q}$*, i.e. children are indifferent to the outside option (formal care),*
   (b) $Q_{j(a^*)} = \underline{Q}$*, i.e. the caregiving child is exactly compensated for its effective cost of caregiving,*
   (c) $Q_j = 0$ *for all* $j \neq j(a^*)$*, i.e. the allocation for all non-caregiving children is the same as under formal care.*
2. *If the children have all bargaining power (*$\mu_p = 0$*), then* $Q^* = \bar{Q}$ *and the parent is indifferent to the outside option (formal care).*

3.3 Discussion of the cooperative benchmark

We adopt a cooperative sibling framework because it provides a parsimonious way to incorporate multiple children into the caregiving allocation problem. It preserves child-specific heterogeneity in both non-monetary willingness to provide care and financial caregiving costs, while yielding a transparent family decision rule. This tractability is central for our purposes, because our main object of interest is how monetary and non-monetary forces shape care-arrangement choices and the within-family allocation of caregiving in a static cross section.

The central implication of this framework is that the family selects the care arrangement and caregiver assignment that minimize total effective family cost. At the same time, the approach abstracts from strategic frictions among siblings, such as free-riding, incomplete compensation, limited commitment, or bargaining breakdowns. Alternative approaches instead model caregiving as a strategic interaction problem, sometimes in dynamic settings with adjustment in labor supply, location, or future care responsibilities (e.g. Hiedemann et al., 2018; Hunt, 2026).

These distinctions are likely to matter most for the allocation of caregiving responsibilities across siblings rather than for the broad choice between child-involving and purely formal care. In our setting, cooperation primarily governs which child provides care, whereas the choice between formal and child-involving care depends on the family's aggregate effective cost of providing care. Strategic frictions may therefore distort caregiver assignment within the family without necessarily overturning the overall care arrangement, although

in environments with substantial free-riding or inefficient assignment they could also affect the formal-versus-family care margin. One suggestive point from the empirical structural literature is that even models with explicit sibling strategic interaction do not uniformly find strong distortions in caregiver assignment; for example, they do not always generate strong birth-order effects (Byrne et al., 2009; Fontaine et al., 2009).

These considerations also matter for the interpretation of estimated child-specific non-monetary caregiving costs. In the data, daughters are substantially more likely to provide care than sons. In our framework, this difference is captured by a lower estimated psychic cost of caregiving for daughters. However, in the presence of strategic interaction among siblings, such gender differences may reflect not only intrinsic preferences or norms, but also equilibrium effects arising from intra-family interaction. As a result, the estimated gender coefficient should be interpreted broadly: it may reflect both underlying preferences or norms and the outcome of intra-family interactions that operate outside the model. Our results should therefore be read as characterizing care choices under efficient within-family allocation, while allowing that some strategic frictions may be embedded in reduced form in the estimated child-side cost parameters.

3.4 How does preference heterogeneity affect elasticities?

Before estimating the full model, we switch gears and use a *simplified model* to clarify the central mechanism of the paper: preference heterogeneity dampens the response of care arrangements to financial incentives. The full model contains several margins – formal versus informal care, mixed care, child selection – that are important quantitatively but can obscure this intuition. This subsection isolates the mechanism in a transparent way, i) collapsing the care menu to two choices, ii) assuming a parametric distribution for care costs across the population, and iii) showing how elasticities differ when calibrating a model with and without preference heterogeneity to data. Appendix Section A.12 derives the elasticity formula used here.

Care choices and costs We collapse the richer care menu from the full model into a binary choice between formal care (FC) and child-involving care (IC).[14] As for the costs of care choices, we will restrict attention to *net effective costs* of IC versus FC to the family, as this is the only relevant statistic according to Theorem 1. Let $C_e \sim N(\mu_e, \sigma_e^2)$ denote

[14]When removing the FHC and mixed options from the full model and setting the number of children to $K = 1$, we obtain a *collapsed model* that corresponds exactly to this simplified model, the mapping of care arrangements being $(NH, IC_1) \to (FC, IC)$. Alternatively, one can construe the FC option in the simplified model as the best available formal-care option for a family (a_F) and the IC option the best available child-involving care option (a^C) in the full model.

the net *monetary* cost of IC (or net economic advantage of FC), where μ_e and σ_e can be calibrated using data on care expenditures and opportunity costs. Let $C_p \sim N(\mu_p, \sigma_p^2)$ be the net *psychic* costs of IC, which we assume to be independent of C_e.[15] [16] We define the total net cost of IC (to the family) as

$$C = C_e + C_p \sim N(\mu_e + \mu_p, \underbrace{\sigma_e^2 + \sigma_p^2}_{\equiv \sigma_c^2}),$$

where, crucially, $\sigma_c^2 \geq \sigma_e^2$. We now consider two versions of the model: i) a preference-homogeneity (**economics-only**) model with $\sigma_p^2 = 0$ and a **preference-heterogeneity** model with $\sigma_p^2 > 0$.

Matching care choices For the sake of our argument, we will treat preference heterogeneity σ_p^2 as fixed, but we will set μ_p such that the model matches the prevalence of FC. Specifically, we require

$$\hat{FC} = Pr(C > 0) = 1 - F_C(0) = 1 - \Phi\left(\frac{-\mu_e - \mu_p}{\sqrt{\sigma_e^2 + \sigma_p^2}}\right), \tag{10}$$

where $\hat{FC} \in (0, 1)$ is a given FC share from the data, $F_C(\cdot)$ denotes the cdf of C and $\Phi(\cdot)$ the standard-normal cdf. Note that this equation will imply different calibrations $\mu_p = \mu_{p,econ}$ for the economics-only and $\mu_p = \mu_{p,het}$ for the preference-heterogeneity model.

FC elasticity Denoting by FC the fraction of the population that chooses FC in the model, we will be interested in the elasticity of FC use with respect to a price-reducing subsidy $\Delta S > 0$:

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

where $\Delta p_{fc} = -\Delta S$. For a small subsidy increase ΔS, this elasticity is approximately

$$|\epsilon_{FC}| \simeq \frac{f_C(0)}{\hat{FC}} p_{fc}, \tag{11}$$

where $f_C(\cdot)$ is the pdf of C. $f_C(0)$ captures the marginal change in the FC share triggered by the subsidy. This equation reveals that policy responsiveness is governed by how much probability mass in the care-cost distribution lies near the decision threshold.

[15] In the collapsed version of the full model, the net monetary cost is $C_e = M_k(IC_1) - M_p(NH) = OC_1 - p^{NH}$ and the net psychic cost is $C_p = \theta_k(IC_1) - \theta_p(NH) = \theta_1^{IC} - \theta^{NH}$.

[16] Our argument goes through more generally whenever adding non-monetary heterogeneity increases the variance of effective net costs, i.e. if $Var(C) > Var(C_e)$.

Comparing elasticities As both models are calibrated to match the same formal-care share, the decision threshold lies at the same quantile of the cost distribution. Specifically, from (10) we can define the normalized threshold as

$$\hat{z} = \Phi^{-1}(1 - \hat{FC}),$$

Then, the marginal increase in the FC share in the two models is given by

$$f_{C,econ}(0) = \frac{\phi(\hat{z})}{\sigma_e} \qquad > \qquad f_{C,het}(\theta_0^c) = \frac{\phi(\hat{z})}{\sigma_c},$$

where ϕ is the standard normal density. Because $\sigma_e^2 < \sigma_c^2$, the economics-only has lower density at the margin and therefore a larger elasticity:

$$|\epsilon_{FC,econ}| > |\epsilon_{FC,het}|.$$

Intuitively, preference heterogeneity spreads families out over a wider range of latent net costs. Holding the baseline formal-care share fixed, this lowers the density of families at the decision margin, so fewer families switch in response to a subsidy.

4 Empirical discrete-choice framework

We now take the family model to the data. Theorem 1 implies that families choose the care-giving arrangement with the lowest total effective cost, where effective cost combines monetary and non-monetary components. This characterization maps directly into a discrete-choice framework that we use to estimate the economic and preference parameters governing care arrangements.

4.1 Discrete-choice specification

Empirical choice set. For family i, let $a \in \mathcal{A}_i$ denote a feasible care arrangement in the empirical specification. Consistent with the model, the empirical choice set contains nursing-home care (NH), formal home care (FHC), and child-specific informal-care options (IC_j). Relative to the theoretical model, however, the empirical specification replaces the child-specific mixed-care options $(Mix_j)_{j=1}^K$ by a single mixed-care option (Mix). This keeps estimation tractable in our setting: allowing every child to be paired with both informal care and mixed care would sharply increase the number of alternatives to be evaluated for each family. We therefore assign to the mixed-care option the child who is most plausibly the

caregiver based on observables such as distance, opportunity costs, and gender. Appendix Section A.3 describes this Mix child-assignment rule.

Mixed care also raises a measurement problem in SHARE, as the data do not identify the child-specific formal/informal composition of mixed arrangements cleanly and consistently across waves.[17] This prevents us from calibrating the formal-care share λ in mixed care directly. Instead, we set $\lambda = 0.5$ as a parsimonious benchmark. This yields a natural three-point approximation, with IC, Mix, and FHC corresponding to $\lambda = 0$, 0.5, and 1, respectively.

Effective cost. Let c_{ia} denote the total effective cost of arrangement a for family i, the empirical counterpart of the theoretical object C_a. We write

$$c_{ia} = m_{ia} + n_{ia}, \tag{12}$$

where m_{ia} is the monetary-cost component and n_{ia} is the systematic non-monetary component. In the structural model, transferable utility implies that monetary costs enter latent utility cost with coefficient one. Let

$$V_{ia}^* = m_{ia} + n_{ia}^* + \varepsilon_{ia}^*,$$

where ε_{ia}^* is assumed to be independently and identically distributed Type-I Extreme Value with location parameter zero and scale parameter σ. As in any multinomial logit model, σ is not separately identified. Dividing through by σ, we work with the normalized latent utility cost

$$V_{ia} = \alpha m_{ia} + n_{ia} + \varepsilon_{ia}, \tag{13}$$

where $\alpha \equiv 1/\sigma$, $n_{ia} \equiv n_{ia}^*/\sigma$, and $\varepsilon_{ia} \equiv \varepsilon_{ia}^*/\sigma$. We note that the common coefficient on monetary costs follows directly from the model's transferable-utility structure: nursing-home spending, formal-home-care spending, and informal-care opportunity costs all enter choices through their effect on effective family resources. The parameter α therefore measures the marginal effect of monetary costs on care choices relative to the scale of the unobserved shocks, regardless of whether those costs arise through formal-care spending or child opportunity costs.

[17] Waves 1 and 2 record weekly hours of formal home care and contain some outside-informal-care hours information, but even the latter is reported at the household rather than child level.

Monetary costs. For family i the monetary-cost component of arrangement $a \in \mathcal{A}_i$ is

$$m_{ia} = \begin{cases} p_i^{NH} & \text{if } a = \text{NH}, \\ p_i^{FHC} & \text{if } a = \text{FHC}, \\ OC_{ij} & \text{if } a = \text{IC}_j, \\ \lambda p_i^{FHC} + (1-\lambda) OC_{i\, j_i^{Mix}} & \text{if } a = \text{Mix}. \end{cases}$$

Here, j_i^{Mix} denotes the child assigned to the mixed-care option under our empirical assignment rule. Furthermore, p_i^{NH} and p_i^{FHC} denote the household-specific out-of-pocket costs of nursing-home care and formal home care, and OC_{ij} is the opportunity cost of child j.

Crucially, in our estimation p_i^{NH} varies by country, income group, and year, and p_i^{FHC} varies along those same dimensions and additionally with care needs. The FHC schedule is piecewise linear in weekly care hours, based on points at 6, 22, and 41 hours, with interpolation between those points and top-coding above 41 hours. On the income margin, we apply separate low-, median-, and high-income out-of-pocket shares. Each household is then assigned the resulting FHC cost based on its country, year, income group, and imputed care needs. Thus, while both formal-care cost measures reflect institutional price schedules, only p_i^{FHC} varies with care needs. This distinction is important for identification: cross-country and income-group variation help identify substitution between formal and child-provided care more broadly, while within-country variation in care needs is especially informative for the margin between formal home care, mixed care, and informal care. Appendix Section A.4 explains the formal-care cost construction in detail.

A key input into child caregiving costs is the parent's care need, measured in daily care hours. Together with the time required to travel to the parent, this determines how much of a child's potential labor-market time is absorbed by informal caregiving. We value that time using the child's potential wage. In addition, distance also generates a direct monetary commuting cost. Concretely,

$$OC_{ij} = \text{time cost}_{ij} + \text{annual commuting cost}_{ij}.$$

Higher care needs, longer travel times, and higher earnings potential all translate into higher opportunity costs.

The time-cost component is constructed as

$$\text{time cost}_{ij} = w_{ij}^{\text{pot,LFP}} \cdot \frac{\min\{\text{daily care hours}_i + \text{daily commuting time}_{ij},\, 12\}}{12}.$$

Here $w_{ij}^{\text{pot,LFP}}$ denotes child j's potential annual wage adjusted for labor-force participation, constructed from Eurostat's Structure of Earnings Survey. These externally constructed potential wages are based on child gender, education, country, and year, rather than observed labor-market outcomes in SHARE, since observed employment and earnings may themselves be shaped by caregiving. The labor-force-participation adjustment partly accounts for systematic differences in labor-force attachment across groups, but the resulting measure should be interpreted as a reduced-form benchmark rather than as a full labor-supply model.

We interpret 12 hours as the child's maximum daily time available for market work and cap the combined burden of care and commuting at that level. Daily commuting time is assigned from the reported distance between the child and the parent using approximate European travel-time benchmarks (see Appendix Table A15). The direct commuting-cost component is the predicted annual monetary cost of travel, assigned by distance category using corresponding benchmark fuel and short-haul airfare assumptions (see Appendix Table A16). Because the model is static, these opportunity costs should be interpreted as contemporaneous annual burdens rather than full lifetime caregiving costs. In particular, they abstract from dynamic career effects such as future wage losses or slower career progression induced by caregiving spells.

Non-monetary costs. The systematic non-monetary component is

$$n_{ia} = \begin{cases} \theta^{NH} + \gamma_{g_i}^{NH} & \text{if } a = \text{NH}, \\ \theta^{FHC} + \gamma_{g_i}^{FHC} & \text{if } a = \text{FHC}, \\ \mathbf{x}_{ij}'\beta & \text{if } a = \text{IC}_j, \\ \theta^{Mix} + \gamma_{g_i}^{Mix} & \text{if } a = \text{Mix}, \end{cases}$$

where $g_i \in \{\text{High, Middle, Low}\}$ denotes family i's LTC-generosity group. We normalize

$$\gamma_{\text{High}}^{NH} = \gamma_{\text{High}}^{FHC} = \gamma_{\text{High}}^{Mix} = 0,$$

so that θ^{NH}, θ^{FHC}, and θ^{Mix} represent the high-generosity-group non-monetary costs relative to IC, while the γ_g terms capture how these relative costs differ in the middle- and low-generosity groups. For IC, $\mathbf{x}_{ij}$ contains child-level characteristics used to proxy child-side non-monetary caregiving costs, namely indicators for whether the child is a daughter, has a partner, or is a non-biological child, as well as the child's birth order and the number of children in the sibling group. Because we assign a child to the Mix option mechanically using observable characteristics, we do not also include child-level covariates in the Mix utility term.

Multinomial logit model. The resulting multinomial logit specification is therefore

$$V_{ia} = \begin{cases} \alpha p_i^{NH} + \theta^{NH} + \gamma_{g_i}^{NH} + \varepsilon_{ia} & \text{if } a = \text{NH}, \\ \alpha p_i^{FHC} + \theta^{FHC} + \gamma_{g_i}^{FHC} + \varepsilon_{ia} & \text{if } a = \text{FHC}, \\ \alpha OC_{ij} + \mathbf{x}_{ij}'\beta + \varepsilon_{ia} & \text{if } a = \text{IC}_j, \\ \alpha\big(0.5\, p_i^{FHC} + 0.5\, OC_{i\, j_i^{Mix}}\big) + \theta^{Mix} + \gamma_{g_i}^{Mix} + \varepsilon_{ia} & \text{if } a = \text{Mix}. \end{cases} \tag{14}$$

We estimate the multinomial logit model by maximum likelihood using the observed care choices in our SHARE estimation sample (Appendix Section A.7 describes the estimation procedure).

4.2 Estimation results

Table 3 reports the estimated parameters. Four results stand out.

Table 3: Parameter estimates and Euro equivalents

Parameter	Estimate	Units	Euro equiv.
θ^{NH}: utility cost of NH	-1.047***	utils	-9826.1
	(0.203)		
θ^{FHC}: utility cost of FHC	-0.830***	utils	-7796.5
	(0.206)		
θ^{Mix}: utility cost of Mix	-0.804***	utils	-7551.6
	(0.193)		
α: monetary cost	1.065***	10K Euro/year	
	(0.130)		
β: daughter	-0.540***	dummy	-5074.0
	(0.120)		
β: non-biological	-0.052	dummy	-486.1
	(0.431)		
β: has partner	0.248*	dummy	2330.4
	(0.140)		
β: first-born	-0.160	dummy	-1503.4
	(0.112)		
β: num of children	-0.042	1 child	-396.5
	(0.053)		
γ: Middle generosity $\times$ NH	1.649***	utils	15483.5
	(0.227)		
γ: Low generosity $\times$ NH	2.090***	utils	19626.4
	(0.280)		
γ: Middle generosity $\times$ FHC	1.179***	utils	11071.7
	(0.200)		
γ: Low generosity $\times$ FHC	1.719***	utils	16138.1
	(0.240)		
γ: Middle generosity $\times$ Mix	0.690***	utils	6481.5
	(0.190)		
γ: Low generosity $\times$ Mix	1.859***	utils	17458.1
	(0.220)		

Parameter estimates from the multinomial logit model in equation (14) based on our estimation sample. Informal care (IC) is the reference arrangement, and the high-generosity group is the reference country group. The θ coefficients therefore represent arrangement-specific non-monetary utility costs relative to informal care in the high-generosity group, while the γ coefficients capture how these relative costs differ in the middle- and low-generosity groups. Positive coefficients imply higher latent utility costs (lower utility), and negative coefficients imply lower latent utility costs (higher utility). The "Euro equiv." column reports the monetary equivalent of each parameter, calculated by dividing the parameter estimate by the coefficient on the monetary cost variable and multiplying by 10,000 euros. Values are expressed in annual euros based on 2015 Purchasing Power Standard (PPS). NH-adjusted household weights are applied. Standard errors are reported in parentheses. *** Significant at 1% level, ** Significant at 5% level, * Significant at 10% level.

First, monetary costs are a central determinant of care choices: the estimated coefficient on monetary cost, α, indicates that both formal-care prices and children's opportunity costs have economically meaningful effects on the relative attractiveness of different care arrangements. It implies that, for example, a EUR 10,000 increase in the opportunity cost of informal caregiving is about twice as strong as the daughter effect – one of the strongest determinants of informal care identified in the literature.

Second, observable child characteristics proxy for an important part of the non-monetary cost of caregiving. Being a daughter lowers the utility cost of caregiving by 0.54 units, equivalent to about EUR 5,000, while having a partner raises it by about EUR 2,300. The coefficients on non-biological status, birth order, and number of children in the sibling group are estimated less precisely. The absence of a strong birth-order effect is consistent with the existing structural literature, including models with non-cooperative sibling interaction (Byrne et al., 2009; Fontaine et al., 2009). Because the model already accounts for gender differences in opportunity costs through potential wages, the daughter coefficient is best interpreted as capturing reduced-form non-monetary caregiving considerations, such as social expectations or filial norms, rather than a single identified mechanism.[18] More generally, the child covariates should be interpreted as proxies for latent caregiving costs rather than as separately identified structural primitives.

Third, there is substantial heterogeneity across policy environments. In the high-generosity reference group, the non-monetary cost terms for NH, FHC, and mixed care are all negative, implying that formal arrangements are more attractive than informal care, ceteris paribus. Relative to this benchmark, the middle- and low-generosity interaction terms imply additional non-monetary costs of using NH, FHC, and mixed care. Table 4 expresses these estimates more intuitively as group-specific non-monetary costs relative to informal care. Formal arrangements are relatively attractive in the high-generosity group, but much less so in the middle- and low-generosity groups. The contrast is especially pronounced for NH, suggesting that cross-regional differences concern not only the overall attractiveness of formal care, but also the desirability of institutional care. These differences could be due to country-specific preferences or social norms, but also due to a higher quality of and easier access to formal care in the high-generosity group.

[18] For example, Barigozzi et al. (2020) study a collective model in which daughters face a utility cost from deviating from expected gender norms in caregiving.

Table 4: Group-specific non-monetary costs relative to informal care

Region	NH	FHC	Mix
High	-9,800	-7,800	-7,600
Middle	5,700	3,300	-1,100
Low	9,800	8,300	9,900

Entries report the full group-specific non-monetary costs of each arrangement relative to informal care, expressed in annual euro equivalents. Negative values indicate that the arrangement has lower latent utility cost, and is therefore more attractive, than informal care.

Finally, substantial residual heterogeneity remains within groups. Under the multinomial-logit normalization, the idiosyncratic preference shock has standard deviation $\sqrt{\pi^2/6} \approx 1.28$. Using the estimated coefficient on monetary cost to translate latent utility units into consumption-equivalent terms, this corresponds to roughly EUR 12,000. This is more than twice as large as the daughter effect, about EUR 5,000, which is our most important observed child characteristic. It is also similar in magnitude to the baseline arrangement-specific non-monetary terms. This residual captures latent between- and within-family heterogeneity in attitudes toward care that are unrelated to caregiver observables.

4.3 Robustness of estimation results

We subject the baseline estimates to two robustness checks that address natural concerns in this setting. First, one may worry that there are family-level attitudes toward care, such as family values or other unobserved care-relevant characteristics, that are correlated among siblings. In technical terms, our baseline model with independent shocks imposes a restrictive sibling-level independence-of-irrelevant-alternatives structure. Table A18 compares the baseline specification to a nested-logit model that places child-specific informal-care alternatives in a common nest. The nested-logit estimates imply a within-family correlation across sibling-specific informal-care options of roughly 0.4, suggesting that these alternatives share meaningful family-level unobservables but remain far from perfectly substitutable. Importantly, allowing for this richer dependence structure leaves the main coefficients very stable: the monetary-cost coefficient –which governs the care elasticities– declines modestly, within one standard deviation of estimation error; the daughter effect remains large, negative, and precisely estimated.

Second, our baseline estimation uses NH-adjusted household weights that we construct to correct for the underrepresentation of nursing-home residents in SHARE. Appendix A.9 reports two complementary checks. First, we re-estimate the model using an alternative NH-weight correction constructed from observed nursing-home status only, rather than our

preferred forward-looking correction that also incorporates pre-NH households; this alternative matches the OECD nursing-home shares by construction. Second, we re-estimate the model on the subset of country-wave cells in which nursing-home residents are documented as belonging to the baseline sampling frame, using the original SHARE household weights rather than our NH-adjusted weights. Table A19 reports both exercises. Reassuringly, the main qualitative conclusions remain intact across both checks: the monetary-cost coefficient stays positive and sizeable, daughters remain substantially more likely to provide care, and substantial group-specific differences in non-monetary arrangement costs persist.

Taken together, these exercises indicate that our core conclusions do not hinge either on the strict multinomial-logit dependence structure or on the NH-sampling correction used in the baseline estimation.

4.4 Model validation

A natural question is whether the estimated framework can reproduce care-allocation patterns that are not directly parameterized in the model. We first note that due to the multinomial-logit structure, by construction the model i) can perfectly account for variation in care arrangements across observable dimensions (such as daughter status, country-groups) and ii) can rationalize any family choice due to the preference shocks. To validate our model, we thus resort to variation in an important observable that we did not include in the covariates due to power concerns: country. Figure A4 shows that care arrangements vary substantially even within the same LTC-generosity group, while the model allows formal-care non-monetary terms to vary only at the group level. However, Appendix A.1.3 shows that the model tracks the observed country-level arrangement shares reasonably well. Figure A2 reports the broad formal-care margin by country, while Figure A3 reports the full four-arrangement country-level comparison. The key takeaway is that the model captures a substantial amount of the country-level variation even within generosity groups, despite estimating formal-care non-monetary terms only at the group level.

5 Counterfactuals

Using the estimated model, we conduct four counterfactual exercises. We begin by quantifying how preference heterogeneity shapes the responsiveness of care arrangements to formal-care subsidies. Next, we study how care choices change under the formal-care price environments of different countries. We then decompose cross-group differences in formal-care use into economic and preference components, and finally project how caregiving arrangements

evolve under expected demographic change.

Methodology In all counterfactuals, we hold fixed the estimated latent cost parameters and alter only the relevant right-hand-side variables. The exercises therefore ask how care choices would change if economic or demographic conditions shifted while the estimated behavioral forces governing choices remained fixed. Denoting the counterfactual latent utility cost of option j in family i by $\tilde{V}_{ij}$, we compute the implied choice probability as

$$\tilde{P}_{ij} = \frac{\exp(-\tilde{V}_{ij})}{\sum_{j=0}^{K} \exp(-\tilde{V}_{ij})}. \tag{15}$$

We then aggregate these probabilities across families using the household weights. For example, the population share of NH ($j = 0$) is

$$NH = \sum_{i=1}^{N_{fam}} \omega_i \tilde{P}_{i0}, \tag{16}$$

where N_{fam} is the number of families in the sample and ω_i denotes the normalized household weight. For counterfactuals that modify only economic variables, such as formal-care prices or children's opportunity costs, this is sufficient. For the projection counterfactual, we simulate modified family compositions, such as the number of children or the prevalence of stepchildren, recompute choice probabilities, and average outcomes across repeated draws. Appendix Section A.10 describes the counterfactual implementation.

5.1 Elasticities and the role of preference heterogeneity

Section 3.4 shows in a stylized setting that preference heterogeneity dampens policy responses. We now quantify this mechanism by comparing the baseline specification to an *economics-only* version of the same environment without preference heterogeneity, i.e., without idiosyncratic preference shocks and the child-level non-monetary utility shifters. For comparability, we calibrate the group-specific arrangement constants of the economics-only model to match the observed baseline care shares in each generosity group. Appendix Section A.11 gives the exact construction and calibrated parameter values.

We begin with the aggregate European response to a 20% subsidy applied to the baseline cost schedules of NH and FHC. Table 5 reports the resulting percentage-point changes in arrangement shares.

Table 5: Changes in arrangements under a joint NH+FHC subsidy

Model	Status quo	ΔNH	ΔFHC	ΔMix	ΔFHC^{all}	ΔFC
baseline	46.6%	+1.15 pp	+0.72 pp	+0.01 pp	+0.73 pp	+1.88 pp
economics-only	46.8%	+0.60 pp	+1.42 pp	+3.00 pp	+2.92 pp	+3.52 pp

The first column (Status quo) reports the model-predicted formal-care-content share, $FC \equiv NH + FHC + 0.5Mix$. Columns two to four show percentage-point changes in arrangement shares under the joint NH+FHC subsidy. Column five is $FHC^{all} \equiv FHC + 0.5\,Mix$, and the final column reports the percentage-point change in formal-care content, $\Delta FC = \Delta NH + \Delta FHC^{all}$. The aggregate European response is computed on the full NH-adjusted weighted estimation sample.

In the baseline specification, NH and FHC both expand modestly, while mixed care is nearly unchanged. In the economics-only model, by contrast, formal home care and mixed care respond much more strongly, and the increase in total formal-care content is substantially larger. This is precisely the smoothing role of preference heterogeneity emphasized in Section 3.4: with heterogeneity, families are dispersed across margins and policy responses are less lumpy.

To summarize these responses, we report the elasticity of formal-care content, $FC \equiv NH + FHC + 0.5\,Mix$. We calculate the elasticity as

$$\varepsilon_{FC} = \frac{\left(\frac{\Delta FC}{FC}\right)}{\frac{\tau(p_i^{NH,0}+p_i^{FHC,0})-(p_i^{NH,0}+p_i^{FHC,0})}{p_i^{NH,0}+p_i^{FHC,0}}} = \frac{\Delta FC/FC}{\tau - 1},$$

where τ is the proportional cost scale applied to both NH and FHC in the counterfactual, so that $p_i^{NH,1} = \tau p_i^{NH,0}$ and $p_i^{FHC,1} = \tau p_i^{FHC,0}$. Under the 20% subsidy, $\tau = 0.8$.

Table 6 reports the resulting proportional changes and elasticities. In the baseline model, FC increases by 4.0%, implying an elasticity of -0.20, whereas in the economics-only model the same subsidy raises FC by 7.5%, implying a much larger elasticity of -0.38.

Table 6: Formal care elasticity

Model	$\Delta FC/FC$	elasticity
baseline	4.0%	-0.20
economics-only	7.5%	-0.38

The elasticity is computed as the proportional change in FC divided by the proportional change in the common NH+FHC cost scale.

Preference heterogeneity is therefore a first-order force dampening policy responsiveness: without it, formal-care demand becomes close to twice as elastic.

Table 7 shows where the changes in the baseline care arrangements come from. In the high-generosity group, the main effect is reallocation within the formal sector: NH rises, while both FHC and mixed care fall, so total formal-care content increases only modestly. In the middle- and low-generosity groups, by contrast, the subsidy raises both NH and formal home care, with the largest increase in total formal-care content occurring in the low-generosity group. Thus, in generous systems the subsidy mainly reshuffles care within the formal sector, whereas in less generous systems it induces broader entry into formal care.

Table 7: Group-specific arrangement changes in the baseline model

Group	Status quo	ΔNH	ΔFHC	ΔMix	ΔFHC^{all}	ΔFC
High generosity	71.8%	+2.62 pp	-1.15 pp	-0.75 pp	-1.52 pp	+1.09 pp
Middle generosity	52.3%	+0.72 pp	+0.83 pp	-0.03 pp	+0.81 pp	+1.53 pp
Low generosity	29.9%	+1.35 pp	+1.15 pp	+0.29 pp	+1.30 pp	+2.65 pp

Status quo reports the baseline model-predicted benchmark. Here, $FHC^{all} \equiv FHC + 0.5\,Mix$ denotes total formal home-care content and $FC \equiv NH + FHC^{all}$ denotes total formal-care content, so $\Delta FC = \Delta NH + \Delta FHC^{all}$. All reported shares and counterfactual changes are weighted using the NH-adjusted household weights.

Finally, Table 8 shows that the aggregate European response conceals a steep responsiveness gradient: the same subsidy has relatively little bite in already-generous systems (-0.08), but much larger effects where formal care is least generous (-0.44).

Table 8: Group-specific formal care elasticity

Group	$\Delta FC/FC$	elasticity
High generosity	1.52%	-0.08
Middle generosity	2.92%	-0.15
Low generosity	8.84%	-0.44

This table reports baseline-model responses to the same joint 20% NH+FHC subsidy used in Table 6, now separately by generosity group. Formal-care content is defined as $FC \equiv NH + FHC + 0.5\,Mix$. The elasticity is computed as the proportional change in FC divided by the proportional change in the common NH+FHC cost scale.

From elasticities to transplanting country-specific policies The subsidy elasticities summarize local policy responsiveness around the observed baseline cost environment. We now consider larger financing counterfactuals based on observed country-specific LTC policies. Specifically, we transplant the NH and FHC schedules of three salient LTC systems – Sweden, France, and Spain. We implement these by assigning a country's NH out-of-pocket cost schedule and its FHC-hour-cost schedule to all households.

Table 9 reports the resulting counterfactual shares. Each row shows how a given group's formal-care share would change under the LTC financing system of Sweden, France, or Spain. Panel A shows that Sweden is the most expansionary benchmark for FC overall. By contrast, the France and Spain transplants produce little change for the low-generosity group. Panel B shows that the formal-home-care margin is hard to increase: FHC^{all} only rises in the low-generosity group, and the increase is modest outside the Swedish transplant.

Table 9: Country-specific LTC system transplants

Group	Status quo	Sweden	France	Spain
Panel A: Formal-care content (FC)				
High generosity	71.8%	76.3%	69.1%	67.8%
Middle generosity	52.3%	57.0%	50.0%	49.1%
Low generosity	29.9%	41.4%	30.5%	31.4%
Panel B: Formal home-care content (FHC^{all})				
High generosity	49.4%	39.2%	42.0%	48.1%
Middle generosity	35.3%	34.5%	36.5%	39.5%
Low generosity	17.6%	21.2%	17.4%	20.7%

Status quo reports the baseline model-predicted benchmark. The remaining columns report model-based counterfactual predictions when all households face the NH and FHC cost schedules of Sweden, France, or Spain. Panel A reports $FC \equiv NH + FHC + 0.5Mix$. Panel B reports $FHC^{all} \equiv FHC + 0.5Mix$. NH-adjusted household weights are applied.

5.2 Country-group differences: culture or economics?

The previous counterfactual shows that LTC affordability matters, but also that cross-group differences in care arrangements are far too large to be explained by financing alone. We therefore ask how much of the gap in formal-care use across country groups is accounted for by differences in formal-care affordability – *economics* – and how much by the estimated non-monetary arrangement-specific utility terms – *culture*, interpreted broadly to include norms, attitudes, and other non-monetary institutional features.

To isolate these channels, we construct a representative high-generosity formal-care cost schedule based on the countries in that group: Sweden, the Netherlands, Denmark, and Belgium. For both NH and FHC, we do so separately by income group. In each income bin, we take the country-specific affordability shares from the OECD data and assign the midpoint of the cross-country range, that is, the average of the minimum and maximum shares within the group. This yields a three-point NH affordability schedule for low-, middle-, and high-income households. For FHC, we apply the same midpoint logic at a finer level of detail, since the home-care cost schedule also varies by year and care needs.

Table 10 reports the counterfactual formal-care-content (FC) shares when imposing only the high-generosity formal-care cost schedule (column 2), only the estimated high-generosity arrangement-specific non-monetary utility terms (column 3), and both jointly (column 4), on all three country groups. The baseline FC gap between the high- and low-generosity groups is 41.9 percentage points. Equalizing formal-care costs alone reduces this gap by 9.2 percentage points. Equalizing the estimated NH, FHC, and Mix utility terms reduces it much more, by 32.0 percentage points. When both channels are equalized simultaneously, the gap falls to 3.0 percentage points.

The order of equalization matters, implying that costs and utility terms are not additive. When costs are equalized second, the FC gap falls by 6.8 percentage points, whereas when utility terms are equalized second it falls by 29.7 percentage points. To account for this non-linearity, we apply a Shapley-style decomposition. Under this decomposition, *culture* accounts for 79.5% of the reduction in the high-low FC gap, while *economics* – differences in formal-care financing – accounts for the remaining 20.5%.

Table 10: Formal-care content in the absence of country-group differences

Group	(1) Status quo	(2) Equalize formal-care cost only	(3) Equalize utility terms only	(4) Equalize both
High generosity	71.8%	72.9%	71.8%	72.9%
Middle generosity	52.3%	55.6%	71.6%	73.5%
Low generosity	29.9%	40.2%	62.0%	69.8%
Gap: High - Low	**41.9 pp**	32.7 pp	9.8 pp	**3.0 pp**
Total gap reduction				**38.8 pp**
Cost (1st / 2nd)		9.2 pp		6.8 pp
Utility (1st / 2nd)			32.0 pp	29.7 pp

This table reports formal-care content under counterfactual scenarios in the baseline model, where $FC \equiv NH + FHC + 0.5\,Mix$. Column (1) reports the baseline model-predicted benchmark. Column (2) equalizes only formal-care costs by assigning the synthetic High-generosity NH and FHC cost schedules to all households. Column (3) equalizes only the NH, FHC, and Mix utility terms by assigning the estimated High-generosity values to all groups. Column (4) applies both counterfactuals simultaneously. The row "Gap: High - Low" reports the percentage point difference between the High- and Low-generosity groups. The final two rows make the sequencing explicit: cost closes the High-Low gap by 9.2 percentage points when imposed first and by 6.8 percentage points when imposed after utility equalization; utility closes the gap by 32.0 percentage points when imposed first and by 29.7 percentage points when imposed second. NH-adjusted household weights are applied.

5.3 Projecting formal-care use: Europe in 2050

Finally, we ask how demographic and social changes may reshape care arrangements by 2050. We consider four changes: fewer potential child caregivers, stronger labor-force attachment

among women, more stepchildren, and greater geographic distance between parents and children.

1. Fewer children. We randomly remove children so that the average number falls from 2.24 in 2010 to 1.25 in 2050, based on Eurostat population projections for the ratio of individuals aged 45–65 to those aged 70–90 in EU countries.

2. Higher female opportunity costs. We close the 2010 EU gender wage gap of 16.0%, scaling daughters' labor-market opportunity costs up to $\tilde{OC}_{ij} = 1.16\, OC_{ij}$. We interpret this as an upper bound on the effects operating through this channel.

3. More blended families. We convert biological children in the baseline to stepchildren with a probability chosen to generate a 10% increase in the stepchild margin.[19]

4. Greater geographic distance. We multiply parent-child distance by 1.8, based on current cross-country variation in SHARE.[20]

Table 11 shows the resulting formal-care content (FC) as these changes are introduced sequentially. In every country group, the dominant force is the decline in potential child caregivers: FC increases by 10.6 percentage points in the high-generosity group, 16.4 percentage points in the middle-generosity group, and 21.4 percentage points in the low-generosity group. This effect is intuitive: as the number of children declines sharply, parents have fewer chances that at least one child combines low opportunity costs, favorable preferences, and close geographic proximity. Closing the gender wage gap and increasing the prevalence of stepchildren play relatively minor roles. Greater geographic distance has a more noticeable effect, reflecting mainly the time costs of traveling and commuting for children. Overall, once the decline in available children is accounted for, additional changes matter comparatively little.

[19] Direct measures of non-biological children in European families are unavailable. Eurostat reports a 3.6% increase in single-parent families for 2005–2030. Extrapolating to 2050, we use a 10% adjustment as an upper bound.

[20] In SHARE, the share of children living within 25km of their parents varies from about 50% in the more geographically dispersed country groups to about 80% in the less dispersed groups, while the corresponding shares within 50km vary from about 30% to 60%. Averaging the two ratios – $(80/50 + 60/30)/2$ – yields a distance multiplier of approximately 1.8.

Table 11: Formal-care content in Europe in 2050

Group	(1) Status quo	(2) #kids↓	(3) y_{fem} ↑	(4) step↑	(5) dist.↑
High	71.8%	82.4%	83.0%	83.0%	83.7%
Middle	52.3%	68.7%	69.7%	69.7%	70.8%
Low	29.9%	51.3%	52.1%	52.0%	53.1%

Status quo reports the baseline model-predicted benchmark. This table reports how formal-care content, defined as $FC \equiv NH + FHC + 0.5\,Mix$, changes as we sequentially adopt the projected changes. NH-adjusted household weights are applied.

Table 12: Nursing-home and formal-home-care use in Europe in 2050

Group	(1) Status quo	(2) #kids↓	(3) y_{fem} ↑	(4) step↑	(5) dist.↑
	NH share				
High	22.4%	27.6%	27.8%	27.8%	28.1%
Middle	17.0%	24.8%	25.3%	25.3%	25.7%
Low	12.4%	22.2%	22.7%	22.7%	23.2%
	FHC^{all} share				
High	49.4%	54.8%	55.2%	55.1%	55.6%
Middle	35.3%	43.9%	44.4%	44.4%	45.1%
Low	17.6%	29.0%	29.4%	29.4%	29.9%

Status quo reports the baseline model-predicted benchmark. This table complements Table 11 by showing how NH and $FHC^{all} \equiv FHC + 0.5Mix$ changes. Since total formal-care is defined as $FC \equiv NH + FHC + 0.5Mix$, the NH and FHC^{all} panels add up to the corresponding entries in the formal-care-content table. NH-adjusted household weights are applied.

Table 12 decomposes this increase in formal-care content into NH and total formal-home-care content FHC^{all}. The decline in potential child caregivers raises both components. Roughly one-half of the increase in total formal-care content comes through FHC^{all} in the high- and middle-generosity groups, and slightly more in the low-generosity group.

In view of the sizable increase in NH, a follow-up question is whether more generous home-care subsidies could preserve aging at home despite these demographic shifts. To study this, we start from the full 2050 scenario and replace the formal home-care schedules with Sweden's, first on its own and then jointly with Sweden's nursing-home affordability schedule. Table 13 reports the results.

Table 13: 2050 price variants: Sweden FHC versus Sweden NH+FHC

Group	Status quo	+ changes (cols. 2-5)	+ Sweden FHC	+ Sweden NH+FHC
	NH share			
High	22.4%	28.1%	28.6%	45.0%
Middle	17.0%	25.7%	23.1%	32.7%
Low	12.4%	23.2%	17.5%	31.8%
	FHC^{all} share			
High	49.4%	55.6%	54.8%	41.6%
Middle	35.3%	45.1%	48.7%	41.4%
Low	17.6%	29.9%	39.4%	30.1%

Status quo reports the baseline model-predicted benchmark. Sweden's price schedule is added to the 2050 counterfactual after the four changes shown in Table 12. Column three implements only Sweden's FHC schedule whereas column four additionally implements Sweden's NH affordability. Here, $FHC^{all} \equiv FHC + 0.5Mix$. NH-adjusted household weights are applied.

Starting from the full 2050 scenario, replacing the FHC schedules with Sweden's raises formal-home-care content substantially in the low-generosity group, from 29.9% to 39.4%. When also imposing Sweden's NH schedule, formal-home-care content in the low-generosity group is nearly unchanged at 30.1%, while the NH share rises from 17.5% to 31.8%. Thus, more generous home-care subsidies can meaningfully expand "aging at home," whereas a broader Swedish-style formal-care system mainly shifts households toward nursing-home care and would likely do so at much higher fiscal cost.

Overall, our projections suggest that the declining ratio of children to elderly will put substantial pressure on future caregiving arrangements, shifting care away from informal provision and toward formal care. This implies both higher demand for formal-care services and greater financial pressure on future elderly households and governments.

6 Conclusion

Our results suggest three important policy lessons. First, preference heterogeneity is central for policy elasticities. In our estimates, omitting preference heterogeneity raises the elasticity of formal-care use with respect to a joint nursing home and formal-home care subsidy in absolute value from 0.20 to 0.38. Second, long-term-care reforms cannot be evaluated across the board. Subsidies do matter, but their effects depend strongly on the family and institutional environment in which they operate. The same price reform can therefore generate very different responses across countries because families differ not only in economic conditions, but also in their willingness to rely on institutional care, formal home care, or child-provided

care, making the number of policy-sensitive households vary strongly. Additionally, policies targeted specifically at home-based formal care can support "aging in place" while buffering shortfalls in informal care; broad formal-care generosity achieves the latter but expands institutional care much more. Third, demographic change – specifically the declining ratio of adult children to elderly parents – is likely to place strong upward pressure on future formal-care demand. This is especially the case for countries that have traditionally relied more heavily on family-provided care. Governments should therefore prepare not only to finance more formal care, but also to expand the capacity needed to deliver it, including nursing-home slots, home-care provision, and the labor supply of formal caregivers. This may require investment in care infrastructure, training, and retention, and, where relevant, immigration policies aimed at easing labor shortages in the formal-care sector.

While our framework allows for substantial heterogeneity, it also misses how policies may affect some long-run margins. The elasticities we estimate may thus understate the long-run elasticities and should rather be interpreted as short- to medium-run objects. A natural next avenue for research would be a dynamic extension which would make it possible to study how families prepare for future care needs through savings, labor-supply adjustments, mobility decisions, and the timing of formal-care use. It would also allow caregiving to have persistent labor-market consequences beyond the static opportunity costs we measure here and to shed more light on timing decisions, such as how long families delay nursing-home entry under different policies.

More broadly, our results point to the need for a better understanding of the formal-care labor market, including how wages, working conditions, and workforce shortages shape the availability of care, as well as of the appropriate role of government in financing and providing long-term care relative to private markets and family care.

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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.[21]

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.

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

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	

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 Nursing-home underrepresentation and NH-adjusted weights

A key concern in SHARE is that nursing-home residents are underrepresented in some country-wave cells. To address this issue, we retain the observed baseline nursing-home indicator in the main sample definition, but correct the sample's nursing-home prevalence through household weights. We now base our sample on the country-wave sampling information using the 2025 SHARE sampling documentation[22] and rebuild the cleaned data using SHARE release 9, while continuing to use release 8 for Wave 2 because of a data issue in the CH module of release 9.

Even in countries where the initial sampling frame does not include nursing-home residents, we do observe nursing-home residents in the baseline interview if they have moved to a nursing home between initial sampling and the first interview. As two years or more go by, more respondents move into nursing homes, bringing the SHARE sample closer to

[22]Specifically, we use *SHARE Sample Technical-Document No. 104-2025*, available at https://share-eric.eu/fileadmin/user_upload/SHARE_Working_Paper/SHARE_WP_104-2025.pdf.

the true nursing-home share. This motivates the following construction of forward-looking nursing-home indicators. This next-wave information is available only for respondents who are re-observed in SHARE. Using these data, we construct several alternative SHARE-side nursing-home prevalence measures among individuals aged 65 and over. Our preferred measure combines current-wave nursing-home residence with next-wave institutionalization and applies household weights. In practice, an individual is counted toward this prevalence measure if she is observed in a nursing home at baseline or enters a nursing home by the next survey wave. This forward-looking adjustment is used only for the prevalence correction in the weights. Importantly, it does not relabel the observed baseline care arrangement in the main specification, as the estimation relates the *current* conditions of the respondent (disability level etc.) to the *current* observed care arrangement (IC, FHC, NH etc.).

Table A2: Documented nursing-home sampling status in SHARE by country: countries in the estimation sample

Ctry	W1	W2	W4	W5	W6	W8	N
AUT	N	-	N	-	-	Y	190
BEL	NA	NA	Y	Y	Y	Y	286
HRV	-	-	-	-	N	Y	95
CZE	-	NA	N	N	-	Y	335
DNK	Y	N	N	N	N	Y	154
FIN	-	-	-	-	-	Y	52
FRA	N	N	N	N	N	N	255
DEU	Y	N	-	N	-	Y	200
GRC	Y	N	-	-	NA	-	146
IRL	-	NA	-	-	-	-	27
ITA	N	N	N	N	N	-	153
LTU	-	-	-	-	-	N	223
LUX	-	-	-	N	Y	-	46
NLD	Y	Y	Y	Y	N	-	160
POL	-	NA	-	-	N	N	114
SVN	-	-	N	N	N	N	7
ESP	Y	Y	Y	Y	-	-	193
SWE	Y	Y	-	Y	-	Y	107

The table reports the documented nursing-home sampling status from the updated SHARE sampling workbook for the SHARE waves used in this paper (Waves 1, 2, 4, 5, 6, and 8) for countries that enter the estimation sample. 'Y' indicates that nursing-home residents were documented as sampled at baseline in that country-wave cell, 'N' indicates that they were not, and 'NA' indicates that the sampling documentation does not deliver a clean yes/no classification. 'N' in the last column reports the number of households from that country in the estimation sample. Country abbreviations use standard ISO-style three-letter codes.

Table A3: Documented nursing-home sampling status in SHARE by country: countries outside the estimation sample

Ctry	W1	W2	W4	W5	W6	W8	N
BGR	-	-	-	-	-	N	0
CYP	-	-	-	-	-	N	0
EST	-	-	N	-	Y	Y	0
HUN	-	-	Y	-	-	N	0
LVA	-	-	-	-	-	N	0
MLT	-	-	-	-	-	Y	0
PRT	-	-	Y	-	-	-	0
ROU	-	-	-	-	-	N	0
SVK	-	-	-	-	-	N	0
CHE	N	N	N	-	-	N	0

The table reports the same sampling-status information for countries with zero households in the estimation sample. We include these countries to document the broader sampling environment underlying the NH-adjustment exercise and the country-level diagnostic comparisons. The coding of 'Y', 'N', and 'NA' follows the same convention as in Table A2.

The NH-adjusted weights are constructed as follows:

1. We use next-wave institutionalization (nursing-home) information from the following waves: Wave 2 NH status for Wave 1 baseline respondents, Wave 4 for Wave 2, Wave 5 for Wave 4, Wave 6 for Wave 5, Wave 8 for Wave 6, and Wave 9 for Wave 8.

2. Due to small samples sizes in certain country cells, we pool Waves 1 and 2 into one period and Waves 4, 5, 6, and 8 into a second period.

3. For each country and pooled period, we compute the weighted SHARE nursing-home prevalence among those aged 65 or older using SHARE's original household weights, which we denote by p_{cw}^{SHARE}, using the expanded nursing-home indicator.

4. For the same country and pooled period, wed compute the corresponding OECD nursing-home prevalence, denoted p_{cw}^{OECD}.

5. We then convert the prevalence gap into an odds-ratio adjustment factor,

$$A_{cw} = \frac{p_{cw}^{OECD}/(1-p_{cw}^{OECD})}{p_{cw}^{SHARE}/(1-p_{cw}^{SHARE})} = \left(\frac{1-p_{cw}^{SHARE}}{p_{cw}^{SHARE}}\right)\left(\frac{p_{cw}^{OECD}}{1-p_{cw}^{OECD}}\right),$$

and assign each observed baseline nursing-home household in country c and pooled period w the adjusted weight

$$w_i^{NHadj} = w_i \cdot A_{cw},$$

while all other households retain their original weight w_i.

For countries without comparable OECD nursing-home prevalence data, we replace A_{cw} by the mean adjustment factor within the corresponding country group. The resulting NH-adjusted household weights increase the influence of observed nursing-home households in cells where SHARE appears to under-sample nursing-home residents. These weights are then used consistently in the descriptive analysis and estimation reported in the main text. By construction, this is a correction on the nursing-home prevalence margin, not a full reconstruction of the joint distribution of nursing-home households along all observed and unobserved characteristics.

Figure A1 shows that, once these weights are applied, the weighted SHARE nursing-home prevalence move markedly closer to the OECD benchmark for most countries. The left panel shows the SHARE nursing-home prevalence using the original household weights, while the right panel shows the corresponding prevalence after applying the NH-adjusted weights constructed above. Some outliers (marked abbreviations 'EE' etc.) belong to countries that are not in the estimation sample. Remaining outliers reflect countries with very few observed nursing-home residents, limited OECD information, and the fact that the adjustment is designed to approximate rather than mechanically impose the external benchmark.

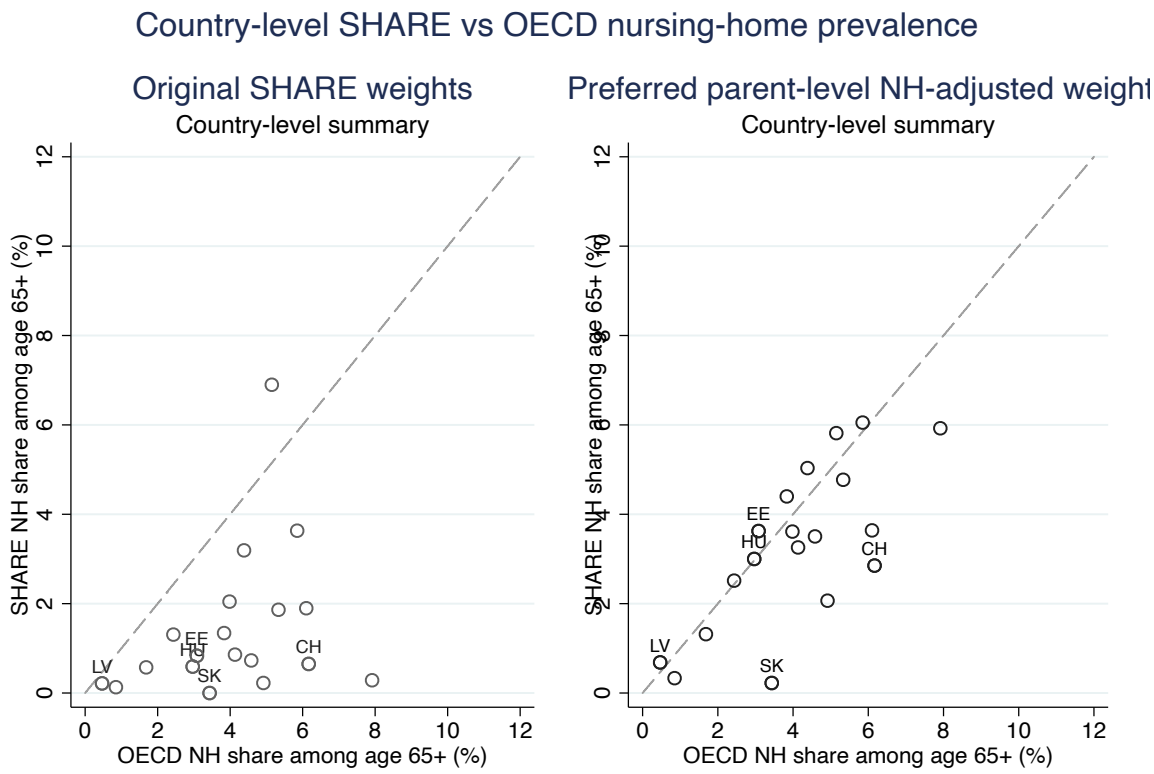


Figure A1: SHARE versus OECD nursing-home prevalence before and after NH-adjusted weights

Each point is a country, averaging across all SHARE waves and matched OECD years used in the diagnostic, for countries with at least 50 respondents aged 65 and over in the cleaned SHARE sample. The left panel uses the original SHARE household weights and therefore reflects the raw underrepresentation of nursing-home residents. The right panel uses the NH-adjusted household weights constructed in this appendix. After the adjustment, the weighted SHARE nursing-home shares move substantially closer to the OECD benchmark for most countries, showing that the correction improves the representativeness of nursing-home prevalence in SHARE. The marked abbreviations 'EE', 'HU', 'CH', 'SK', and 'LV' identify countries that have no observations in the estimation sample; their case counts are reported in Table A3. Remaining outliers reflect countries with very few observed nursing-home residents, limited OECD information, and the fact that the adjustment is designed to approximate rather than mechanically impose the external benchmark.

A.1.3 Model validation: arrangement shares

By construction, the model reproduces care-arrangement shares across the three generosity groups very closely, since the estimation includes group-level arrangement shifters. This is reassuring, but it is not a demanding test of the model. We therefore focus on the more informative question of whether the model can also account for country-level variation in care arrangements *within* these groups.

We begin with the broad formal-care margin that is central to the paper's policy analysis, defined as formal-care content $FC \equiv NH + FHC + 0.5\,Mix$. Figure A2 compares observed

and model-predicted country-level formal-care content. Because the model does not include country-specific arrangement intercepts, matching these country-level formal-care shares is not mechanical: once the generosity-group shifters are fixed, the remaining variation must be generated through differences in household composition, child characteristics, and cost variables. The figure shows that the model captures this broad policy-relevant margin reasonably well across countries.

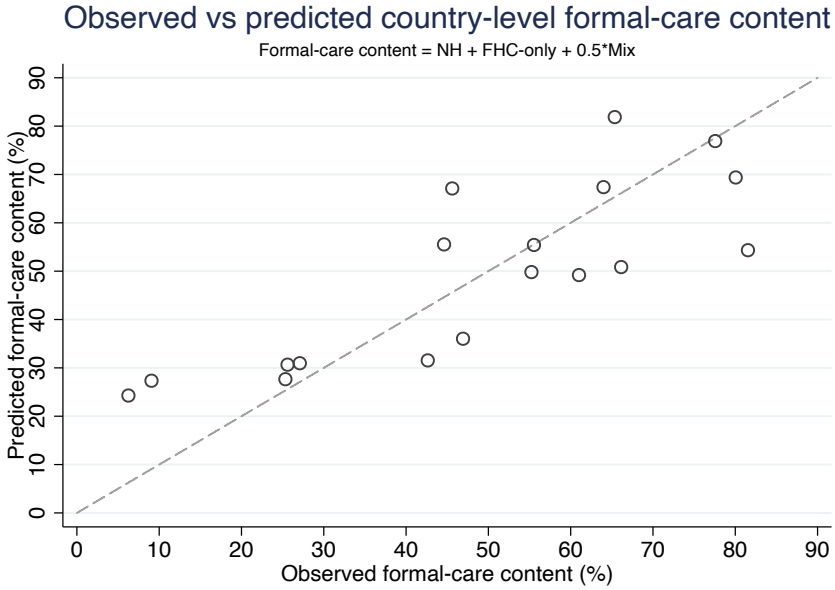


Figure A2: Observed and model-predicted country-level formal-care content

Each point is a country in the estimation sample. The horizontal axis reports the observed weighted country-level formal-care content, defined as $FC \equiv NH + FHC + 0.5\,Mix$, and the vertical axis reports the corresponding in-sample model prediction from the preferred baseline MNL. The dashed line is the 45-degree line.

We then turn to the more demanding decomposition into the four care arrangements. Figure A3 reports observed and model-predicted country-level shares for NH, FHC, Mix, and IC in the preferred baseline MNL. Each point is a country. The figure shows that the model tracks the broad cross-country patterns reasonably well. The fit appears strongest for FHC and IC, while it is somewhat less precise for NH and Mix in a few countries. We view this as a useful and deliberately demanding validation exercise for the empirical specification used in the counterfactual analysis.

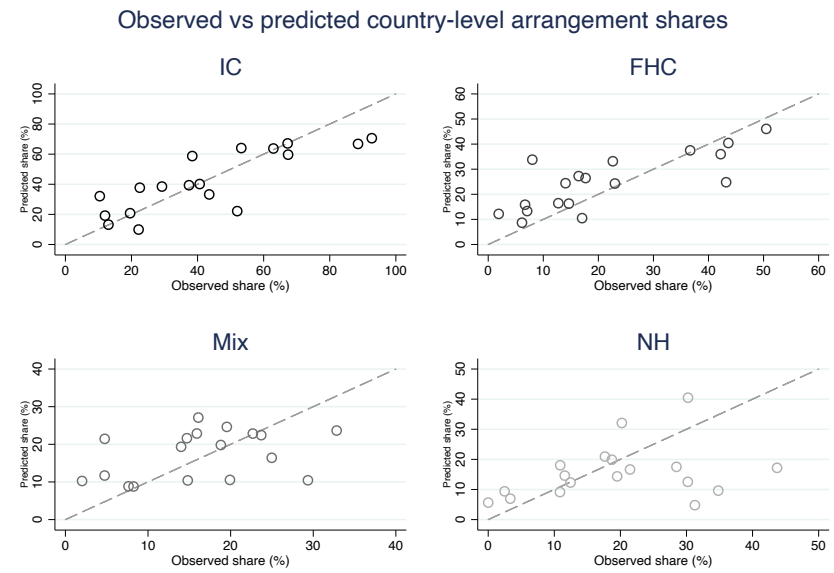


Figure A3: Observed and model-predicted country-level arrangement shares

Each point is a country in the estimation sample. The horizontal axis reports the observed weighted country share of the indicated care arrangement, and the vertical axis reports the corresponding in-sample model prediction from the preferred baseline MNL. The dashed line is the 45-degree line. By construction, the model reproduces generosity-group averages very closely; this figure therefore focuses on the more demanding country-level variation within groups.

A.1.4 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 in Table A4.

Table A4: 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

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.[23] However, if we want to do future analyses at the individual parent level, then we would need to identify which of the parents received OIC. Second, the type of OIC (personal care, practical household help, and help with paperwork) is not reported in Wave 5. While this information is useful in determining intense IC, we decide not to distinguish among the types of OIC for consistency across waves.[24] Lastly, among elderly individuals aged 65 and older without a spouse, only 23.23% of OIC cases involve care provided "about daily," as shown in Appendix Table A5. To increase the sample size, we define both "about daily" and "about every week" OIC as intense informal care. Additionally, we classify all IIC

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

[24]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).

as intense informal care, since by definition in the SHARE survey, IIC occurs on an almost daily basis.

Table A5: 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

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.

A.1.5 SHARE sample selection

Table A6: Number of parent-child pairs after applying selection criteria, Baseline SHARE

Selection step	Parent-child observations
None	248,647
Parent aged 65+	114,445
No spouse	39,816
At least one child	36,678
On intensive LTC margin (NH, FHC, Mix, or IC)	10,551
Non-missing care-needs measure	10,534
Child aged 20–60	8,672
No missing key child covariates	7,835
Final estimation sample	5,971

Table A6 reports how the estimation sample is constructed. The counts are at the parent-child level. The largest reductions occur when we move from the full SHARE baseline to single parents aged 65 or older with children, and then when we restrict attention to the intensive LTC margin studied in the paper: nursing-home care, formal home care, mixed formal-home and child-provided care, or child-provided informal care. Additional reductions come from requiring a non-missing care-needs measure, restricting attention to children aged 20–60, and dropping observations with missing key child covariates. The estimation sample

contains 5,971 parent-child observations, corresponding to 2,743 households.

Table A7: Broad care-arrangement distribution before final estimation-sample restrictions

Arrangement	Households	Share (%)
No intensive LTC arrangement	10,670	74.0
Nursing home	298	2.1
Formal home care only	863	6.0
Mixed formal-home and child care	810	5.6
Child informal care only	1,783	12.4

This table is at the household level. It starts from single parents aged 65+ with at least one child aged 20–60 in baseline SHARE Waves 1, 2, 4, 5, 6, and 8, before imposing the final estimation-sample restrictions. "No intensive LTC arrangement" includes households that are outside the intensive LTC margin studied in the paper, including households with no formal care and no at-least-weekly child caregiving.

Table A7 shows why the paper focuses on a narrower target population. Even after restricting to older single parents with working-age children, 74.0% of households are outside the intensive LTC margin altogether. Among the remainder, child-provided informal care is the most common arrangement, followed by formal home care and mixed care, while nursing-home care remains relatively rare in raw baseline SHARE. This motivates both the paper's focus on the intensive LTC margin and the need for the NH-sampling correction discussed in Appendix A.1.2.

A.1.6 Family characteristics by country group

Table A8: 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
High generosity	2.25	32733.41	23833.45	0.73	69.06	0.02	0.70
Middle generosity	2.05	35691.17	24756.81	0.69	80.30	0.03	0.67
Low generosity	2.18	22119.87	14815.46	0.67	51.30	0.01	0.76

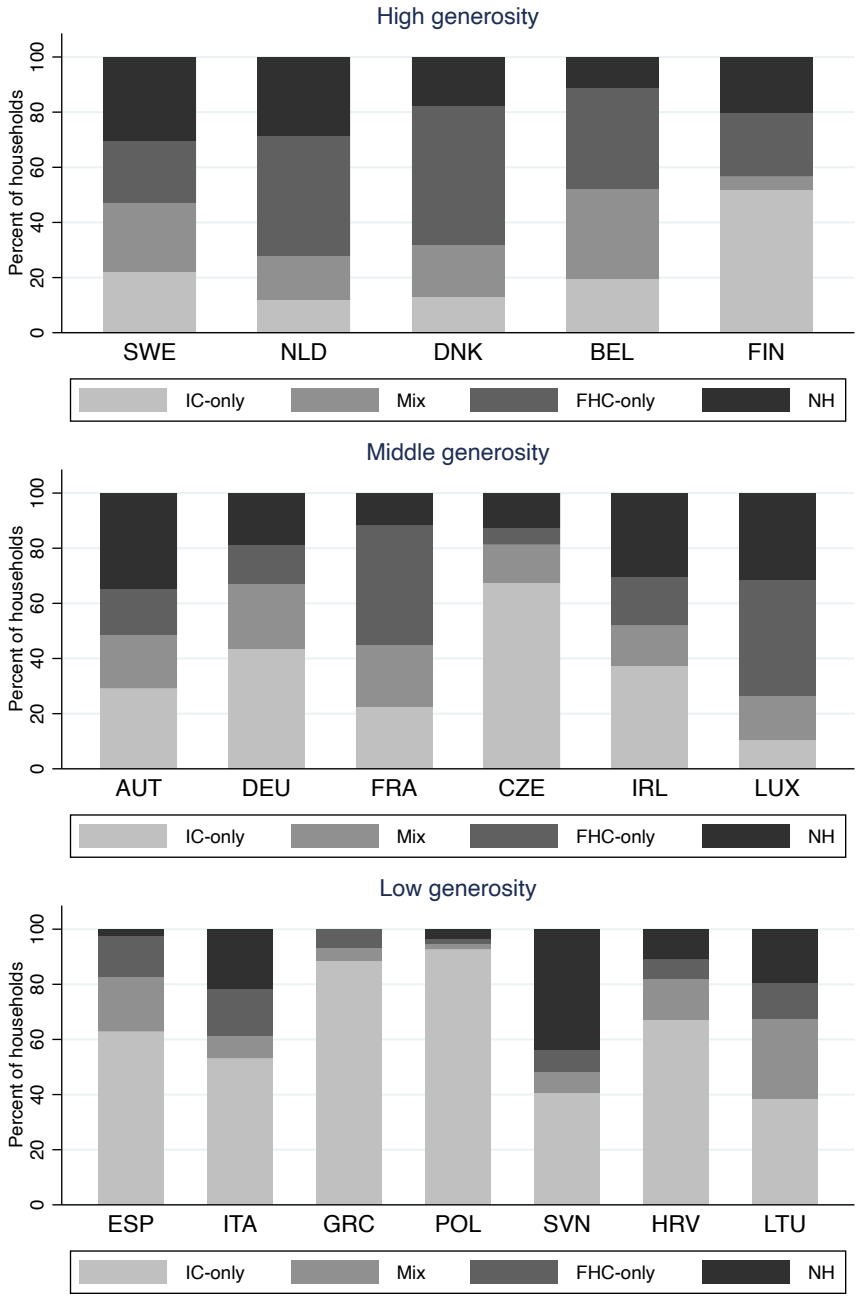
This table presents mean family/child characteristics by country group in our SHARE estimation sample. The sample selection criteria are detailed in Section 2.1. "Number of children" refers to the number of children aged 20-60 that the SHARE elderly have. Household weights are applied.

Table A9: Strict-generosity grouping and household counts in the final estimation sample

Generosity group	Country	Gov't LTC spending (% GDP)	N households
High	Belgium	2.3	286
High	Netherlands	3.7	160
High	Denmark	3.0	154
High	Sweden	3.3	107
High	Finland	2.2	52
Middle	France	1.9	255
Middle	Germany	1.2	200
Middle	Austria	1.2	190
Middle	Czechia	1.3	335
Middle	Luxembourg	1.0	46
Middle	Ireland	1.3	27
Middle	Switzerland	1.7	0
Low	Spain	0.7	193
Low	Croatia	0.2	95
Low	Greece	0.1	146
Low	Italy	0.7	153
Low	Poland	0.3	114
Low	Estonia	0.4	0
Low	Slovakia	0.9	0
Low	Slovenia	0.9	7
Low	Hungary	0.2	0
Low	Latvia	0.4	0
Low	Lithuania	0.9	223

Countries are grouped using bins of government long-term-care spending as a share of GDP in 2015: High if spending exceeds 2% of GDP, Middle if spending lies between 1% and 2%, and Low if spending is below 1% of GDP. The spending measure is constructed from OECD long-term-care expenditure data as the sum of the health and social LTC components under government and compulsory schemes ('HC3 + HCR1'), expressed as a share of GDP. Household counts are taken from the current final four-option estimation sample.

Figure A4: Care arrangement shares by country within generosity groups



A.1.7 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.1.8 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 A4 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. This construction is intended to provide a tractable benchmark for children's earnings potential when they are not caregiving, not a literal description of every child's realized labor-supply state. In particular, it abstracts from a richer labor-supply menu with part-time work, non-employment, and job-offer uncertainty.

We construct two versions of potential wages. The first version does not consider the labor force participation rates of different social groups, while the second version incorporates these participation rates. The rationale behind incorporating participation rates in the second version is to address the overestimation of potential income, particularly for social groups with lower labor force participation, such as women. If individuals in these groups are unlikely to participate in the labor force even when not providing informal care, it is crucial to account for this in their potential income estimates. In particular, the adjustment is gender-specific, so daughters and sons are assigned different participation-adjusted potential wages by country and year.

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

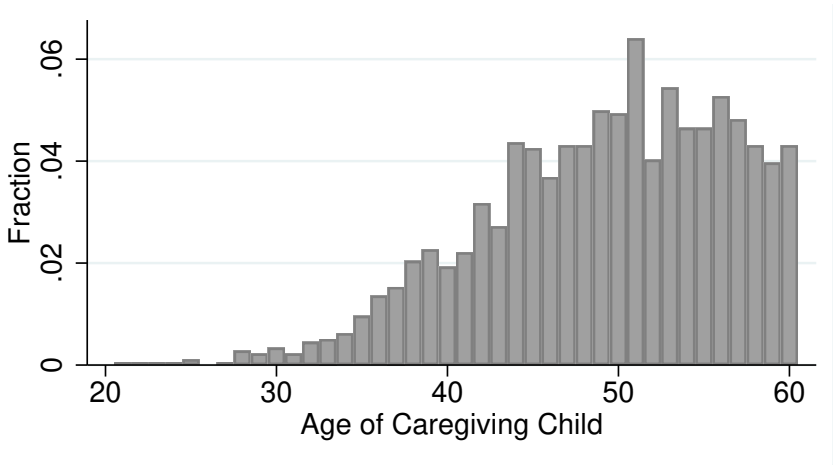
$$\begin{aligned} PotentialWage_{gecy}^{Adjusted} = LFPR_{gcy} * PotentialWage_{gecy} \\ + (1 - LFPR_{gcy}) * \frac{1}{2}(MinimumWage_{gcy}) \end{aligned}$$

where $LFPR_{gcy}$ is the labor force participation rate of gender g in country c in year y, and

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

For the current analysis, $LFPR_{gcy}$ is based on the labor force participation rate of people aged 45-65 in each gender and country group for each year. The reason why we chose this age range is because approximately 75% of caregiving children in our SHARE sample are over age 45, as shown in Appendix Figure A5. 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.[25] We plan to update our potential wage estimates once we gain access to the Eurostat microdata.

Figure A5: 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 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.

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

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 A10. For consistency, we need to construct synchronized educational categories that are consistent across years.

Table A10: 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

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:

$$Wage_{g,c,2014,5\text{–}8} = \underbrace{\left(\frac{NumEmployees_{g,c,2014,5\text{–}6}}{NumEmployees_{g,c,2014,5\text{–}8}}\right)}_{\text{Weight for level 5–6}} Wage_{g,c,2014,5\text{–}6} + \underbrace{\left(\frac{NumEmployees_{g,c,2014,7\text{–}8}}{NumEmployees_{g,c,2014,5\text{–}8}}\right)}_{\text{Weight for level 7–8}} Wage_{g,c,2014,7\text{–}8}$$

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:

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

  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:

$$\underbrace{GenderWage_{c,y=2010,e}}_{Imputed} = GrowthGenderWage_{c=EU,e}^{2006-2010} \underbrace{GenderWage_{c,y=2006,e}}_{Observed} \quad (17)$$

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 Assignment rules

This appendix subsection records two assignment rules used in the empirical implementation.

1. Primary caregiver assignment in child-involving households. We first identify *intense* child caregivers, defined as children who provide inside-household informal care or outside-household informal care at least weekly. Among households with child involvement in care, we retain only cases with an identifiable primary child caregiver. If exactly one child is an intense caregiver, that child is designated as the primary caregiver. If multiple children are intense caregivers, we apply the following sequence:

- If exactly one child provides inside-household informal care, that child is designated as the primary caregiver.
- Otherwise, among households with only outside-household informal caregivers, we compare caregiving frequency and retain the child with the highest observed frequency of care.
- If multiple children still remain tied after these steps, the household is excluded from the estimation sample.

Thus, at the sample-construction stage, we retain IC households with a unique most-intense child caregiver. We also retain mixed-care households only when the child informal-care margin can be reduced to a unique lead child using the same intensity-based procedure. In the estimation itself, however, the child attached to the Mix alternative is assigned using the separate empirical rule described below, because SHARE does not cleanly and consistently identify the child-specific mixed-care alternative across households and waves.

2. Child assignment for the Mix alternative. For the mixed-care option in the structural estimation, we attach a single child to the household's Mix alternative. This assigned child determines the child-specific opportunity-cost component entering the mixed-care option. The assignment rule is sequential:

- We first choose the uniquely closest child if one exists.
- If distance does not deliver a unique child, we choose the lowest-potential-income child among the closest children.
- If ties remain, we prioritize an observed informal caregiver, then a daughter, then the oldest child.
- Only if all of these observable tie-breakers fail do we use a random tie-breaker as a last resort.

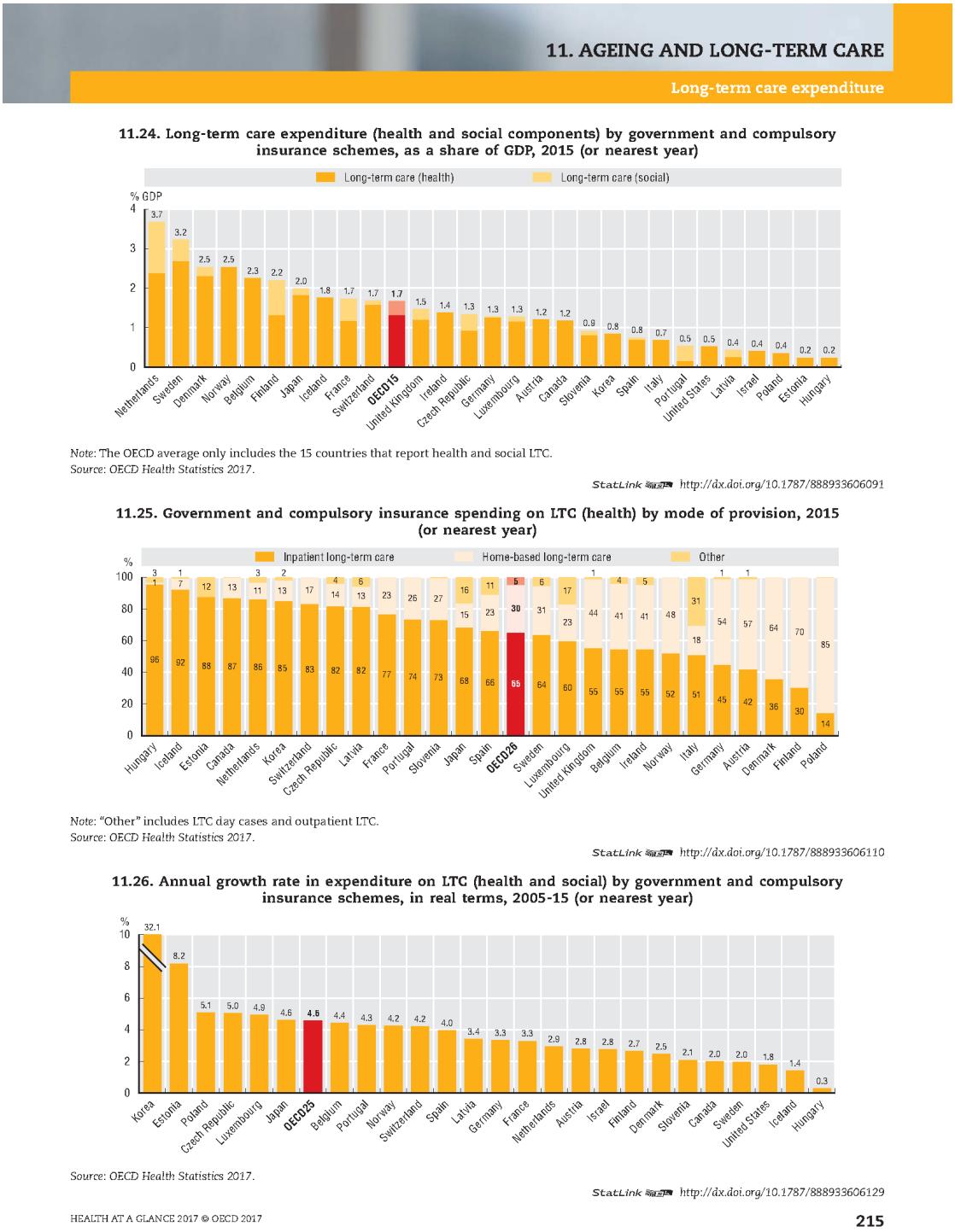
A.4 Details on formal care cost construction

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.

For formal home care, we use country-specific out-of-pocket home-care schedules that vary along two separate dimensions: care needs and income. On the care-intensity side, the source data report out-of-pocket cost shares at approximately 6, 22, and 41 weekly hours of formal home care for a median-income older person. We linearly interpolate the schedule between 6 and 22 hours and between 22 and 41 hours, assign hours 1–5 using a fixed-plus-variable rule anchored to the 6-hour point, and top-code hours above 41 at the 41-hour value. On the income side, the source data report separate out-of-pocket cost shares for low-, median-, and high-income households at a representative care-needs level. We combine these two margins by scaling the care-hours profile with an income-specific multiplier, then convert the resulting shares into annual out-of-pocket costs using country-year old-age disposable income from EU-SILC. Each SHARE household is then assigned the formal-home-care cost corresponding to its country, year, income group, and imputed care needs. Under the mixed-care option, we assume that 50% of the parent's care needs are covered by formal home care, so the formal-care component of the mixed option is one half of the corresponding formal-home-care cost schedule.

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 A6.

Figure A6: 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 A6. 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. These household-level cost schedules are distinct from the generosity-based country grouping used in the main text, which is based on public long-term-care spending rather than formal-care affordability alone.

A.5 Calculating care needs

A.5.1 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 A11.

Using the estimated coefficients from this regression, we predict daily care needs (in hours) for all SHARE respondents. This means that care needs are not mechanically equated with observed informal-care hours in SHARE; rather, observed care hours are used only to estimate a mapping from limitation profiles to expected care hours. This approach relies on the assumption that the relationship between functional limitations and care needs 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 A11: 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

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:

$$h_{it} = \mathbf{X}_{it}\boldsymbol{\beta} + \mu(P_{it}) + \epsilon_{it} \tag{18}$$

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 18, we use the following assumption as used in (Dahl 2002) and (Barczyk & Kredler 2019):

$$E[\epsilon_{it} \mid \mathbf{X}_{it}, \mathbf{Z}_{it}] = 0 \tag{19}$$

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

$$\begin{aligned} E[\epsilon_{it} \mid \mathbf{X}_{it}, \mathbf{Z}_{it}] &= P(NH \mid \mathbf{X}_{it}, \mathbf{Z}_{it})\, E[\epsilon_{it} \mid \mathbf{X}_{it}, \mathbf{Z}_{it}, NH] \\ &\quad + P(C \mid \mathbf{X}_{it}, \mathbf{Z}_{it})\, E[\epsilon_{it} \mid \mathbf{X}_{it}, \mathbf{Z}_{it}, C] \\ &= 0 \end{aligned} \tag{20}$$

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

Applying Equation 20 to Equation 18 leads to the following specification, which we use

to correct care need for nursing home residents in SHARE:

$$\hat{h}_{it}^{NH} = \mathbf{X}_{it}\hat{\beta} - \frac{1-\hat{P}_{it}}{\hat{P}_{it}}\hat{\mu}(\hat{P}_{it}) \tag{21}$$

In practice, we take the following procedures to estimate Equation 21:

- 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 A12.

- Lastly, using the estimated $\hat{\boldsymbol{\beta}}$ and $\hat{\delta}$ from the previous step, we estimate Equation 21 for nursing home residents in SHARE.

Table A12: 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

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.5.2 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.5.1. In the raw SHARE nursing-home sample, the distribution of reported ADL/IADL limitations exhibits a pronounced spike at zero and one reported limitation, whereas the corresponding mobility variables do not show comparable irregularities. This pattern is suggestive of underreporting or miscoding in the ADL/IADL measures for some institutionalized respondents.

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 A13, only 3.86% 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 – 30.84% and 10.28%, respectively – suggesting possible underreporting or misclassification in the SHARE data.

Table A13: ADL/IADL distribution, HRS vs SHARE

Num of (I)ADLs	HRS	SHARE
0	3.86%	30.84%
1	1.69%	10.28%
2	2.02%	6.54%
3	2.54%	7.48%
4	4.52%	7.94%
5	6.26%	4.21%
6	5.97%	4.21%
7	7.62%	4.21%
8	8.80%	6.54%
9	10.96%	3.74%
10	17.07%	5.61%
11	28.69%	8.41%
Obs	2126	206

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 SHARE's 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 A14: 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		

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.6 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 A15. 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 A16. 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 A15: 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, and parking time dominate.
1–5 km	5–15 minutes (car)	City traffic can vary, with average speeds around 20–30 km/h.
5–25 km	15–35 minutes (car)	Suburban or rural roads, or urban highways, with average speeds around 40–60 km/h.
25–100 km	30 minutes–1.5 hours (car)	Mostly highway or rural-road travel, with average speeds around 70–100 km/h.
100–500 km	1.5–6 hours (car)	Highway travel; congestion and tolls add variation, with average speeds around 80–110 km/h.
$>$ 500 km (by car)	6–10+ hours (car)	Depends on country and traffic; overnight or rest stops may be needed.
$>$ 500 km (by air)	1–3 hours (flight) + 2–3 hours prep	Short-haul EU flights; includes check-in, boarding, and airport access.

These time assignments are used to map the SHARE distance categories into one-way commuting times for child caregivers. Daily commuting time in the opportunity-cost calculation doubles the one-way travel time.

Table A16: 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 assigned because the distance is negligible.
1–5 km	Car	0	No cost assigned because the distance is very short.
5–25 km	Car	EUR 2.25	Urban or suburban driving conditions.
25–100 km	Car	EUR 9.02	Longer trips; fuel efficiency may improve on highways.
100–500 km	Car	EUR 45.08	Substantial travel; rest stops may matter.
$>$ 500 km (by car)	Car	EUR 90.16	Long-distance driving; fatigue and accommodation costs may also arise.
$>$ 500 km (by air)	Airplane	EUR 20.69–80+ (set to EUR 80)	Low-cost carriers can offer competitive rates; prices vary by route and timing.

These cost assignments are used to map the SHARE distance categories into one-way monetary travel costs for child caregivers. Daily commuting cost in the opportunity-cost calculation doubles the one-way cost.

A.7 Estimation: Details

To keep the algebra transparent, this appendix presents the likelihood logic using a simplified formal-care versus child-involving-care notation. In the main text, the estimated model expands the formal-care side into nursing-home care, formal home care, and mixed care, but the normalization and maximum-likelihood logic are the same.

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, partner status, step-child status, birth order, and family size) that plausibly correlate with the propensity to provide care.[26]

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:

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

[26] 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 $P_{ik} = 0\ \forall k \neq j^*$.[27]

The scaled utility benefit is given by:

$$\tilde{V}_{ij} = \begin{cases} -\frac{1}{\sigma}p_i^{bc} - \frac{\theta_0}{\sigma} & \text{if } j = 0 \\ -\frac{1}{\sigma}OC_{ij} - (\mathbf{X}_{ij}\frac{\boldsymbol{\beta}}{\sigma}) & \text{if } j > 0 \end{cases} \tag{22}$$

$$= (-1) * \begin{cases} \tilde{\alpha}p_i^{bc} + \tilde{\theta}_0 & \text{if } j = 0 \\ \tilde{\alpha}_0 OC_{ij} + \mathbf{X}_{ij}\frac{\tilde{\boldsymbol{\beta}}}{\sigma} & \text{if } j > 0 \end{cases} \tag{23}$$

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

[27] 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.

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 23: $\{\theta^{FC}, \alpha, \boldsymbol{\beta}\}$. 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.

A.8 Illustrative Counterfactual: Free Nursing-Home Care

To illustrate the quantitative implications of the estimated residual heterogeneity, Table A17 reports an extreme counterfactual in which the out-of-pocket monetary cost of nursing-home care is set to zero for all households, holding all other model components fixed. Even under this stark intervention, home-based arrangements remain prevalent, especially because many families continue to attach substantial non-monetary value to avoiding institutional care.

Table A17: Illustrative counterfactual: making nursing-home care free

	NH share		FHC share		Mix share		IC share	
Region	Status quo	Free NH	Status quo	Free NH	Status quo	Free NH	Status quo	Free NH
High	22.4	40.9	38.7	28.7	21.6	16.6	17.4	13.8
Middle	17.0	28.2	24.0	19.7	22.6	19.7	36.4	32.4
Low	12.4	25.6	12.7	10.4	9.7	8.2	65.2	55.8

Status quo reports the baseline model-predicted benchmark. The remaining columns report model-predicted arrangement shares in an illustrative counterfactual that sets the out-of-pocket monetary cost of nursing-home care to zero for all households, holding all other model components fixed. Shares are reported in percent and sum to 100 within each region up to rounding.

A.9 Robustness of the estimation results

Robustness to the sibling-level IIA assumption. A potential concern is that the multinomial logit model imposes independence across the sibling-specific informal-care alternatives. To assess the importance of this restriction, Table A18 compares our baseline

multinomial logit specification to a nested-logit model that places all child-specific care alternatives in a common IC nest while leaving NH, FHC, and Mix as singleton branches.

The comparison is informative in two ways. First, the nested-logit estimates imply a modest decrease in the monetary-cost coefficient: with arrangement-specific country-group interactions, α falls from about 1.07 in the multinomial logit model to about 0.96 in the nested-logit specification; without those interactions, it falls from about 1.11 to about 1.02. Second, the estimated IC-nest parameter is stable across specifications and equals about 0.63. In a nested-logit model, this implies a within-family correlation in unobserved utility across sibling-specific informal-care options of about $1 - \tau_{IC} \approx 0.4$. This indicates that sibling-specific informal-care options share meaningful family-level unobservables, but remain far from perfectly substitutable. At the same time, the daughter effect remains large, negative, and precisely estimated. Overall, the nested-logit results support the view that modeling correlation across siblings is behaviorally sensible, while also showing that the main qualitative conclusions do not hinge on the strict multinomial-logit independence assumption.

The next two robustness exercises probe how sensitive our baseline estimates are to alternative ways of addressing nursing-home underrepresentation in SHARE.

Robustness to an alternative NH-weight correction. Column (2) of Table A19 uses an alternative NH-weight correction constructed from observed nursing-home status only, without the forward-looking pre-NH adjustment used in our preferred baseline weights. This alternative matches the OECD nursing-home shares by construction. The main qualitative conclusions remain unchanged: the monetary-cost coefficient stays positive and sizeable, the daughter effect remains large and negative, and substantial group-specific differences in non-monetary arrangement costs remain.

Table A18: Comparison of MNL and Nested Logit Specifications

	(1) MNL + FE	(2) Nested Logit + FE	(3) MNL No FE	(4) Nested Logit No FE
Main coefficients				
θ^{NH}	-1.047***	-0.658***	0.636***	0.912***
	(0.203)	(0.234)	(0.172)	(0.199)
θ^{FHC}	-0.830***	-0.509**	0.446***	0.725***
	(0.206)	(0.233)	(0.167)	(0.185)
θ^{Mix}	-0.804***	-0.439*	0.207	0.518***
	(0.193)	(0.225)	(0.157)	(0.181)
α	1.065***	0.963***	1.112***	1.018***
	(0.130)	(0.128)	(0.124)	(0.121)
Daughter	-0.540***	-0.434***	-0.527***	-0.431***
	(0.120)	(0.108)	(0.116)	(0.104)
Non-biological	-0.052	-0.027	0.122	0.121
	(0.431)	(0.358)	(0.441)	(0.368)
Has partner	0.248*	0.203*	0.168	0.153
	(0.140)	(0.109)	(0.132)	(0.104)
First-born	-0.160	-0.050	-0.199*	-0.075
	(0.112)	(0.084)	(0.109)	(0.085)
Number of children	-0.042	-0.013	-0.014	0.004
	(0.053)	(0.043)	(0.050)	(0.040)
Middle generosity × NH	1.649***	1.515***	–	–
	(0.227)	(0.220)	–	–
Low generosity × NH	2.090***	1.973***	–	–
	(0.280)	(0.272)	–	–
Middle generosity × FHC	1.179***	1.116***	–	–
	(0.200)	(0.195)	–	–
Low generosity × FHC	1.719***	1.703***	–	–
	(0.240)	(0.234)	–	–
Middle generosity × Mix	0.690***	0.624***	–	–
	(0.190)	(0.188)	–	–
Low generosity × Mix	1.859***	1.811***	–	–
	(0.220)	(0.216)	–	–
Nest parameter				
τ_{IC}	–	0.626***	–	0.636***
	–	(0.144)	–	(0.143)
Fit statistics				
Log-likelihood	-10801452	-10741409	-11071653	-11011874
Pseudo-R^2	–	–	–	–
Fixed effects	Yes	Yes	No	No

Columns (1) and (3) report multinomial logit (MNL) estimates, while columns (2) and (4) report nested-logit estimates in which the child-specific informal-care alternatives are grouped in a common IC nest. "FE" indicates the specification with arrangement-specific country-group fixed effects; "No FE" omits those interactions. In all columns, the estimated coefficients are reported on the common utility-cost scale used in the paper, and standard errors are reported in parentheses.

Table A19: Robustness of nursing-home adjusted weights

	(1) Baseline	(2) OECD-match weights	(3) NH-sampled cells
θ^{NH}	-1.047***	-1.487***	-1.420***
	(0.203)	(0.217)	(0.314)
θ^{FHC}	-0.830***	-0.705***	-1.145***
	(0.206)	(0.215)	(0.347)
θ^{Mix}	-0.804***	-0.818***	-0.869***
	(0.193)	(0.197)	(0.322)
α	1.065***	1.235***	0.974***
	(0.130)	(0.133)	(0.223)
Daughter	-0.540***	-0.554***	-0.727***
	(0.120)	(0.135)	(0.215)
Non-biological	-0.052	-0.071	1.257
	(0.431)	(0.442)	(1.075)
Has partner	0.248*	0.190	0.271
	(0.140)	(0.149)	(0.255)
First-born	-0.160	-0.128	-0.233
	(0.112)	(0.117)	(0.203)
Number of children	-0.042	-0.067	-0.083
	(0.053)	(0.054)	(0.097)
Middle generosity × NH	1.649***	1.724***	2.578***
	(0.227)	(0.239)	(0.397)
Low generosity × NH	2.090***	1.726***	3.930***
	(0.280)	(0.283)	(0.694)
Middle generosity × FHC	1.179***	1.104***	2.799***
	(0.200)	(0.209)	(0.400)
Low generosity × FHC	1.719***	1.470***	2.319***
	(0.240)	(0.250)	(0.328)
Middle generosity × Mix	0.690***	0.667***	1.422***
	(0.190)	(0.192)	(0.353)
Low generosity × Mix	1.859***	1.768***	1.404***
	(0.220)	(0.222)	(0.299)
Households	2743	2743	938

Column (1) reports the estimated baseline using our preferred NH-adjusted household weights, which are constructed using the forward-looking nursing-home indicator. Column (2) re-estimates the same specification using an alternative NH-weight correction constructed from observed nursing-home status only, without the forward-looking pre-NH adjustment; this alternative correction matches the OECD nursing-home shares by construction. Column (3) reports the estimates on the subset of country-wave cells where nursing-home residents are documented as being in the baseline sampling frame, using the original SHARE household weights. Standard errors are reported in parentheses.

Robustness to comparable NH-sampling frames. Column (3) of Table A19 addresses

the concern that cross-country differences in nursing-home use could partly reflect differences in whether nursing-home residents are sampled in SHARE at baseline. We therefore re-estimate the baseline specification on the subset of SHARE country-wave cells where nursing-home residents are documented as being in the baseline sampling frame, and in that restricted-sample exercise we use the original SHARE household weights rather than the NH-adjusted weights. Table A20 lists the countries and baseline waves that survive this restriction in the estimation sample.

Table A20: Comparable-NH-sampling subset used in the restricted-sample robustness check

Country	Included baseline waves	N households
Austria	8	6
Belgium	4, 5, 6, 8	132
Croatia	8	7
Czech	8	12
Denmark	1, 8	78
Finland	8	37
Germany	1, 8	93
Greece	1	107
Luxembourg	6	5
Netherlands	1, 2, 4, 5	160
Spain	1, 2, 4, 5, 6, 8	193
Sweden	1, 2, 4, 5, 6, 8	107

The table lists the countries and SHARE baseline waves that remain once we restrict the estimation sample to country-wave cells where nursing-home residents are documented as being in the baseline sampling frame. Household counts are reported after all main-sample restrictions have been applied. The corresponding robustness regression reported in Table A19 is estimated on this restricted sample using the original SHARE household weights rather than the NH-adjusted household weights used in the baseline specification.

The restriction is demanding: the number of households falls from 2,743 to 938. Even so, the core economic patterns remain. The monetary-cost coefficient stays positive and close to the baseline estimate, daughters remain substantially more likely to provide care, and households with partnered children remain less likely to rely on child-provided care. At the same time, the arrangement-specific group interactions move more, as one would expect in a much thinner and more selective sample. We therefore interpret this exercise as qualitatively reassuring: once attention is restricted to the cleaner sampling-frame subset, the main qualitative patterns survive even without relying on the NH-adjusted weights.

A.10 Counterfactual implementation details

For counterfactuals that change only economic variables, such as formal-care prices or children's opportunity costs, we replace the relevant entries of $\mathbf{X}$ by their counterfactual values

$\tilde{\mathbf{X}}$ and recompute choice probabilities using equation (15). We then aggregate the resulting probabilities with normalized household weights.

Counterfactuals that alter family structure require simulation because the choice set itself changes. In these exercises, we run $N_{sim} = 1{,}000$ simulations. When the counterfactual changes the number of children, we delete each child with probability p_K, where p_K is chosen so that the simulated sample matches the target average number of children. When the counterfactual changes stepchild prevalence, we convert biological children into stepchildren with probability p_{step} so that the simulated sample matches the target share of non-biological children. All other observed family characteristics are held fixed.

For each simulation draw, we recompute family-level choice probabilities under the modified family composition and aggregate the resulting care shares. Reported counterfactual outcomes are averages across the N_{sim} simulated draws. This procedure preserves the empirical joint distribution of the remaining observables while allowing family structure to vary in a transparent way.

A.11 Economics-only benchmark for the elasticity comparison

This appendix subsection records the deterministic economics-only model used in Section 3.4. Specifically, we set the idiosyncratic shocks and child-level non-monetary utility shifters to zero, and define arrangement-specific utility costs as

$$C_{ia}^{econ} = \begin{cases} \alpha p_i^{NH} + \tilde{\theta}^{NH} + \tilde{\gamma}_{g_i}^{NH} & \text{if } a = \text{NH}, \\ \alpha p_i^{FHC} + \tilde{\theta}^{FHC} + \tilde{\gamma}_{g_i}^{FHC} & \text{if } a = \text{FHC}, \\ \alpha OC_{ij} & \text{if } a = \text{IC}_j, \\ \alpha\big(0.5\, p_i^{FHC} + 0.5\, OC_{i\, j_i^{Mix}}\big) + \tilde{\theta}^{Mix} + \tilde{\gamma}_{g_i}^{Mix} & \text{if } a = \text{Mix}. \end{cases} \tag{24}$$

Families then choose the arrangement with the lowest utility cost,

$$a_i^{econ} \in \arg\min_{a \in \mathcal{A}_i} C_{ia}^{econ}.$$

The high-generosity group is the reference group, so

$$\tilde{\gamma}_{High}^{NH} = \tilde{\gamma}_{High}^{FHC} = \tilde{\gamma}_{High}^{Mix} = 0.$$

The baseline monetary-cost coefficient is held fixed at its estimated value, $\alpha = 1.065$, while the arrangement-specific constants are calibrated so that the model matches the observed

baseline shares of NH, FHC, and Mix within each generosity group.

Table A21: Calibrated parameters of the economics-only benchmark

Parameter	Value	Parameter	Value
α	1.065	$\tilde{\gamma}^{NH}_{Middle}$	0.88
$\tilde{\theta}^{NH}$	-0.39	$\tilde{\gamma}^{NH}_{Low}$	1.02
$\tilde{\theta}^{FHC}$	0.26	$\tilde{\gamma}^{FHC}_{Middle}$	0.04
$\tilde{\theta}^{Mix}$	0.04	$\tilde{\gamma}^{FHC}_{Low}$	-0.12
		$\tilde{\gamma}^{Mix}_{Middle}$	-0.03
		$\tilde{\gamma}^{Mix}_{Low}$	-0.04

This table reports the calibrated parameters of the deterministic economics-only model used in the elasticity comparison. The model retains the baseline monetary-cost coefficient α but shuts down idiosyncratic preference shocks and child-level non-monetary utility shifters. The high-generosity group is the reference group, so $\tilde{\gamma}^{NH}_{High} = \tilde{\gamma}^{FHC}_{High} = \tilde{\gamma}^{Mix}_{High} = 0$. The arrangement-specific constants are calibrated so that the model matches the observed baseline shares of NH, FHC, and Mix within each generosity group.

A.12 Derivation of the stylized elasticity comparison

This appendix derives the elasticity expressions stated in Section 3.4. We retain the simplified binary comparison between formal care (FC) and child-involving care (IC), and denote the baseline formal-care share by $\hat{FC}_0$.

Economic factors only Let $C_e \sim N(\mu_e, \sigma_e^2)$ denote the net monetary advantage of formal care over child-involving care. Formal care is chosen whenever

$$C_e > \theta_0^e,$$

where θ_0^e is calibrated to match the baseline share:

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

A subsidy $\Delta S > 0$ lowers the effective price of formal care, which in this threshold representation is equivalent to shifting the decision threshold from θ_0^e to $\theta_0^e - \Delta S$. The post-subsidy formal-care share is therefore

$$\hat{FC}_S = 1 - F_e(\theta_0^e - \Delta S),$$

so that

$$\Delta FC = \hat{FC}_S - \hat{FC}_0 = F_e(\theta_0^e) - F_e(\theta_0^e - \Delta S).$$

For a small subsidy, a first-order Taylor expansion around θ_0^e gives

$$F_e(\theta_0^e - \Delta S) \simeq F_e(\theta_0^e) - f_e(\theta_0^e)\Delta S,$$

which implies

$$\Delta FC \simeq f_e(\theta_0^e)\Delta S.$$

Since $\Delta p_{fc} = -\Delta S$, the absolute FC elasticity is approximately

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

Economic factors + psychic costs Now let $C_p \sim N(0, \sigma_p^2)$ denote heterogeneous psychic costs associated with child-involving care, independent of C_e, and define

$$C = C_e + C_p.$$

Then C is normally distributed with mean $\mu_c = \mu_e$ and variance

$$\sigma_c^2 = \sigma_e^2 + \sigma_p^2.$$

Let θ_0^c be calibrated so that the model with preference heterogeneity matches the same baseline formal-care share:

$$\hat{FC}_0 = \Pr(C > \theta_0^c) = 1 - F_c(\theta_0^c).$$

Repeating the same steps as above yields

$$\Delta FC \simeq f_c(\theta_0^c)\Delta S$$

and therefore

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

Comparing the two elasticities The two models are calibrated to match the same baseline formal-care share $\hat{FC}_0$, or equivalently the same child-involving-care share $\hat{IC}_0 = 1 - \hat{FC}_0$. Hence the decision thresholds lie at the same percentile of their respective latent-

cost distributions:

$$\hat{IC}_0 = \Pr(C_e < \theta_0^e) = \Phi\left(\frac{\theta_0^e - \mu_e}{\sigma_e}\right),$$
$$\hat{IC}_0 = \Pr(C < \theta_0^c) = \Phi\left(\frac{\theta_0^c - \mu_c}{\sigma_c}\right).$$

Let

$$z_0 = \Phi^{-1}(\hat{IC}_0).$$

Then the densities at the two thresholds can be written as

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

where ϕ is the standard normal density. Because $\sigma_c > \sigma_e$, it follows immediately that

$$f_c(\theta_0^c) < f_e(\theta_0^e),$$

and therefore

$$|\epsilon_{FC}^c| < |\epsilon_{FC}^e|.$$

Thus, once the two models are aligned to match the same baseline formal-care share, preference heterogeneity dampens policy responsiveness by lowering the density of families at the switching margin. In simple terms, if there are powerful non-economic reasons for care decisions, then price changes matter less and it takes large subsidies to sway families' decisions.