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

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Abstract

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

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1 Introduction

Aging populations together with changes in the family structure (e.g. rising divorce rates, fewer children, etc.) will pose significant challenges to governments. The aging of the baby boomers, together with a longer life expectancy and decreasing fertility rates, will make the pool of elderly relative to the working-age population dramatically larger.[1] Because the share of the oldest-old (80 and over) in the population is projected to double over the next few decades, long-term care expenditures are projected to rise (for example, as a percentage of GDP they are projected to increase by 168% in Germany and 149% in Spain between 2000 and 2050; see Comas-Herrera et al., 2003). Demographic changes will thus tighten government budgets and governments will have to reform long-term care policy. Germany, for example, has already done so in 1996, and Japan in 2000.

Long-term care is defined as becoming dependent on assistance from another person in performing everyday life activities (e.g. getting in and out of bed, showering, eating, and so on). Family members are a major source of care. In Barczyk & Kredler (2018) we find that in the United States the vast majority of care is provided by family members at home, in particular, by spouses and adult children. We also find that economic characteristics of the family, such as children's opportunity costs in the labor market and parents' wealth, matter strongly for care arrangements. Informal home-care has also been found to play an important role in many other OECD countries, (see, e.g., Sundstroem et al., 2002, Zukewich, 2003, and Moise et al., 2004). But, there is substantial variation across countries. For example, Barczyk & Kredler (2019) finds that the average monthly hours provided by children to disabled elderly parents in Spain is 12.4, while in Sweden they amount only to 3.4.

Our goal is to build a suitable economic model to address the following questions: (1) How much of the variation in care arrangements across families can be explained by families' economic characteristics (wages, wealth, etc.)?

[1] According to projections by the OECD (2005), by the year 2040 one in four persons is 65 or older, on average, for OECD countries. The old-age dependency ratio (that is, the ratio of persons 65+ to the population 20-64), averaged across the OECD countries, will increase from 23% in 2000 to 46% by 2040 (for Canada it is projected to increase from 20% to 44%).

(2) How much of the differences in care arrangements across countries can be explained by differences in government policy? How much remains unexplained by the model and so points to differences in preferences (*culture*)? (3) Most importantly: **Which policy reforms are preferable from a macroeconomic point of view? How do certain subsidies (e.g. to informal caregivers or to nursing homes) affect welfare of families, and how much do they cost the government?** (4) Who will benefit most from different policies: the old or the young, the poor or the rich? In order to answer these questions we will make use of a European data set (SHARE). Using multiple sources of variation will provide us with better estimates on how strongly families will react to policy incentives than when only considering a single country.

Literature: Byrne et al. (2009) estimate a static model that captures the interaction between parents and children in the choice between formal-home care and informal care.

Van Houtven et al. (2013) and Skira (2015) show that the opportunity costs of caregiving play a crucial role in the caregiving decision.

Literature on who among siblings becomes caregiver.

2 Data

2.1 SHARE

Our analyses rely on SHARE (The Survey of Health, Ageing, and Retirement in Europe), a panel of the European population aged 50 and above. This dataset provides extensive information on the demographic and socioeconomic characteristics of the senior population and their children, household caregiving arrangements, and health-related information. SHARE has been available bi-annually from 2004 to 2020.

Sample selection. We select the analysis sample based on several criteria. First, to focus our attention on the elderly with care needs, we limit the sample to households with at least one person aged 65+ who has at least one mobility limitation. Second, we only keep households with at least one child aged 20 to 60. This is because children outside this age range are either too young or too old to be the potential caregiver. We retain only the households where the demographic variables required for model estimation are complete for all children. Third, we limit to households that either use nursing homes (formal care) or have one intense informal caregiver among children. In the current analyses, we exclude households with multiple child caregivers to facilitate estimating the discrete choice model. Fourth, we drop households that cannot be matched with the constructed potential incomes of children or potential formal care costs. The construction of potential incomes and formal care costs is documented in later subsections.

For the current analyses, we only use the baseline surveys due to several issues with panel dimensions. The first issue is regarding 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. We plan to add non-baseline samples in the future after addressing these challenges. Appendix Table A1 compares the sample size between the full sample and baseline sample.

Furthermore, we do not use Waves 3, 4, and 7 in the current analyses for the following reasons. Waves 3 and 7 differ from other waves in that they are retrospective: they focus on respondents' life histories, not respondents' current life circumstances. Wave 4 is omitted because we cannot identify *which* child provided informal care. This is different from other waves where it is possible to identify the identities of the child caregivers through explicit questions in the Social Support (SP) module. In contrast, in Wave 4, the SP module only asks whether any child provided care, without specifying which one, thus preventing accurate identification of the caregiving child.[2]

[2] 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

After imposing the above sample selection criteria, we have a final sample of 1,829 households with 4,135 parent-child pairs. Appendix Table A2 reports how sample size changes after imposing each of the sample selection criteria.

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

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

Intense informal care (IC) by children is defined using the frequency of informal care. SHARE differentiates between informal care from outside the household (OIC), e.g. from adult children living elsewhere, and informal care from inside the household (IIC), e.g. from the spouse or co-residing children. How OIC and IIC are reported and the associated care frequencies differ across waves, as summarized in Table 1.

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 1: Overview of Informal care (IC) variables in SHARE

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

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

There are a few challenges in defining intense IC consistently across waves. First, in the earlier waves, OIC is reported at the couple level, not at the individual level; in other words, we only know if the respondent *and/or* the spouse received OIC, but not *who* received OIC. In the current analyses, the care need and care is defined at the *couple* level, so this does not pose a problem.[3] 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.[4] Lastly, only about 21% of OIC by child occurs "about daily," as shown

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

[4]Only about 10% of caregivers only provided help with paperwork, which can be considered

in Appendix Table A4. To increase the sample size, we define both "about daily" and "about every week" OIC as intense informal care. Additionally, we classify all IIC as intense informal care, since by definition in the SHARE survey, IIC occurs on an almost daily basis.

2.2 Potential income

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.

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.

Appendix A.2 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.

as a light care. Hence, the majority of reported OIC can be considered as substantial care (personal care, household help).

2.3 Formal care cost

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

In the current version, our out-of-pocket costs are based on OECD statistics. Specifically, we use the OECD report on "Out-of-pocket costs of long-term care as a share of old age median disposable income after public support, for care recipients holding no net wealth, by severity of needs and care setting," as shown in Appendix Figure A1.

To construct formal care costs, we proceed with the following steps. First, we group European countries into three groups based on the expensiveness of formal care: (1) low cost (10∼40% of old-age income), (2) medium cost (50∼80% of old-age income), and (3) high cost (80∼120% of old-age income). The grouping of countries is as follows:

- Group 1 (Low FC cost): Sweden, Netherlands, Germany, Latvia, Denmark, Malta
- Group 2 (Medium FC cost): Italy, Ireland, Slovak Republic, Luxembourg, Finland, France, Slovenia, Austria, Belgium, Lithuania, Greece
- Group 3 (High FC cost): Croatia, Spain, Czech, Poland

Note that not all SHARE countries can be matched to the countries in the OECD report, so unmatched countries are dropped in current analyses.

Second, we take the midpoint for the FC cost share for each group[5] and multiply these values of FC cost share by old-age mean annual income for each country. The old-age mean income data is sourced from Eurostat's Structure of Earning Survey 2004-2018, which contains the mean annual earnings of people aged 65+ for each EU country.

In future analyses, we plan to construct a more detailed version of FC costs that better reflect variations across countries, household income levels, and the severity of care needs.

[5] This is 22.5% for Group 1, 65% for Group 2, and 100% for Group 3

3 Empirical facts

In this section, we document descriptive statistics using our estimation sample. Statistics regarding the full SHARE sample are documented in Appendix A.1.

First, out of the final 1,829 households, 150 households (8.2%) use nursing home (NH) care and the remaining households have one intense child caregiver. It is worth noting that the nursing home usage reported in SHARE is quite minimal; Appendix Table A3 shows that only 1% of SHARE parents aged 65+ who have at least one mobility limitation use nursing home care.[6] Table 2 shows that the mean formal care cost is smaller for nursing home households compared to households with one child IC caregiver.

Table 2: Nursing home cost, NH households vs. IC households

	NH households	IC households
Formal care cost	19,511.2 (11,948.14)	21,090.86 (9,029.71)
Count	150	1,679

Note: This table reports the mean formal care costs for (1) nursing home households and (2) households with one caregiving child in the SHARE final sample. Formal care cost is constructed using the procedures documented in Section 2.3. For more information on SHARE sample selection, see Section 2.1. Formal care cost is reported in Purchasing Power Standard (PPS).

For households with one caregiving child, we compare the characteristics of caregiving children versus non-caregiving children. Caregiving children are more likely to be female, living closer to parents, and have lower potential income relative to non-caregiving children. We do not find meaningful difference regarding biological child status, but this is partially because the sample size for non-biological children is very small in our sample (only 70 cases).

[6]Barczyk & Kredler (2019) discuss the under-sampling issue concerning the nursing home population in SHARE.

Table 3: Characteristics of caregiving children vs. non-caregiving children

	Caregiving Child	Non-Caregiving Child
Female	0.622	0.446
	(0.485)	(0.497)
Non-Biological	0.015	0.016
	(0.124)	(0.129)
Distance	9.39	86.02
	(35.96)	(160.72)
Potential Income	23,466.45	24,149.96
	(10,120.38)	(10,120.38)
Count	1,679	2,130

Note: This table reports the mean value of characteristics of caregiving children vs. non-caregiving children for households with one IC child caregiver in our final SHARE sample. "Non-Biological" is indicator for step-child, adopted child, or foster child. "Distance" refers to the distance between child and parent. Distance for each child is assigned as a mid-value of the reported distance categories: (1) In the same household or building, (2) Less than 1 km, (3) 1-5 km, (4) 5-25 km, (6) 25-100 km, (7) 100-500 km, (8) 500+ km. Potential income for each child is constructed using the procedures in Section 2.2.

4 Discrete-choice model

A family i chooses its caregiving mode j among the following options: formal care (FC) or informal care (IC) provided by one of its children. Hence, the **choice set** $\mathcal{C}_i$ for each family i is the following:

$$\mathcal{C}_i = \{0, 1, 2, \dots, J_i\}$$

where J_i is the total number of children in family i. $j = 0$ refers to FC, and $j > 0$ refers to IC by child j.

Each caregiving option j has its associated cost, C_{ij}, which includes both monetary and psychic components:

$$C_{ij} = p_{ij} + \theta^*_{ij}$$

Monetary costs are given by

$$p_{ij} = \begin{cases} p_i^{bc} & \text{if } j = 0 \\ y_{ij} & \text{if } j > 0 \end{cases}$$

where p_i^{bc} is the price of basic formal care faced by parent i and y_{ij} is the potential income of child j from full-time employment. Psychic costs are given by

$$\theta_{ij}^* = \begin{cases} \theta_{FC}^* + \varepsilon_{i0}^* & \text{if } j = 0 \\ \theta_{IC}^* + \theta_{ij} + \varepsilon_{ij}^* & \text{if } j > 0 \end{cases}$$

where we decompose psychic costs into a systematic part, common across all individuals, and individual-specific parts. The individual-specific part of the FC choice is an unobservable preference shock ε_{i0}^*. For the IC choice, there are also child-specific characteristics contained in θ_{ij}, such as, gender, step-child status, and distance from parents, in addition to an unobservable child-specific preference shock ε_{ij}^*.

To frame the choice problem in the language of standard discrete-choice models, we define the utility benefit stemming from the deterministic part of care arrangement j as the negative of the costs

$$V_{ij} = -p_{ij} - \begin{cases} \theta_{FC}^* & \text{if } j = 0 \\ (\theta_{IC}^* + \theta_{ij}) & \text{if } j > 0 \end{cases}$$

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

$$U_{ij^*} \equiv V_{ij^*} + \epsilon_{ij^*}^* \geq V_{ij} + \epsilon_{ij}^* \equiv U_{ij}, \quad \forall j \in \mathcal{C}_i,\ j \neq j^*$$

Following a large literature on estimating discrete-choice models, we assume that the unobservable choice-specific taste shock ϵ_{ij}^* is i.i.d. and follows an extreme value distribution with scale parameter σ and location parameter zero (EV-1/Gumbel with scale sigma). The probability of observing option j in family i is then given by

$$P_{ij} = \frac{\exp\left(\frac{V_{ij}}{\sigma}\right)}{\sum_{j=0}^{J_i} \exp\left(\frac{V_{ij}}{\sigma}\right)}$$

Here we can see that if the scale parameter is $\sigma > 1$, it acts to attenuate the impact of the "true" deterministic part of the monetary and the psychic costs. In the limit, as σ becomes large, the choice probability converges to the unconditional probability $1/(1 + J_i)$ as observable attributes become uninformative due to the vast heterogeneity in unobserved preferences.

We can also write $\epsilon^*_{ij} = \sigma\eta^*_{ij}$, where η^*_{ij} follows a standard Gumbel distribution with location parameter $\mu = 0$ and scale parameter $\sigma = 1$. The variance of η^*_{ij} is $\pi^2/6$ and that of ϵ^*_{ij} is $\sigma^2(\pi^2/6)$.

5 Estimation

Standard MLE Family i receives utility from care arrangement j given by

$$U_{ij} = V_{ij} + \epsilon^*_{ij}$$
$$\text{where} \quad V_{ij} = \begin{cases} -p_i^{bc} - \theta^*_{FC} & \text{if } j = 0 \\ -y_{ij} - (\theta^*_{IC} + \beta^*_1 \text{gender}_{ij} + \beta^*_2 \text{dist}_{ij} + \beta^*_3 \text{bio}_{ij}) & \text{if } j > 0 \end{cases}$$

and ϵ^*_{ij} follows a Gumbel distribution with location parameter 0 and scale parameter σ. We note that the utility is denominated in the same unit as the consumption good which follows from our specification of the utility functions where psychic costs act to reduce utility-generating consumption. 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.

To identify the parameters of interest, we need to impose two normalizations. First, we need to normalize one of θ^*_{FC} and θ^*_{IC} . We cannot identify both θ^*_{FC} and θ^*_{IC} because only differences in utility matter in the caregiving choice. There are infinite combinations of θ^*_{FC} and θ^*_{IC} that can rationalize the same choice. We choose to normalize θ^*_{IC} to 0, and consequently need to interpret θ^*_{FC} relative to the reference point θ^*_{IC}.

Second, we need to normalize the scale of utility benefit, as the overall scale of utility is irrelevant in discrete-choice models. Following the standard approach, we normalize the scale by normalizing the variance of ε^*_{ij} to $\pi^2/6$, corresponding to a scale parameter $\sigma = 1$. The specification of utility is then given by

$$\frac{U_{ij}}{\sigma} = \frac{V_{ij}}{\sigma} + \eta_{ij}$$

where η_{ij} follows a Gumbel distribution with location parameter 0 and scale parameter 1, and

$$\tilde{V}_{ij} = \begin{cases} -\frac{1}{\sigma}p_i^{bc} - \frac{\theta^*_{FC}}{\sigma} & \text{if } j = 0 \\ -\frac{1}{\sigma}y_{ij} - (\frac{\beta^*_1}{\sigma}\text{gender}_{ij} + \frac{\beta^*_2}{\sigma}\text{dist}_{ij} + \frac{\beta^*_3}{\sigma}\text{bio}_{ij}) & \text{if } j > 0 \end{cases}$$

We can see that the estimated coefficients capture the true effect of a variable relative to the size of 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:

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

Table 4: Estimated parameters

Coefficient	Estimated Value	S.E.	Underlying True Parameter
θ^{FC}	1.990	(0.112)	$\frac{\theta^{*FC}}{\sigma\sqrt{\pi^2/6}}$
β^0 (for monetary cost)	0.110	(0.049)	$\frac{1}{\sigma\sqrt{\pi^2/6}}$
β^1 (for female)	-0.771	(0.080)	$\frac{\beta^{*1}}{\sigma\sqrt{\pi^2/6}}$
β^2 (for step)	0.181	(0.430)	$\frac{\beta^{*2}}{\sigma\sqrt{\pi^2/6}}$
β^3 (for distance)	1.677	(0.146)	$\frac{\beta^{*3}}{\sigma\sqrt{\pi^2/6}}$

Notes: This table reports estimated parameters from Equation **??**. The last column shows the relations to underlying true parameter (Equation **??**) for each estimated parameter. Estimation is done using the SHARE data.

Table 4 shows the estimation results. The interpretations of each coefficient in terms of "true" parameters are as follows:

- θ^{FC} $(= \frac{\theta^{*FC}}{\sigma\sqrt{\pi^2/6}})$: This is the effect of choosing FC instead of IC on utility cost "*relative to*" the standard error of unobserved factors. The estimated value shows statistically significant positive utility cost of choosing FC instead of IC.

- β^0 $(= \frac{1}{\sigma\sqrt{\pi^2/6}})$: This is interpreted as the inverse of the standard error of unobserved factors (multiplied by $\sqrt{\pi^2/6}$)

- $\beta^1 = \frac{\beta^{*1}}{\sigma\sqrt{\pi^2/6}}$: This is the effect of being a female on the utility cost of caregiving "*relative to*" the standard error of unobserved factors. The estimate shows that being a female lowers the utility cost of caregiving, and this effect is statistically significant.

- $\beta^2 = \frac{\beta^{*2}}{\sigma\sqrt{\pi^2/6}}$: This is the effect of being a step-child on the utility cost of caregiving "*relative to*" the standard error of unobserved factors. The estimate shows a very noisy effect of being a step-child, as shown by a large standard error relative to the estimated value.

- $\beta^3 = \frac{\beta^{*3}}{\sigma\sqrt{\pi^2/6}}$: This is effect of increasing a distance by 100 km on the utility cost of caregiving "*relative to*" the standard error of unobserved factors. The estimate shows that a larger distance is associated with higher utility cost of caregiving, and this effect is statistically significant.

MLE with unobserved wage residuals We denote by y_{ij} the (true) opportunity cost of child j in family i, which we cannot observe in the SHARE data. We decompose the opportunity cost into an observed and an unobserved component by writing

$$\ln y_{ij} = \bar{y}_{ij} + \eta_{ij} \tag{1}$$

We impute $\bar{y}_{ij} \equiv \mathbb{E}[\ln y_{ij}|X_{ij}]$ using our estimated coefficients from the Eurostat data based on child j's observables in the SHARE data (gender, country, distance, step status) contained in X_{ij}. η_{ij} is an unobserved wage residual with mean zero.

We assume that the wage residuals among siblings are jointly normally distributed and denote by $\phi_K(\eta_{i1}, \eta_{i2}, \ldots, \eta_{iK})$ the joint normal PDF. The variance of the unobserved wage residual is the same for all children, $\mathbb{E}[\eta_{ij}^2] = \sigma_\eta^2$ for all j; note that we can obtain σ_η^2 from a Mincer regression in our Eurostat data. We allow that the unobservable wage residuals are correlated among siblings, $\mathbb{E}[\eta_{ij}\eta_{ik}] = \rho_\eta \sigma_\eta^2$ for $j \neq k$, where $\rho_\eta \in [-1, 1]$ is the correlation of siblings' earnings. Finally, we assume that η_{ik} is independent of observables $\{X_{ij}\}_{j=1}^{N_i}$[7], where N_i is the number of children in family i.

We will now derive the likelihood function for the care choice in family i given observables $X_i \equiv \{X_{ij}\}_{j=1}^{K_i}$ in family i. The probability that care choice j is chosen given a residual wage vector η is

$$\tilde{P}_j(X_i, \eta; \beta) = \frac{e^{V_{ij}}}{\sum_{j=0}^{K_i} e^{V_{ij}}}, \tag{2}$$

Now V_{ij} for the children $j = 1, \ldots, N_i$ is given by

$$V_{ij} = -\exp\left(\bar{y}_{ij} + \eta_{ij}\right) - \left(\beta_1^* \text{gender}_{ij} + \beta_2^* \text{dist}_{ij} + \beta_3^* \text{bio}_{ij}\right) \tag{3}$$

The crucial difference is that here the shock η enters into the opportunity-cost

[7] In Eq. 1, we see that $\mathbb{E}[\eta_{ij}|X_{ij}] = 0$, but independence, also across children, is a slightly stronger (but not unreasonable) assumption.

term. For formal care, V_{i0} is as before.

In our MLE estimation above we were done at this stage and in a position to construct the likelihood function. Here we still have to deal with the unknown wage residuals, but for which we have imposed distributional assumptions. Since we have assumed η_{ij} to be independent of observables X_i, the likelihood that care option $j \in \{0, 1, \ldots, K_i\}$ is chosen in family i conditional on observables X_i and given parameter vector β is

$$P_{ij} = \int \tilde{P}_j(X_i, \eta; \beta)\phi_{K_i}(\eta)\mathrm{d}\eta. \tag{4}$$

where the integration is over all possible combinations of child wage shocks $\eta = (\eta_{i1}, \ldots, \eta_{K_i})$ using the multi-variate normal density function ϕ_{K_i}.

We approximate the integral in Eq. 4 using multivariate Gaussian quadrature.[8] The integral is approximated by a weighted sum of function values evaluated at quadrature nodes. For example, in the bivariate case we have that

$$P_{ij} \approx \sum_{k_1=1}^{N} \sum_{k_2=1}^{N} w_{k_1} w_{k_2} \tilde{P}_j(X_i, x_{k_1}, x_{k_2}; \beta)$$

where w_{k_i} are quadrature weights and x_{k_i} are quadrature nodes. The quadrature nodes take the form:

$$(x_{k_1}, x_{k_2}) = (\sigma_\eta z_{k_1}, \rho\sigma_\eta z_{k_1} + \sigma_\eta\sqrt{1-\rho^2} z_{k_2})$$

where (z_{k_1}, z_{k_2}) are the two-dimensional Gaussian quadrature nodes for a standard normal variable, and (w_{k_1}, w_{k_2}) are the corresponding quadrature weights.

Why? In order to use Gaussian quadrature we need to express the random variable $\eta = (\eta_1, \eta_2)$ in terms of the standard normal variable $z = (z_1, z_2)$ in the following way:

$$\eta = \mu + Lz = \begin{bmatrix} \sigma_\eta & 0 \\ \rho\sigma_\eta & \sigma_\eta\sqrt{1-\rho^2} \end{bmatrix} \begin{bmatrix} z_1 \\ z_2 \end{bmatrix}$$

[8] See https://www.r-bloggers.com/2015/09/notes-on-multivariate-gaussian-quadrature-with-r-code/ for an implementation in R.

The lower-triangular matrix L is the Cholesky square root of the covariance matrix, $\Sigma = LL^T$. The Cholesky decomposition of the covariance matrix is given by

$$\Sigma = \begin{bmatrix} \sigma_\eta^2 & \rho\sigma_\eta^2 \\ \rho\sigma_\eta^2 & \sigma_\eta^2 \end{bmatrix} = \begin{bmatrix} \sigma_\eta & 0 \\ \rho\sigma_\eta & \sigma_\eta\sqrt{1-\rho^2} \end{bmatrix} \begin{bmatrix} \sigma_\eta & \rho\sigma_\eta \\ 0 & \sigma_\eta\sqrt{1-\rho^2} \end{bmatrix}$$

where the lower triangular matrix L is given by

$$L = \begin{bmatrix} \sigma_\eta & 0 \\ \rho\sigma_\eta & \sigma_\eta\sqrt{1-\rho^2} \end{bmatrix}$$

We can obtain the quadrature nodes and weights from pre-existing computational routines. Likely, we just have to supply the covariance matrix and the number of nodes per dimension. But we have to be mindful about the number of nodes that we stipulate. For example, if we choose $n = 10$ quadrature nodes per dimension, then we have $n^4 = 10,000$ nodes in families with 4 children.

We sketch here the modification of our baseline MLE algorithm:

1. Before the MLE routine:
   (a) Divide families into groups K by the number of children $K \in \{1, \ldots, K_{max}\}$.
   (b) For each group K, obtain a set of quadrature nodes $\{\eta_{K,s}\}_{s=1}^{S_K}$ and weights $\{\omega_{K,s}\}_{s=1}^{S_K}$ from the multivariate Gauss-Hermite quadrature rules for the K-dimensional normal distribution. We aim for S_k on the order of 10 to 100 for a good trade-off between speed and precision. We can use pruning, i.e. set very small weights to zero.
   (c) Compute wages $y_{i,j,s} = \exp(\bar{y}_{i,j} + \eta_{K_i,s})$ for all quadrature nodes s for each child j.
2. Inside the MLE routine:
   (a) Compute the odds ratios $E_{i,j,s}$ for each quadrature node (for each child) from (3), using the wage $y_{i,j,s}$ computed in Step 1(c).
   (b) Use the logit formula (2) to compute the likelihood $\tilde{P}_{i,j,s}$ of observing outcome $j^*(i) = j$ for the quadrature node s.

(c) To obtain the likelihood of outcome j in familiy i, approximate the integral in (4) by the quadrature formula

$$\mathbb{P}(j^*(i) = j | X_i, \beta) \simeq \sum_{s=1}^{S_{K_i}} \omega_{K_i,s} \tilde{P}_{i,j,s}. \tag{5}$$

We expect this procedure to yield higher estimates for β_1, the coefficient on monetary costs, than for the baseline case without wage residuals ($\sigma_\eta^2 = 0$). Why? Consider the care-choice probabilities that the model predicts as a function of $\bar{y}_{ij}$. The logistic function is i) convex on the lower part, increasing predicted probabilities when taking into account shocks η_{ij} (and thus averaging over neighboring wages), and ii) concave on the upper part, decreasing predicted probabilities when averaging over neighboring wages. Thus, we expect the function $\mathbb{P}$ to be flatter in $\bar{y}_{ij}$ as we increase σ_η^2 to above zero, for a fixed β. Thus, to match the observed slope in IC probabilites in the approximate opportunity cost, $\bar{y}_{ij}$, the procedure will identify a higher β.

6 Counterfactuals

7 Embedding the 'Cooperative Siblings Model' into the multi-generational life-cycle model

The purpose of the cooperative siblings model as part of the project is to have a micro-foundation of who among multiple children becomes the designated caregiver in a dynamic context. Children face idiosyncratic income risk so that changes in income can lead to changes in who provides care. In addition to the role heterogeneous opportunity costs in the labor market play, the model also takes into account various other sources of heterogeneity which we have found in our analysis above to matter for the caregiving decision and are likely subject to change over the foreseeable future. These include factors such as the number of children, the geographical distance between children and parents, and the complexity of the family structure, such as, patchwork families, where step children may differ from biological children in their propensity to provide care. Modelling these factors explicitly allows us to better predict the evolution of the supply of informal caregiving in an aging population, and to more comprehensively quantify the response of informal caregiving to changes in government policy.

One major challenge for our full structural economic model is how to accommodate the various sources of heterogeneity while ensuring that the dimensionality of the state space remains computationally tractable. Our strategy for parsimony is to incorporate a "utility cost" in the utility functions, which serves as a proxy for the psychological factors that are behind the pre-disposition to provide care. By using this approach, we introduce merely one more state variable, namely, the utility cost, in lieu of several state variables (gender, distance, step-child, etc.). It is precisely this approach that has given rise to our discrete-choice specification above which we have exploited so as to get our hands on the empirical estimates informing us about the importance of the various factors using SHARE data. These estimates are the central novel element required for embedding the Cooperative Siblings Model into our project framework.

To do this we will likely have to stick to the unitary framework, i.e., the weights on the siblings are constant over time. Preferences are specified as in our static model but otherwise the environment should be as in BK2018. We need to draw the utility costs from some distribution that we still need to think about how to parameterize. Perhaps we can get our hands on the empirical distribution.

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A Appendix

A.1 Additional information on SHARE

A.1.1 SHARE sample selection

As documented in Section 2.1, we only use baseline samples in the current analyses due to the data issues with using panel dimensions. Baseline sample includes households that participated in SHARE for the first time in each wave. Table A1 compares sample size between full sample and baseline samples. Note that these counts are before applying any of our sample selection criteria. Further note that the reported sample sizes are not at the household level; it includes both respondents and their spouses.

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

Wave	Full	Baseline	Note
1	30,419	30,419	
2	37,143	14,405	
3	28,463		Retrospective survey
4	58,000	36,717	Not used in current analyses because child caregivers cannot be identified
5	66,065	21,356	
6	68,085	10,769	
7	77,202		Retrospective survey
8	46,733	9,349	Baseline sample was added in Wave 7 (retrospective survey), but these respondents participated in the regular survey for the first time in Wave 8
Total	383,647	123,015	

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

Table A2: Number of parent-child pairs after applying selection criteria, Baseline SHARE only

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

Table A2 shows how the sample size changes after applying each of the sample selection criteria. Note that these counts are at the parent-child level, not at the household level. Column “1. Sick elderly aged 65+" shows that the sample size substantially decreases after limiting to respondents and their spouses who report having at least one mobility limitation and are aged 65+. Column “3. Either NH or one IC child" reports sample size after limiting to elderly who either (i) are in nursing home care or (ii) have one caregiving child. This selection criteria further reduces the sample size by a large margin.

In fact, Table A3 shows that most parents with at least one mobility limitation does not get formal care or is cared by any of their children. Specifically, 84% of parents aged 65+ with at least one mobility limitation are not cared for by any of their children, and 99% of such parents are not in nursing home care. In future analyses, we will examine whether these individuals are cared for by their spouses or if altering the definition of "care need" affects the frequencies of informal and formal care.

After imposing additional sample criteria as shown in Table A2, we have a final sample size of 4,120 household-child pairs and 1,829 households.

Table A3: Distribution of IC and FC for parent-child pairs, Sick elderly aged 65+ with child aged 20-60, Baseline SHARE

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

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

Table A4: Distribution of OIC and IIC intensity, Sick elderly aged 65+ with child aged 20-60, Baseline SHARE

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

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

Table A4 reports the distribution of OIC frequency as well as IIC status for children aged 20-60 who have parent aged 65+ with at least one mobility limitation. There are two main observations. First, most caregiving children provide OIC, as shown by much lower frequencies of IIC by children. Second, weekly OIC is the most common intensity among OIC caregiving children.

A.1.2 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.1.3 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 1 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 Additional details on potential wage construction

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 A5. For consistency, we need to construct synchronized educational categories that are consistent across years.

Table A5: Education Categories, Eurostat's Structure of Earnings Survey

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

$$
\underbrace{GenderWage_{c,y=2010,e}}_{Imputed} = GrowthGenderWage^{2006-2010}_{c=EU,e} \underbrace{GenderWage_{c,y=2006,e}}_{Observed} \tag{6}
$$

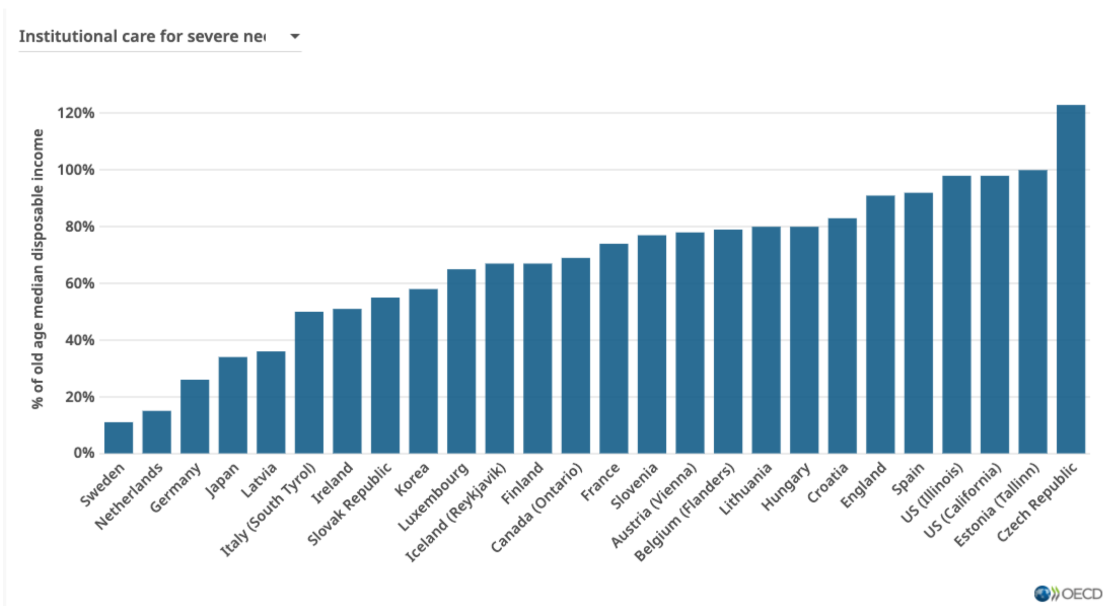
  where $GrowthGenderWage^{2006-2010}_{c=EU,e}$ is the gender wage growth rate between 2006 and 2010 for education e at the EU-level. Note that there is no wage information at the EU-level.

  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 differing survey years between SHARE and Eurostat: Even after addressing missing values and synchronizing education categories, we still cannot match Eurostat wages to SHARE children due to differing survey years. To resolve this, 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 Additional details on formal care cost construction

Figure A1: Out-of-pocket costs of long-term care as a share of old age median disposable income after public support, for care recipients holding no net wealth, by severity of needs and care setting



Source: OECD "Social protection for older people with long-term care needs"
[Link to the web source]