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In the mid2030s, the health of the baby boomers will have deteriorated and many in these large cohorts will be in need of formal and/or informal long-term care.

This “**care wave**” will transform two generations: the baby boomers in need of care and their children who may supply care. It will have significant implications for labour supply, especially for women, saving behaviour, and therefore for productivity, economic growth and its inclusiveness.

The overarching objective of BB-Future is to understand the size and the implications of the care wave on economic and social outcomes, to appreciate the quality of this second ageing-related transformation and to develop policy recommendations for advance planning on the EU and Memberstate levels.

This deliverable is a scientific working paper that examines the relationship between intergenerational distance and parents’ long-term care needs in Europe and develops a quantitative model to study the resulting trade-offs in children’s location choices, productivity, and caregiving to elderly parents. Using data from the Survey of Health, Ageing and Retirement in Europe (SHARE), we document four key facts: (i) intergenerational distance is largely determined by the time children reach age 30; (ii) there is substantial cross-country variation in distance, which correlates positively with the generosity of formal long-term care systems; (iii) most co-residence with parents is long-standing rather than triggered by health shocks; and (iv) parental disability induces only limited relocation toward parents.

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Too Far to Care: Parents' Long-Term Care Needs and Children's Location Choices

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Abstract

This paper examines the relationship between intergenerational distance and parents' long-term care needs in Europe and develops a quantitative model to study the resulting trade-offs in children's location choices, productivity, and caregiving to elderly parents. Using data from the Survey of Health, Ageing and Retirement in Europe (SHARE), we document four key facts: (i) intergenerational distance is largely determined by the time children reach age 30; (ii) there is substantial cross-country variation in distance, which correlates positively with the generosity of formal long-term care systems; (iii) most co-residence with parents is long-standing rather than triggered by health shocks; and (iv) parental disability induces only limited relocation toward parents. These findings motivate a structural model of long-term care provision à la Barczyk & Kredler (2018), augmented with an early, discrete location choice by children. Estimating the model on SHARE and demographic data will allow us to quantify the productivity losses arising from distorted location choices and assess the implications of long-term care and mobility-enhancing policies for the spatial distribution and earnings of adult children.

Keywords: migration choices; informal care; intergenerational transfers; family insurance; risk-sharing; dynamic game

JEL codes: D15; D64; C73; E21

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1 Introduction

Locating further from the parent household is often associated with lifetime economic gains. Children who live further from their parents have, on average, higher levels of education (e.g., Compton & Pollak, 2015). Moving away allows them to tap into alternative local labor markets that, while often distant, may offer higher initial earnings and better career opportunities (e.g., Roca & Puga, 2017). More educated individuals also sort into high-skill cities, which also feature more developed amenities (e.g., Diamond, 2016). While beneficial for educational and labor-market outcomes, these migration decisions also imply higher costs of caregiving when parents experience health shocks (e.g., Barczyk et al., 2025). These costs can include longer commutes or the need to relocate closer to parents, higher expenditures on formal care, and a greater value of forgone earnings.

This paper studies the trade-off between the lifetime gains from moving far from the parental household and the costs of providing care when parents age and their long-term care needs rise. This trade-off is likely to become even more salient as longevity increases and long-run health improvements stall across developed countries (e.g., Börsch-Supan et al., 2021). The challenges posed by population ageing and rising long-term care needs are further amplified by shortages of health and care workers (e.g., WHO, 2022), which make formal care – an alternative to children living nearby and providing informal care – less affordable.

We begin by assembling a set of empirical facts on children's location choices and their relationship to parents' long-term care needs using SHARE data. First, we document a sharp increase in intergenerational distance until children reach age 30, followed by a relatively flat trend thereafter. Second, we highlight substantial cross-country variation in the share of children living far from their parents, which correlates positively with the generosity of formal long-term care systems. Third, drawing on retrospective SHARE data, we find that most co-residence arrangements with parents are long-standing rather than triggered by parental health shocks. Fourth, we show that episodes of co-residence initiated in response to sudden care needs represent only a small fraction of all co-residence cases.

Taken together, these patterns suggest that children's location choices are largely determined early in life and can be well approximated by a single moving decision at the beginning of adulthood. This view is also consistent with the fact that in countries with more generous long-term care systems and/or weaker family norms, children's location choices appear subject to fewer restrictions. This motivates a quantitative model of children's location choices and within-family bargaining over long-term care arrangements. We augment Barczyk & Kredler's (2018) life-cycle environment with a one-time location decision made at the beginning of adulthood: each child chooses whether to live close to or far from the parent. Moving far entails an idiosyncratic migration cost but grants access to a higher expected initial productivity draw, whereas staying close is associated with lower earnings potential but lower future caregiving costs when the parent's health deteriorates.

There are two children linked to the same parent who choose locations sequentially in a dynamic game: the older child moves first, anticipating the younger child's best response location choice, and the younger child then chooses where to live given the older sibling's decision. Both children's decision are subject to a migration cost shock, thus allowing for preference heterogeneity over locations. This structure allows for families with two potential caregivers and captures the first-mover advantage documented in the literature, whereby the older child can partially shape both siblings' future caregiving roles through her location choice (e.g., Konrad et al., 2002, Maruyama & Johar, 2017).

After both locations are chosen, and each child's initial earnings and psychic cost of providing care are realized, the family designates one child as the caregiver to maximize joint lifetime welfare. The designated child then enters the Barczyk & Kredler (2018) game with the parent, bargaining period-by-period over the mode of care provision (informally by the child or formal), while the non-designated child follows an individual savings-consumption problem and may receive a bequest at the end of the parent's life.

A preliminary simulation of the model shows that indeed there is a first-mover advantage for the first child: The first child has a higher migration probability. Conditional on the first child migrating, the second child is more likely to stay close to the parent. For both children, migration probabilities depend positively on the migration wage premium and negatively on migration costs, as expected.[1]

Once estimated on SHARE and demographic data, the model will allow us to quantify the productivity losses generated when children's location choices are distorted by parental long-term care needs. We will use it to assess how higher public long-term care provision affects both the spatial distribution of children and their earnings: by enabling more children to locate in high-productivity labor markets, such policies can raise aggregate earnings

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[1] In this preliminary model, migration is negatively associated with parent income and wealth since i) child income is positively associated to parent income, as in the data, and ii) staying home is a luxury good under our additive migration-cost specification. Depending on the patterns in the data, we may have to adapt the migration-cost specification to bring the predictions in line with the data on children's location choices.

and, in turn, expand the tax base available to finance long-term care spending. The framework also permits an evaluation of how the first-mover advantage of older siblings distorts the location choice of potentially more productive younger children. If older children's location decisions crowd potentially more productive younger siblings into less productive locations, mobility subsidies for younger children could improve welfare.

2 Empirical Facts

We begin this section with a brief description of the SHARE dataset and then present a set of empirical facts on the relationship between parental long-term care needs and the location choices of adult children. These facts are placed in the broader perspective of the existing literature, providing a context for interpreting their significance.

SHARE Data. We use the Survey of Health, Ageing and Retirement in Europe (SHARE) to construct the empirical facts on parent-child proximity and long-term care needs that motivate the modeling choices developed in the later sections. SHARE is a cross-country longitudinal survey of nationally representative samples of individuals aged 50+ and their households in Europe (and Israel). It collects harmonized information on health, functional status, socioeconomic conditions, intergenerational linkages—including co-residence, distance between children and parents, transfers, and long-term-care arrangements.

When comparing living distances in families with severely and not severely disabled parents, we use repeated cross-section of the regular SHARE waves. To construct the repeated cross-section, in each wave, we take only the households that were interviewed for the first time, leaving out the follow-up interviews. While SHARE data, in principle, has a longitudinal structure, the updating scheme of the living distances of kids in the follow-up surveys suffers from a number of shortcomings, making it virtually impossible to make sure whether the distances have indeed not changed between the waves or just were not updated appropriately. We therefore limit our analysis to the repeated cross-section and, for a reference, compare our results to Bergeot et al. (2024) who actually attempted the longitudinal analysis on the SHARE data.[2]

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[2] We compare repeated cross-sectional data based on first-time interviews with the longitudinal SHARE data in Table A.1 across parent age, gender, number of (I)ADLs, number of children, and nursing home residence status. The similarity of sample means and standard deviations suggests that there is no considerable selection on these variables in the first-time interviews and that our repeated cross-section data is closely representative of the overall available sample.

Table 1: SHARE First Interview Data. Summary Statistics

	Location of Children			
	At Least 1 Co-Resident Child (N=6,508)	At Least 1 Child Within 25 km (N=21,614)	All Children at Least 25 km Away (N=14,530)	Total (N=42,652)
Parent Variables				
Parent Age (Years)	73.38 (7.06)	73.98 (6.55)	73.65 (6.59)	73.78 (6.65)
Gender	1.54 (0.50)	1.56 (0.50)	1.54 (0.50)	1.55 (0.50)
N of (I)ADLs	1.38 (2.87)	0.98 (2.29)	0.83 (2.09)	0.99 (2.33)
Nursing Home Resident				
No	6,485 (99.6%)	21,399 (99.0%)	14,335 (98.7%)	42,219 (99.0%)
Yes	23 (0.4%)	215 (1.0%)	195 (1.3%)	433 (1.0%)
Number of Kids	2.85 (1.76)	2.58 (1.34)	2.10 (1.07)	2.46 (1.36)
Family Status				
Single	2,853 (43.8%)	8,653 (40.0%)	5,824 (40.1%)	17,330 (40.6%)
Couple	3,655 (56.2%)	12,961 (60.0%)	8,706 (59.9%)	25,322 (59.4%)
Children Variables				
Avg. N of Own Kids	1.17 (1.00)	1.68 (0.94)	1.58 (1.01)	1.57 (0.99)
Average Age	42.43 (9.39)	45.51 (7.27)	45.13 (7.69)	44.91 (7.84)
Avg. Share of Females	0.46 (0.34)	0.50 (0.35)	0.50 (0.38)	0.50 (0.36)
Avg. Share of College Educated	0.25 (0.36)	0.31 (0.39)	0.45 (0.44)	0.35 (0.41)
Avg. Share Married	0.49 (0.35)	0.75 (0.33)	0.70 (0.37)	0.69 (0.36)
Any Foster/Adopted/ Step-Children				
No	6,282 (96.7%)	20,500 (95.0%)	13,529 (93.2%)	40,311 (94.6%)
Yes	216 (3.3%)	1,082 (5.0%)	988 (6.8%)	2,286 (5.4%)

Note: The data consists of the first interviews pooled across waves of SHARE. Included SHARE waves: 1-2, 4-6, and 8. Values in parenthesis for continuous/count and categorical variables stand, respectively, for standard deviations and percentages calculated within each child location group.

Table 1 summarizes the key variables of the cross-sectional portion of SHARE data used in our analysis. In describing the data, as well as in the subsequent analysis of distance facts, we divide families into three broad categories with respect to the living distance of children[3]: families with *at least one co-resident child*, families with *at least one child living within 25 km*, and families in which *all children live at least 25 km away*. Here we treat 25 km as an upper distance bar above which it becomes prohibitively costly to provide informal care to parents on a regular basis.

As a standard measure of parent health status, we use the count of the reported difficulties with the Instrumental Activities of Daily Living ((I)ADL). From Table 1, the average number of (I)ADL problems in the overall sample is close to 1. When presenting key distance facts, we use this value as a threshold defining severe disability: parents with (I)ADL

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[3] SHARE data provides information on living distance of each child in the categorical form. The categories include: living in the same HH, in the same building, $<$ 1 km away, between 1 and 5 km, between 5 and 10km, and so on, up to $>$ 500 km away.

> 1, i.e., with the number of reported (I)ADL problems above overall sample average, are considered severely disabled.

Families with at least one co-resident child exhibit the highest average number of (I)ADL limitations (1.38), suggesting that co-residence is more common when parents have greater care needs. However, since the average remains close to 1, this indicates that many co-residing children live with parents who have no or mild limitations, implying that co-residence may be influenced by factors beyond immediate caregiving needs.

Related to parent health status, we can also observe a limited number of cases when parents are nursing home (NH) residents. By construction, besides a few cases, parents' NH residency excludes the possibility of co-residence with a child. NH residents are likely to be severely disabled more often than parents in the rest of our sample, and are therefore of high relevance for our analysis of child movement potentially induced by parent disability.

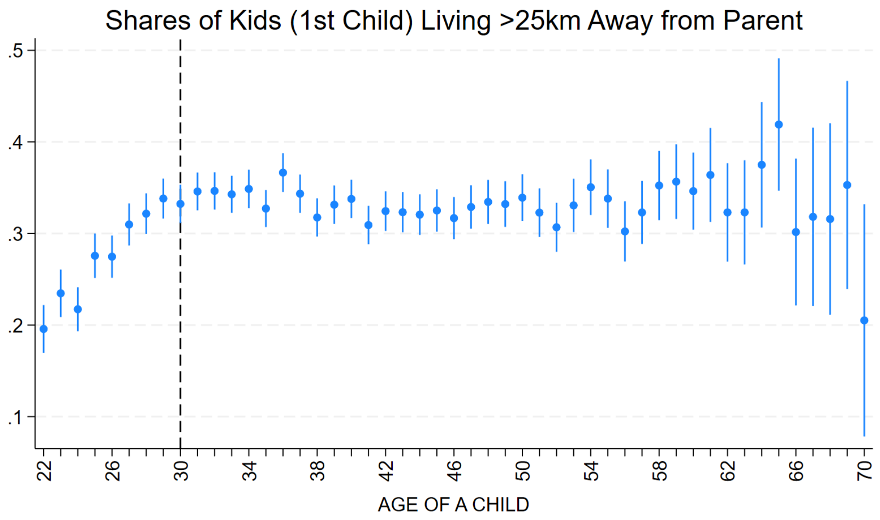
Due to high non-response rates among nursing home residents, there is a substantial under-representation of families with such parents in our data. To take this issue into account, we follow the procedure proposed in Barczyk & Kredler (2019), whereby we up-weight the available observations of NH residents to match the country-specific OECD NH resident shares.

Table A.2 in the Appendix provides summary statistics for the same variables of the cross-sectional SHARE sample as Table 1, but with OECD weights applied. As compared to the unweighted data, once we account for the under-representation issue, the share of NH residents in the overall sample increases 3 times, with the most of the increase coming from families where all kids live at least 25 km away.

As for children characteristics, families where children are older, more educated, have higher number of their own kids, and are married tend to have larger parent-child distances. Additionally, the presence of non-standard parent-child relationships, when at least one child is either foster, adopted, or is a step-child, appears to co-occur more frequently with long-distance family arrangements.

Fact 1: Intergenerational distance is largely determined early in adulthood. Having described the data that we use in our analysis, we now turn to the first empirical fact: the life-cycle profile of the distance between children and parents. Figure 1 shows the share of children living at least 25 km away from their parents at each age. In early adulthood, the share of children living at least 25 km away from their parents increases steeply, from about 20% to 33% by age 30. After age 30, however, there are no apparent downward or upward trends in the share of kids living far away from their parents.

Figure 1: Shares of Kids Living $\geq$ 25 km Away from Parents by Kids' Age



Note: Each point in the figure reports the unconditional share of children of a given age living at least 25 km away from their parents, together with 95% confidence intervals. For families with multiple children, we measure distance using the oldest child.

The life-cycle patterns above align with prior evidence indicating that intergenerational distance is largely determined early in adulthood. Choi et al. (2021) document life-cycle patterns of child-parent distance in U.S. panel data over 47 years. They show that proximity declines sharply as children leave the parental home, then stabilizes through midlife, with substantial persistence in proximity states.

According to Compton & Pollak (2015), who provide national evidence on proximity and co-residence of adult children and mothers in the U.S., proximity is strongly related to age and education. As demonstrated by Table 2, educational levels and location of adult children in Europe are also correlated. The highest share of co-resident children is observed among high school graduates, while the probability of living more than 25 km away is higher for those with at least college education.

Table 2: Education and Living Distance of Children

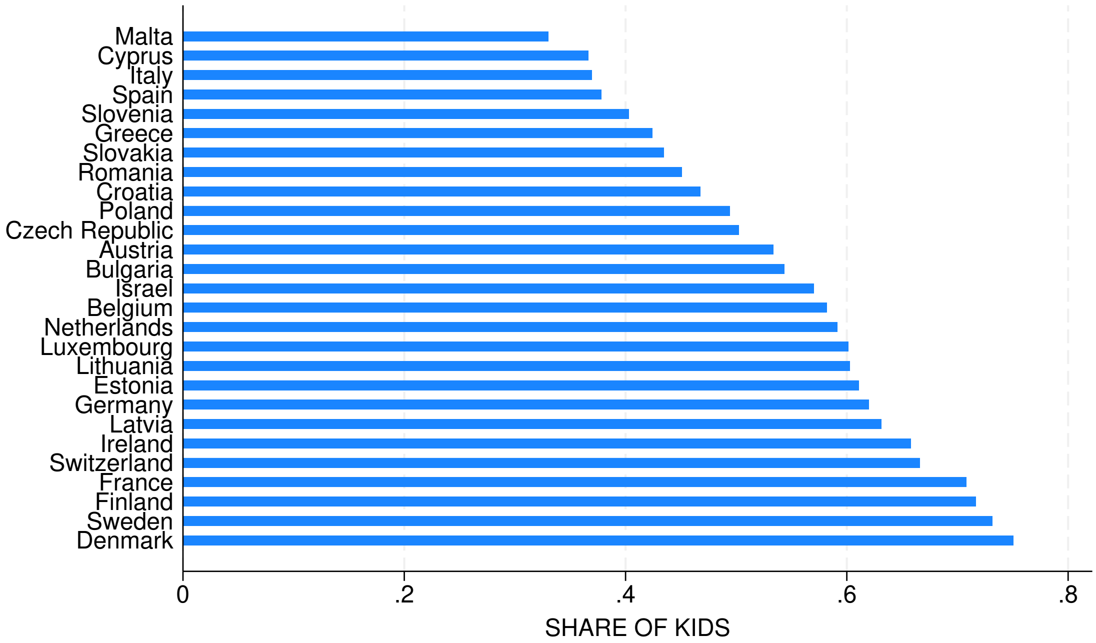
	Child Education			
	High School (N=23,771)	College (N=17,223)	Doctoral (N=941)	Total (N=41,935)
Location of Child				
Co-Resident	1,630 (7.1%)	788 (4.7%)	23 (2.5%)	2,441 (6.0%)
Within 25 km	14,359 (62.5%)	8,582 (51.5%)	343 (37.3%)	23,284 (57.4%)
More Than 25 km Away	7,002 (30.5%)	7,283 (43.7%)	554 (60.2%)	14,839 (36.6%)

Note: The data consists of the first interviews pooled across waves of SHARE. Included SHARE waves: 1-2, 4-6, and 8. Individual child observations are used, with potentially more than 1 child coming from the same family. Only children of at least 30 y.o. are included. Values in parenthesis stand for percentages calculated within each child *education* group.

Fact 2: Large cross-country variation in intergenerational distance. The shares of kids of different age living far away from their parents in Figure 1 are calculated using the sample of all SHARE countries. At the same time, as demonstrated by Figure 2, there is a substantial degree of heterogeneity in the location of kids relative to their parents' households across countries. For countries such as Spain and Italy, the proportion of kids living at least 25 km away from their parents is below 40%. This is in contrast to Sweden and Denmark where the share of such kids is above 75%. From Figure A.1 in the appendix, countries characterized by higher shares of adult children living further away are also, in most of the cases, below average in terms of shares of children co-residing with their parents.

Overall, the variation in the average distance follows the North-South gradient that is largely attributable to the differences in the generosity of long-term care provision and different family traditions prevailing in the studied countries. In line with our results, Isengard (2013) documents substantial cross-country differences in the distance between adult children and parents in Europe, with Southern Europe exhibiting much higher co-residence and near residence than Northern Europe. Hank (2007) reports a similar North-South gradient using SHARE, showing that intergenerational living arrangements are systematically closer in countries with stronger family norms. Barczyk & Kredler (2019) estimate total hours of informal vs. formal care across Europe and the U.S. and find that informal care is far more prevalent in Southern Europe, while Northern Europe relies heavily on public LTC.

Figure 2: Shares of Kids Living $\geq$ 25 km Away from Parents by Countries



Note: Calculated as the share of kids living at least 25 away from their parents' household. All kids are $\geq$ 30y.o., all parents are $\geq$ 65y.o. For families with multiple children, we measure distance using the oldest child.

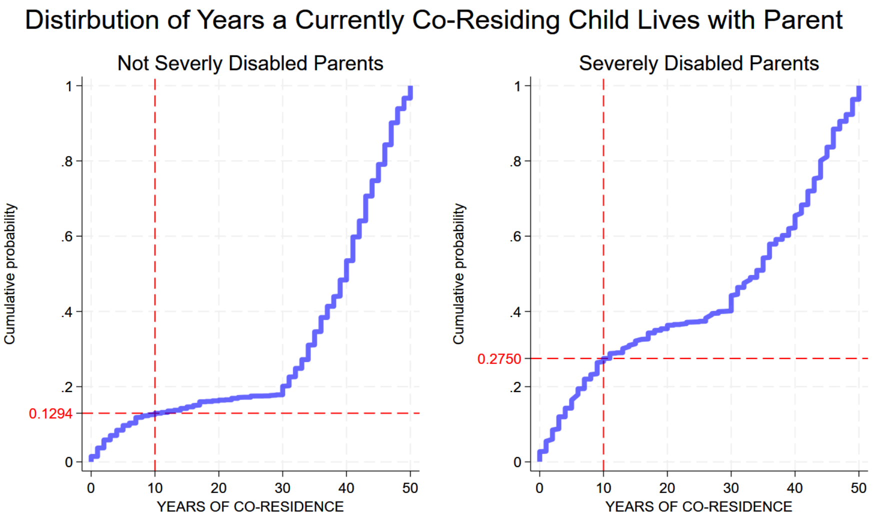
It should be noted that, even for the Northern countries, the proportion of kids living close to their parents is non-negligible suggesting a substantial within-country variation in the distances between kids and their parents.

Fact 3: Most co-residency with parents is a long-standing arrangement. When in life is the decision of a child to co-reside with a parent with care needs taken? The retrospective wave of SHARE data allows us to look back in time to calculate the number of years that adult children were living together with their parents by the moment of interview. Using the retrospective data, Figure 3 shows distributions of co-residence years for children who are at least 30 years old. The two panels of Figure 3 are for children whose parents are not severely disabled, defined as parents having at most one (I)ADL, and for those whose parents are severely disabled, i.e., with at least two (I)ADLs. As one might expect, both distributions have a kink at 30 years of co-residence, which is due to those kids who were co-residing with their parents since the year they were born.

More strikingly, the number of cases when kids have just recently moved in constitutes a rather small share of all co-residents. According to the retrospective data, the share of adult children who have moved in in the last 2 years is 5.8% for parents without severe disability and is only 2.7 percentage points higher for severely disabled parents. Over the 10-year horizon, the difference increases to 14.6 percentage points. Provided that the arising severe disability requires immediate help and that the state of severe disability is absorbing, we see this difference as a an upper bound on the movements potentially induced by worsening of parents state suggested by retrospective data.

On the other hand, the long-term co-residence arrangements, including cases when kids are co-residing with their parents since the year they were born, are prevalent in the data and constitute more than 70% of co-residences even among the households with severely disabled parents.

Figure 3: Distribution of Years a Currently Co-residing Child Lives with Parent



Note: Parent is “severely” disabled if the sum of (I)IADLs≥ 2 for that parent. All kids considered are $\geq$30 y.o., and parents are $\geq$ 65 y.o. Only one parent (family respondent) is considered from each family. Longest years of co-residence are taken in case of multiple co-residing kids. Observations are weighted by SHARE calibrated household weights.

Children in countries with low long-term-care provision by the government may have a stronger incentive to move in with their parents to provide care. To see to which extent this plays out in the data, we divide the retrospective sample into the two sub-samples of low and mid-high public LTC expenditure countries. Figure A.2 shows that, for low LTC expenditure countries, the difference in the share of child co-residence between households with severely and not severely disabled parents over 10-year horizon increases to 18 percentage points, while for mid-high expenditure group the difference drops to 5 percentage point. Thus, it is indeed the case that in countries with lower government LTC provision, parent disability changes the coresidence patterns more than when governments have a more active role. In terms of levels, the share of those who moved together with their parents over the past 10 years in the total number of co-residence cases is considerably higher in mid-high LTC expenditure countries (Figure A.3). This higher share corresponds to the overall low share of co-residence cases in such countries, as demonstrated by figure A.1.

Fact 4: Limited movement induced by disability of parents. To corroborate that our findings from the retrospective questions (which include moving decisions taken several decades ago) carry on to the current data, we use repeated cross-section of the regular SHARE waves, comparing living distances in families with severely and not severely disabled parents. While the retrospective wave is gathering only the basic characteristics of parents and their children, repeated cross-section data also allows us to take into account a broad variety of child and parent characteristics and to control for country- and year-specific effects.

We first compare co-residence of disabled parents to (otherwise similar) non-disabled parents in an OLS setting. If disability is assumed to be an exogenous and unforeseen, these estimates can be interpreted as the causal effect of disability on co-residence. Table 3 shows the estimates from the regressions of a coresidence indicator variable (equal to 1 if at least one child lives with the parent) on the disability status of that parent. Throughout columns 1 to 6 of Table 3, we are extending our regression specification with country and year fixed effects, children and parent controls, and applying different versions of sample weights. The coefficient of interest ("Disabled", first row) is small and relatively stable across regressions. Our preferred specification, column 6, indicates that parent disability is associated with a modest 3 percentage-point more coresidence. To bring this in context, the baseline share of co-residors (in families with non-disabled parents) is 14.6% co-reside, see the constant term in column 1. among the This suggests that parent disability is associated with 20.5% higher probability of co-residence.

Interpreting this magnitude in light of prior evidence, Smits (2010), using Dutch registry data, shows that moves toward parents following parental events are rare even conditional on widowhood, retirement, or disability, the probability of moving closer is very low and often comparable to the probability of no move implying that most co-residence reflects long-standing arrangements rather than on-impact relocation. Consistent with this view, Bergeot et al. (2024) estimate an average increase of about 1.4 percentage points in co-residence over the four years following a parental health shock in Europe (roughly a 5.2% rise relative to the sample mean), which is modest compared to our coefficient.

Table 3: Parent Disability and Co-Residence with Children

Dep. Var.: I($\geq$1 child living with parent)	(1)	(2)	(3)	(4)	(5)	(6)
Disabled	0.063***	0.041***	0.058***	0.034***	0.051***	0.030**
	(0.014)	(0.007)	(0.007)	(0.004)	(0.006)	(0.012)
Constant	0.146***	0.110***	0.580***	1.652***	2.053***	1.959**
	(0.021)	(0.008)	(0.055)	(0.373)	(0.641)	(0.709)
Country & Year FE		✓	✓	✓	✓	✓
Children Controls			✓	✓	✓	✓
Parent Controls				✓	✓	✓
SHARE Weights					✓	✓
OECD-SHARE Weights						✓
Observations	29540	29540	29540	29540	29540	29540
Adjusted R^2	0.004	0.077	0.172	0.196	0.247	0.240

Note: Standard errors in parentheses are clustered at country level in all specifications. **Disabled** is a dummy variable equal to 1 if parent is "severely" disabled, i.e., if the sum of (I)IADLs$\geq$ 2 for that parent. All kids considered in regressions are $\geq$30 y.o., and parents are $\geq$ 65 y.o. Only one parent (family respondent) is considered from each family. **Children controls** include, on family level: *share of those with at least college education, share of females, share of full-time employed, share married, average number of own kids, average age, dummies for any child being adopted/foster-/step-child*. **Parent controls** include: *age, age squared, number of kids, gender*.

Differences with previous studies in outcome definitions (health shocks vs. disability status), timing (event-study dynamics vs. a static specification), and composition of co-residence (potentially long-standing vs. reactive episodes) suggest that our cross-sectional estimate should be viewed as an upper bound for the cumulative location response to parent disability over time. To further explore the possibility that our cumulative response may include location decisions made in anticipation of the future worsening of parents' state or other endogeneity concerns, we also obtain co-residence estimates using 2-stage regressions, using strokes and fractures as an instrument for disability. Our findings are very similar to the OLS estimates, which is in line with the interpretation that disability is indeed exogenous.

Specifically, in the first stage of our 2-stage specification, we predict the disability status of a parent with the binary variable equal to 1 if that parent is currently suffering from the consequences of stoke and/or fracture. Predicted disability status is then used as explanatory variable in the second stage, where again the co-residence indicator (at least one adult child co-residing with parent) is the dependent variable. Similarly to Bergeot et al. (2024), we interpret cases of strokes and fractures as sudden and unpredictable health shocks. Predicting disability status with such shocks, we are focusing on the variation in disability that cannot be anticipated by children in-advance.

Table 4: Sudden Health Shocks, Disability, and Co-Residence

	OLS Estimates			**2SLS Estimates**		
Dep. Var.: I($\geq$1 child living with parent)	(1)	(2)	(3)	(4)	(5)	(6)
Disabled	0.034*** (0.004)	0.051*** (0.006)	0.030** (0.012)	0.051* (0.027)	0.131*** (0.051)	0.032 (0.064)
Constant	1.652*** (0.373)	2.053*** (0.641)	1.959** (0.709)	1.595*** (0.234)	1.802*** (0.392)	1.944*** (0.424)
SHARE Weights		✓			✓	
OECD-SHARE Weights			✓			✓
Observations	29540	29540	29540	29513	29513	29513
Adjusted R^2	0.196	0.247	0.240	0.196	0.241	0.239

Note: **Columns 1-3** present results form OLS regressions of a dummy for at least one child living with parent on a dummy for being disabled. **Columns 4-6** present results from 2SLS regressions, where in the first stage the disability is predicted with the binary variable equal to 1 for those parents who are currently suffering from the consequences of stroke and/or fracture. Standard errors in parentheses are clustered at country level in all specifications. Sample restrictions and controls are the same as in regression specifications from Table 3.

Table 4 compares the estimates from 1-stage regressions (i.e. our previous OLS results) with the estimates that we obtain instrumenting disability with sudden health shocks. Our preferred specification (Column 6) is very much in line with the OLS estimate, thus reinforcing our claim that disability induces a 3pp increase in co-residence.

Note on OLS-IV differences. However, the 2-stage estimates from unweighted regressions and regressions weighted with native SHARE weights (columns (4)-(5)) are somewhat larger than their 1-stage counterparts (columns (1)-(2)), although their confidence intervals overlap. We found that this can be largely attributed to strokes and fractures inducing more severe disability, along several (I)ADLs. Since the severity of disability is not captured by our binary disability variable, we run additional 1- and 2-stage regressions where we directly use the (I)ADL count as the measure of parent health state. Table A.3

in the appendix shows the results of such regressions, taking into account the intensity of health shocks. The comparison of the respective columns in Table A.3 suggest much smaller differences in the magnitudes between different specifications than in the case of binary disability variable. We conclude, also in light of this evidence, that the OlS estimates are unbiased and that disability.

While the intensity of the disability induced by sudden health shocks can be taken into account, it should be mentioned that all unweighted and SHARE-weighted specifications are also suffering from the under-representation of nursing home residents, as per Barczyk & Kredler (2019). At the same time, our preferred specifications, using OECD-SHARE weights to correct for this under-representation issue, are suggesting similar magnitudes across 1- and 2-stage specifications, for both extensive (binary disability) and intensive ((I)ADL count) parent health state measures.

Taking stock. In the section above we document four key facts: (i) a steep increase in the average distance between children and parents up to age 30, followed by a flattening of the trend thereafter; (ii) substantial cross-country variation in the share of children living far from their parents, which correlates with the generosity of formal long-term care systems; (iii) evidence that most cases of co-residence are long-standing (about 80%) rather than initiated in response to parental health shocks (about 20%). Taken together, these findings provide the empirical foundation for the quantitative model developed in the subsequent sections.

3 Location choice model

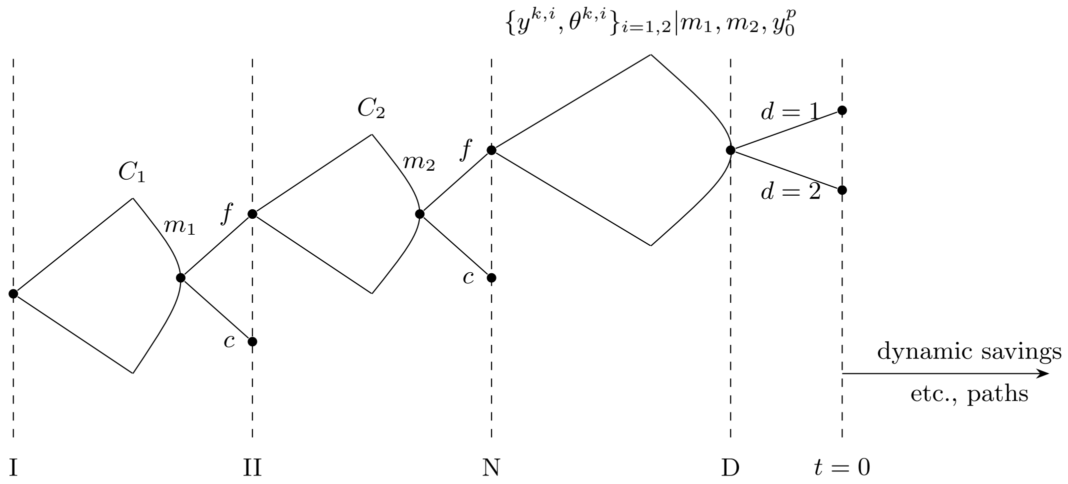
This section describes the dynamic game in which two adult children choose whether to live close to or far from their parent. The game unfolds over four stages within the same time period. Initially, the parent enters with some level of wealth and labor productivity drawn from an initial distribution. In the first stage, child 1 (the older sibling) draws an idiosyncratic migration cost and decides whether to live close or far from the parent. In the next stage, child 2 observes child 1's location, draws her own migration cost, and makes the same close-far decision. Moving far allows a child to access labor markets with higher expected earnings but entails a migration cost and, in the long run, higher psychic costs of providing care to the parent.

After both children have chosen where to live, the family learns the children's initial earnings prospects and caregiving tastes and then designates a potential caregiver which maximizes joint family welfare.

Child 1 enjoys a strategic first-mover advantage: by choosing to live far, child 1 can shape the subsequent designation problem so that child 2 is more likely to be the eventual caregiver. Child 1 may prefer this outcome as it makes informal care more likely, thereby protecting parent's wealth from a spent-down on formal care, and thus raising child 1's expected bequest.

3.1 The structure of the location game

Parents enter with initial state $(a_0^p, y_0^p) \sim F_{init}^P$. Two children – child 1 and child 2 – make sequential location choices, $m_i \in \{c, f\}, i = 1,2$, where c denotes "close" and f denotes "far". State transitions and information sets evolve over stages $j \in \{I, II, N, D\}$ as outlined in Figure 3.1.



We now describe the four stages in detail.

Stage I: Child 1's location choice The state is $\bar{x}_I = (a_0^p, y_0^p)$ – this is the information that is currently available and is relevant for evaluating future payoffs. Child 1 draws an idiosyncratic migration cost:

$$C_1 \sim F_C(\cdot \mid \bar{x}_I),$$

where F_C is the CDF of C_1. The information available now also includes C_1 in addition to $\bar{x}_I$. Child 1's Stage I value is:

$$V_I^{k,1}(a_0^p, y_0^p, C_1) = \max_{m_1 \in \{c,f\}} \left\{ -\mathbb{I}\{m_1 = f\} C_1 + E_{C_2 | \bar{x}_{II}} [V_{II}^{k,1}(a_0^p, y_0^p, m_1, C_2)] \right\}, \tag{1}$$

where $\bar{x}_{II} \equiv (a_0^p, y_0^p, m_1)$. If the child chooses far (f) her value is given by:

$$V_I^{k,1}(a_0^p, y_0^p, C_1 \mid m_1 = f) = -C_1 + E_{C_2 | (a_0^p, y_0^p, f)} [V_{II}^{k,1}(a_0^p, y_0^p, f, C_2)],$$

and when she chooses close (c) her value is given by:

$$V_I^{k,1}(a_0^p, y_0^p, C_1 \mid m_1 = c) = E_{C_2 | (a_0^p, y_0^p, c)} [V_{II}^{k,1}(a_0^p, y_0^p, c, C_2)],$$

The child forms expectations about her continuation value, $V_{II}^{k,1}(a_0^p, y_0^p, m_1, C_2)$, which depends on child 2's random migration cost C_2. Child 1's policy function is:

$$M_1(a_0^p, y_0^p, C_1) = \arg \max_{m_1 \in \{c,f\}} \left\{ -\mathbb{I}\{m_1 = f\} C_1 + E_{C_2 | \bar{x}_{II}} [V_{II}^{k,1}(a_0^p, y_0^p, m_1, C_2)] \right\}. \tag{2}$$

Stage II: Child 2's location choice The state in this stage is $\bar{x}_{II} = (a_0^p, y_0^p, m_1)$. Child 2 draws an idiosyncratic migration cost

$$C_2 \sim F_C(\cdot \mid \bar{x}_{II}).$$

After observing C_2, child 2's Stage II value is:

$$V_{II}^{k,2}(a_0^p, y_0^p, m_1, C_2) = \max_{m_2 \in \{c,f\}} \left\{ -\mathbb{I}\{m_2 = f\} C_2 + E_{x | \bar{x}_N} \left[V_D^{k,2}\left(a_0^p, y_0^p, y_0^{k,1}, \theta^{k,1}, y_0^{k,2}, \theta^{k,2}\right) \right] \right\} \tag{3}$$

Here, $\bar{x}_N = (a_0^p, y_0^p, m_1, m_2)$ is the state upon entering Stage Nature, x is the vector of shocks nature draws in the subsequent stage, and $V_D^{k,2}$ is child 2's Stage D (designation) value.

Child 2's policy function is:

$$M_2(a_0^p, y_0^p, m_1, C_2) = \arg \max_{m_2 \in \{c,f\}} \left\{ -\mathbb{I}\{m_2 = f\} C_2 + E_{x|\bar{x}_N} \left[V_D^{k,2} \left(a_0^p, y_0^p, y_0^{k,1}, \theta^{k,1}, y_0^{k,2}, \theta^{k,2} \right) \right] \right\}. \tag{4}$$

Stage N: Nature The state is: $\bar{x}_N = (a_0^p, y_0^p, m_1, m_2)$. Nature draws shocks:

$$\varepsilon_{y_i},\ \varepsilon_{d_i},\ \varepsilon_{\theta_i}$$

Initial productivity $y_0^{k,i}$ of child i is given by

$$y_0^{k,i} = \beta_{y,0} + \beta_{IGE} y_0^p + \mathbb{I}_{m=f} \beta_f + \varepsilon_{y_i} \tag{5}$$

The indicator function $\mathbb{I}_{m=f}$ equals 1 if a child's migration choice is far (f) and 0 if it is close (c). The coefficient β_f reflects an earnings premium when locating far. The coefficient β_{IGE} on parent's income is the intergenerational elasticity of child's income with respect to parent's income.

Psychic caregiver cost $\theta^{k,i}$ for child i is given by

$$\theta^{k,i} = \mu_\theta + \beta_d d^{k,i} + \sigma_\theta \varepsilon_{\theta_i}$$

which depends on the child's distance $d^{k,i}$ from the parent:

$$d^{k,i} = \mu_d + \mathbb{I}_{m=f} \beta_{dm} + \varepsilon_{d_i}$$

Substitute $d^{k,i}$ into the equation for $\theta^{k,i}$:

$$\theta^{k,i} = (\mu_\theta + \beta_d \mu_d) + \mathbb{I}_{m=f} \beta_d \beta_{dm} + \beta_d \varepsilon_{d_i} + \sigma_\theta \varepsilon_{\theta_i} \tag{6}$$

Given our assumptions, our interest lies in the joint normal distribution of (y_0^k, θ^k), as defined by equations (5) and (6). The conditional mean vector is:

$$\boldsymbol{\mu}_m = \begin{pmatrix} \beta_{y,0} + \beta_{IGE} y_0^p + \mathbb{I}_{m=f} \beta_f \\ (\mu_\theta + \beta_d \mu_d) + \mathbb{I}_{m=f} \beta_d \beta_{dm} \end{pmatrix}$$

The covariance between y_0^k and θ^k is:

$$Cov(y_0^k, \theta^k) = Cov(\varepsilon_y, \beta_d \varepsilon_d + \sigma_\theta \varepsilon_\theta) = \beta_d Cov(\varepsilon_y, \varepsilon_d) + \sigma_\theta Cov(\varepsilon_y, \varepsilon_\theta) = \rho_{y\theta} \sigma_y \sigma_\theta^2$$

We assume that ε_y and ε_d are independent ($Cov(\varepsilon_y, \varepsilon_d) = 0$) but allow for correlation of ε_y and ε_θ, denoting it by $\rho_{y\theta}$. Variances are:

$$Var(y_0^k) = \sigma_y^2 \quad \text{and} \quad Var(\theta^k) = \beta_d^2 \sigma_d^2 + \sigma_\theta^2$$

The covariance matrix is given by

$$\begin{pmatrix} \sigma_y^2 & \rho_{y\theta} \sigma_y \sigma_\theta^2 \\ \rho_{y\theta} \sigma_y \sigma_\theta^2 & \beta_d^2 \sigma_d^2 + \sigma_\theta^2 \end{pmatrix}$$

In summary:

$$\left. \begin{pmatrix} y_0^k \\ \theta^k \end{pmatrix} \right| m, y_0^p \sim \mathcal{N}(\boldsymbol{\mu}_m, \boldsymbol{\Sigma})$$

Stage D: Designation The state is $\bar{x}_D = (a_0^p, y_0^p, y_0^{k,1}, \theta^{k,1}, y_0^{k,2}, \theta^{k,2})$, and the family designates the potential child caregiver. The family designates the child in such a way that the sum of parent and children's value function is maximized. The family value function is given by

$$V^{fam}(\bar{x}_D) = \max_{d \in \{1,2\}} \left\{ V^{fam}(\bar{x}_D; d) \right\}$$

where

$$V^{fam}(\bar{x}_D; d) = V^p(a_0^p, y_0^p, y_0^{k,d}, \theta^{k,d}) \; + \; V^d(a_0^p, y_0^p, y_0^{k,d}, \theta^{k,d}) \; + \; V^{nd}(y_0^{k,-d}, a_0^{k,-d} = 0, m_b).$$

Here, V^d is the BK value for the designated caregiver, and V^{nd} is the value for the non-designated child. The family's designation rule is:

$$D^*(\bar{x}_D) = \arg \max_{d \in \{1,2\}} \{ V^{fam}(\bar{x}_D; d) \}$$

3.2 Solving the location game: Backward induction

At $t = 0$ (see Figure 3.1), we are given value functions for children – when designated as caregiver and when not – and for parents. These arise from solving the BK long-term care problem. Using these, we construct the optimal designation rule $D^*(\bar{x}_D)$, and assign child i's value:

$$V_D^{k,i}(\bar{x}_D) = \mathbb{I}_{\{D^*(\bar{x}_D)=i\}} V^d(\bar{x}_D(d)) + \mathbb{I}_{\{D^*(\bar{x}_D)=-i\}} V^{nd}(y_0^{k,-i}, a_0^{k,-i} = 0, m_b),$$

where $\bar{x}_D = (a_0^p, y_0^p, y_0^{k,1}, \theta^{k,1}, y_0^{k,2}, \theta^{k,2})$, and $\bar{x}_D(d) = (a_0^p, y_0^p, y_0^{k,d}, \theta^{k,d})$. In words, for each possible state of the world $\bar{x}_D = (a_0^p, y_0^p, y_0^{k,1}, \theta^{k,1}, y_0^{k,2}, \theta^{k,2})$, we have an answer to the question which of the two children is the potential caregiver of the parent and which child lives autonomously.

Stage N: Nature The state at entry to Stage N is $\bar{x}_N = (a_0^p, y_0^p, m_1, m_2)$ which is the payoff-relevant information known before Nature moves. Nature then determines

$$x = \left(y_0^{k,1}, \theta^{k,1}, y_0^{k,2}, \theta^{k,2}\right)$$

Child i's value prior to the realization of uncertainty is given by:

$$\begin{aligned}\tilde{V}_N^{k,i}(\bar{x}_N) \equiv & E\left(V_D^{k,i}(a_0^p, y_0^p, y_0^{k,1}, \theta^{k,1}, y_0^{k,2}, \theta^{k,2}) \mid a_0^p, y_0^p, m_1, m_2\right) = \\ & \int_{\mathscr{Y}}\int_{\Theta}\int_{\mathscr{Y}}\int_{\Theta} V_D^{k,i}\left(a_0^p, y_0^p, y_0^{k,1}, \theta^{k,1}; y_0^{k,2}, \theta^{k,2}\right) f\left(y_0^{k,1}, \theta^{k,1} \mid m_1, y_0^p\right) f\left(y_0^{k,2}, \theta^{k,2} \mid m_2, y_0^p\right) dy_0^{k,1}\, d\theta^{k,1}\, dy_0^{k,2}\, d\theta^{k,2}.\end{aligned}$$

Stage II: Child 2's location choice We can then calculate child 2's Stage II value – equation (3):

$$V_{II}^{k,2}(a_0^p, y_0^p, m_1, C_2) = \max_{m_2 \in \{c,f\}} \left\{-\mathbb{I}\{m_2 = f\} C_2 + \tilde{V}_N^{k,2}(\bar{x}_N)\right\}$$

The two option values are:

1. If $m_2 = c$:
$$V_{II}^{k,2}(\cdot \mid m_2 = c) = 0 + \tilde{V}_N^{k,2}(a_0^p, y_0^p, m_1, c)$$

2. If $m_2 = f$:

$$V_{II}^{k,2}(\cdot \mid m_2 = f) = -C_2 + \tilde{V}_N^{k,2}(a_0^p, y_0^p, m_1, f)$$

Child 2 chooses f if:

$$-C_2 + \tilde{V}_N^{k,2}(a_0^p, y_0^p, m_1, f) \geq \tilde{V}_N^{k,2}(a_0^p, y_0^p, m_1, c)$$

i.e.

$$C_2 \leq \tilde{V}_N^{k,2}(a_0^p, y_0^p, m_1, f) - \tilde{V}_N^{k,2}(a_0^p, y_0^p, m_1, c) \equiv \Delta_{m_2} \tilde{V}_N^{k,2}(\bar{x}_N)$$

The child chooses to locate far if the gain in her lifetime value, $\Delta_{m_2} \tilde{V}_N^{k,2}(\bar{x}_N)$, exceeds her migration cost, C_2. Child 2's policy function – equation (4) – is:

$$M_2(a_0^p, y_0^p, m_1, C_2) = \begin{cases} f & \text{if } C_2 \leq \Delta_{m_2} \tilde{V}_N^{k,2}(\bar{x}_N) \\ c & \text{if } C_2 > \Delta_{m_2} \tilde{V}_N^{k,2}(\bar{x}_N) \end{cases}$$

Child 2's probability of locating far is:

$$m_2^*(a_0^p, y_0^p, m_1) = \int \mathbb{I}\left\{M_2(a_0^p, y_0^p, m_1, C_2) = f\right\} dF_C(C_2) = \mathbb{E}_{C_2}\Big[\mathbb{I}\left\{M_2(a_0^p, y_0^p, m_1, C_2) = f\right\}\Big]$$

Since $\mathbb{I} = 1$ if $M_2 = f$ and 0 if $M_2 = c$,

$$\mathbb{E}_{C_2}\Big[\mathbb{I}\left\{M_2(a_0^p, y_0^p, m_1, C_2) = f\right\}\Big] = \mathbb{P}(M_2 = f) \cdot 1 + \mathbb{P}(M_2 = c) \cdot 0 = \mathbb{P}(M_2 = f)$$

Since $M_2 = f \iff C_2 \leq \Delta_{m_2} \hat{V}_N^{k,2}(\bar{x}_N)$, we have:

$$\mathbb{P}(M_2(a_0^p, y_0^p, m_1, C_2) = f) = \mathbb{P}(C_2 \leq \Delta_{m_2} \hat{V}_N^{k,2}(\bar{x}_N)) = F_C(\Delta_{m_2} \tilde{V}_N^{k,2}(\bar{x}_N))$$

Thus, $m_2^*(a_0^p, y_0^p, m_1) = F_C(\Delta_{m_2} \tilde{V}_N^{k,2}(\bar{x}_N))$ is child 2's probability of choosing f.

Child 1's **pre**-shock stage II value is:

$$\tilde{V}_{II}^{k,1}(a_0^p, y_0^p, m_1) = E_{C_2 \mid \bar{x}_{II}}[V_{II}^{k,1}(a_0^p, y_0^p, m_1, C_2)]$$

The **post**-shock Stage II value for child 1 is

$$V_{II}^{k,1}(a_0^p, y_0^p, m_1, C_2) = \tilde{V}_N^{k,1}(a_0^p, y_0^p, m_1, M_2(a_0^p, y_0^p, m_1, C_2))$$

Because $M_2 \in \{c, f\}$ with

$$\mathbb{P}(M_2(\bar{x}_{II}, C_2) = f) = m_2^*(\bar{x}_{II})$$

we obtain

$$\tilde{V}_{II}^{k,1}(a_0^p, y_0^p, m_1) = m_2^*(\bar{x}_{II})\tilde{V}_N^{k,1}(a_0^p, y_0^p, m_1, f) + [1 - m_2^*(\bar{x}_{II})]\tilde{V}_N^{k,1}(a_0^p, y_0^p, m_1, c)$$

Stage I: Child 1's location choice Given $\tilde{V}_{II}^{k,1}(a_0^p, y_0^p, m_1)$ child 1's **post**-shock stage I value – equation (1) – is:

$$V_I^{k,1}(a_0^p, y_0^p, C_1) = \max_{m_1 \in \{c,f\}} \left\{ -\mathbb{I}\{m_1 = f\} C_1 + \tilde{V}_{II}^{k,1}(a_0^p, y_0^p, m_1) \right\},$$

Child 1 chooses f if:

$$C_1 \leq \tilde{V}_{II}^{k,1}(a_0^p, y_0^p, f) - \tilde{V}_{II}^{k,1}(a_0^p, y_0^p, c) \equiv \Delta_{m_1} \tilde{V}_{II}^{k,1}(\bar{x}_{II})$$

Child 1's **post**-shock policy function – equation (2) – is:

$$M_1(a_0^p, y_0^p, C_1) = \begin{cases} f & \text{if } C_1 \leq \Delta_{m_1} \tilde{V}_{II}^{k,1}(\bar{x}_{II}) \\ c & \text{if } C_1 > \Delta_{m_1} \tilde{V}_{II}^{k,1}(\bar{x}_{II}) \end{cases}$$

Child 1's probability of locating far is:

$$m_1^*(a_0^p, y_0^p) = \int \mathbb{I}\left\{M_1(a_0^p, y_0^p, C_1) = f\right\} dF_C(C_1) = \mathbb{E}_{C_1}\left[\mathbb{I}\left\{M_1(a_0^p, y_0^p, C_1) = f\right\}\right]$$

Since the indicator is 1 if $M_1 = f$ and 0 if $M_1 = c$,

$$\mathbb{E}_{C_1}\left[\mathbb{I}\left\{M_1(a_0^p, y_0^p, C_1) = f\right\}\right] = \mathbb{P}(M_1 = f) \cdot 1 + \mathbb{P}(M_1 = c) \cdot 0 = \mathbb{P}(M_1 = f)$$

Since $M_1 = f \iff C_1 \leq \Delta_{m_1} \tilde{V}^{k,1}_{II}(\bar{x}_{II})$, we have:

$$\mathbb{P}(M_1(a^p_0, y^p_0, C_1) = f) = \mathbb{P}(C_1 \leq \Delta_{m_1} \tilde{V}^{k,1}_{II}(\bar{x}_{II})) = F_C(\Delta_{m_1} \tilde{V}^{k,1}_{II}(\bar{x}_{II}))$$

Thus, $m^*_1(a^p_0, y^p_0) = F_C(\Delta_{m_1} \tilde{V}^{k,1}_{II}(\bar{x}_{II}))$ is child 1's probability of choosing f – the fraction of children that choose f given state (a^p_0, y^p_0).

Child 1's strategic consideration Child 2's best-response probability of choosing f in stage II, given the state $\bar{x}_{II} = (a^p_0, y^p_0, m_1)$, is

$$m^*_2(\bar{x}_{II}) = F_C\Big(\tilde{V}^{k,2}_N(a^p_0, y^p_0, m_1, f) - \tilde{V}^{k,2}_N(a^p_0, y^p_0, m_1, c)\Big).$$

Given $m^*_2(\bar{x}_{II})$, child 1's post-shock stage I value, after observing C_1, is

$$\begin{aligned} V^{k,1}_I(a^p_0, y^p_0, C_1) = \max_{m_1 \in \{c,f\}} \Big\{ & -\mathbb{I}\{m_1 = f\} C_1 + m^*_2(\bar{x}_{II}) \tilde{V}^{k,1}_N(a^p_0, y^p_0, m_1, f) \\ & + \big[1 - m^*_2(\bar{x}_{II})\big] \tilde{V}^{k,1}_N(a^p_0, y^p_0, m_1, c)\Big\}. \end{aligned}$$

4 Model results (preliminary!)

We now present some preliminary results from the location game described in the previous section.

We feed in a value function V_{fam} into the designation stage from a version of the BK game that we calibrated to European SHARE data. As for the model parameters, we assume that migration costs are drawn from an extreme-value distribution with mean $\mu_c = 0.5$ and standard deviation to $\sigma_c = 0.2$. The parameters governing the child's income draw are $\beta_{0,y} = 0.2$ (intercept), $\beta_{IGE} = 0.001$ (inter-generational earnings elasticity), $\beta_f = 0.3$ (migration wage premium) and $\sigma_y = 1$ (conditional standard deviation). The parameters governing the child's distance draw are $\beta_d = 0$ (intercept) and $\beta_{dm} = 4$ (relationship migration and distance to parent). The parameters governing the child's care-cost draw are $\mu_\theta = -0.66$ (intercept), $\beta_{d\theta} = 1$ (correlation of distance and care cost) and $\sigma_\theta = 0.5$ (conditional st.dev.)[4]

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[4] To solve the BK game after the designation stage, we use $N_y = 5$ grid points for productivity, $N_\theta = 3$ grid points for care costs $N_a = 20$ grid points for assets.

Fig. 4 shows how both children's migration probabilities change in the mean migration cost, μ_c. As expected, higher migration cost decrease migration of both children. Furthermore, Child 2 is less likely to migrate if Child 1 has done so in the first stage. Since Child 1 is unlikely to assume the care burden, Child 2 stays close to the parent in order to lower the costs of caregiving to the parent. Thus, there is indeed a first-mover advantage for Child 1. However, we also observe that Child 2 is slightly more likely to migrate than Child 1 if Child 1 stays close, showing how Child 2 optimally reacts to Child 1's migration decision. These effects would become quantitatively stronger if we decreased the variance of migration costs, thus giving more prominence to the care-related aspects of the migration decision.

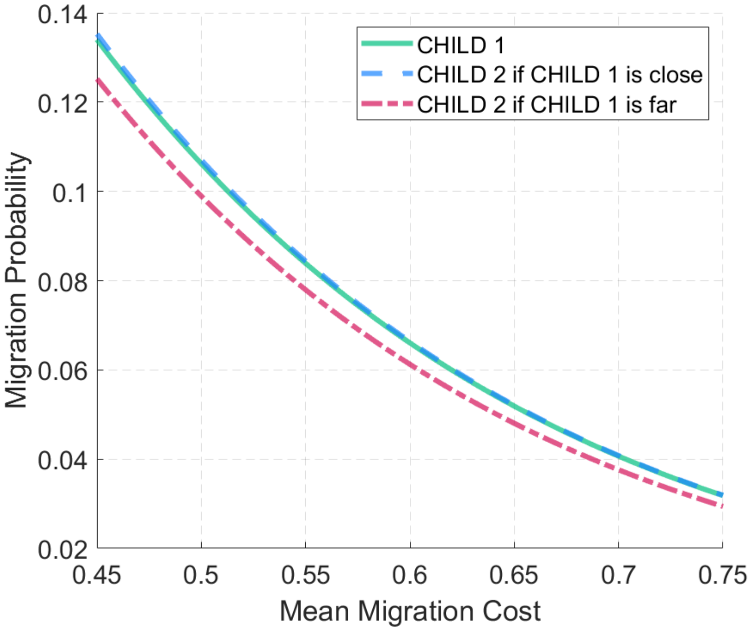

Figure 4: Model migration probability as function of mean migration cost

Fig. 5 shows a similar pattern for the dependence of location decisions on the migration wage premium, β_f. Unsurprisingly, the more that a child can gain from migrating, the more migration takes place. Again, we can appreciate the strategic interaction of children and the first-mover advantage for Child 1.

We find the strongest strategic interaction effects between children when we consider migration involving distances that make caregiving prohibitively expensive. Fig. 6 shows how migration probabilities change when increasing the distance migrated, i.e. the coefficient β_{dm} that relates log-distance to the migration decision. For high values of this pa-

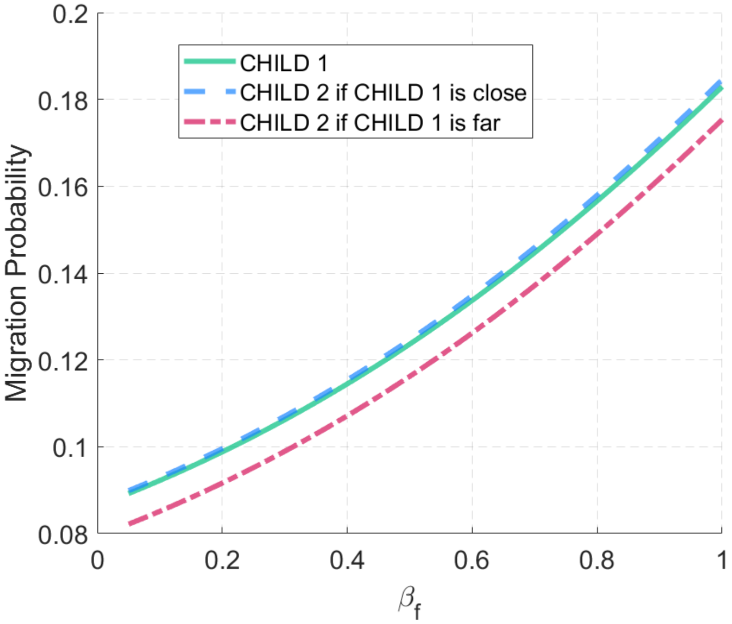

Figure 5: Model migration probability as function of migration wage premium

rameter ($\beta_{dm} \geq 4.5$), Child 2's migration probability is cut in half when Child 1 migrates instead of staying close to the parent. Child 1's migration decision is close to what Child 2 does if Child 1 locates close to the parent, again attesting to the first-mover advantage.

Finally, our preliminary model results allow us to study how parent characteristics, i.e. their income and wealth, influence children's migration choices. Figures 7 and 8 show the children's migration probabilities across three categories of parent wealth and income, respectively. We see that migration is negatively associated with both parent income and wealth. A first channel at work goes through child income and works as follows: Child income is assumed to be positively associated with parent income in our model ($\beta_{IGE} > 0$, as it is in the data). But staying close to the parent is a luxury good under our additive migration-cost specification: As the power-utility coefficient is 1 ($\gamma = 2$) in the solution of the BK game, the marginal value gain of a fixed percentage increase in expected wages (the migration wage premium β_f) is smaller for richer children. Thus the additive migration cost carries a higher weight for rich children and they tend to migrate less. A second channel at play is as follows: Children gain more from staying close to a wealth-rich parent than to a wealth-poor parent; as they give informal care to the rich parent, they protect the parent's estate from being spent down and thus secure a higher bequest.[5]

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[5] Depending on the migration patterns conditional on income that we find in the data, we may have to

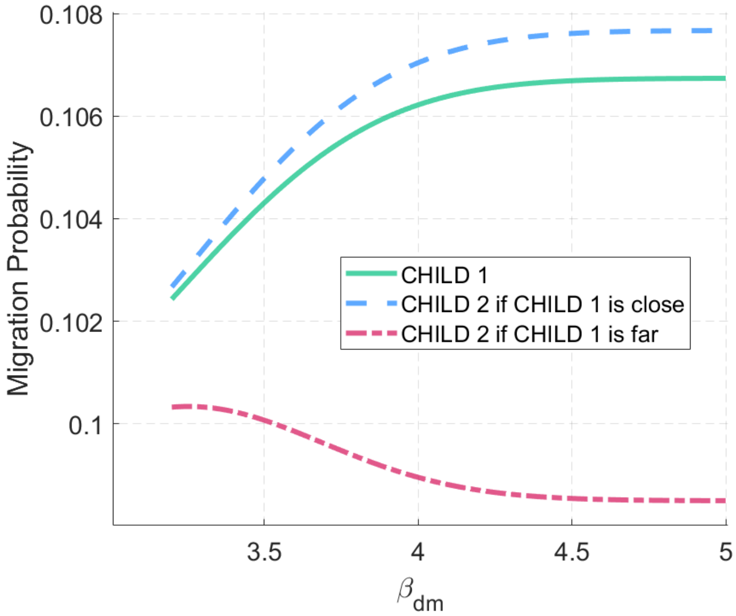

Figure 6: Model migration probability as function of distance migrated

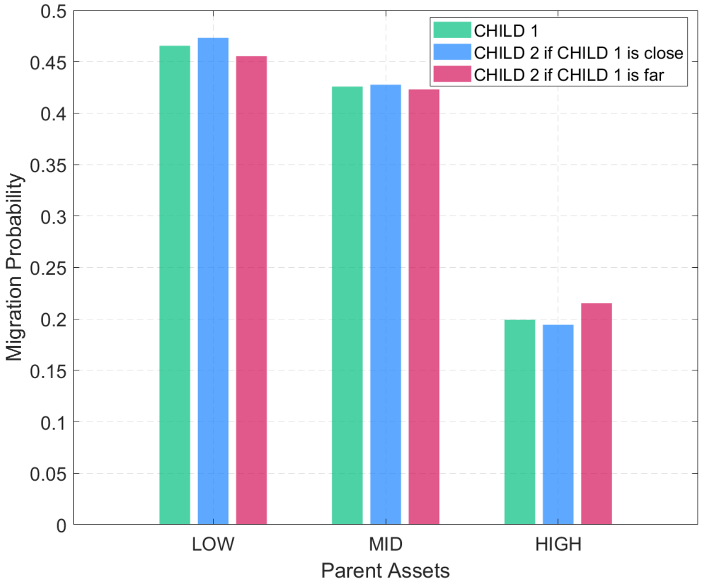

Figure 7: Model migration probabilities by parent wealth

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adapt the migration-cost specification to bring the predictions in line with the data on children's location choices.

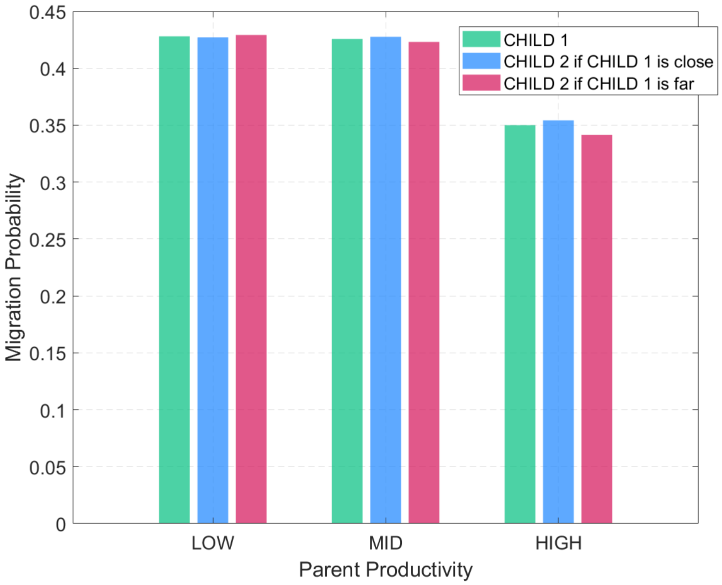


Figure 8: Model migration probabilities by parent income

References

Barczyk, D., Koh, Y. K. & Kredler, M. (2025), ‘Preference heterogeneity versus economic incentives: What determines the choice to give care to the elderly?’, *Available at SSRN 5738769* .

Barczyk, D. & Kredler, M. (2018), ‘Evaluating long-term-care policy options, taking the family seriously’, *The Review of Economic Studies* **85**(2), 766–809.

Barczyk, D. & Kredler, M. (2019), ‘Long-term care across europe and the united states: The role of informal and formal care’, *Fiscal Studies* **40**(3), 329–373.
URL: *https://onlinelibrary.wiley.com/doi/10.1111/1475-5890.12200*

Bergeot, J., Ferrari, I. & Gao, Y. (2024), ‘The effect of parental health shocks on living arrangements and employment’, *Health Economics* **33**, 2798–2837.
URL: *https://onlinelibrary.wiley.com/doi/10.1002/hec.4893*

Börsch-Supan, A., Ferrari, I. & Salerno, L. (2021), ‘Long-run health trends in europe’, *The Journal of the Economics of Ageing* **18**, 100303.

Choi, H., Schoeni, R. F., Xu, H., Reyes, A. M. & Thomas, D. (2021), ‘Proximity to mother over the life course in the united states: Overall patterns and racial differences’, *Demographic Research* **45**(23), 769–806.
URL: *https://www.demographic-research.org/articles/volume/45/23*

Compton, J. & Pollak, R. A. (2015), ‘Proximity and co-residence of adult children and their parents in the united states: Descriptions and correlates’, *Annals of Economics and Statistics* (117/118), 91–114.
URL: *https://ideas.repec.org/a/adr/anecst/y2015i117-118p91-114.html*

Diamond, R. (2016), ‘The determinants and welfare implications of us workers’ diverging location choices by skill: 1980–2000’, *American economic review* **106**(3), 479–524.

Hank, K. (2007), ‘Proximity and contacts between older parents and their children: A european comparison’, *Journal of Marriage and Family* **69**(1), 157–173.
URL: *https://onlinelibrary.wiley.com/doi/10.1111/j.1741-3737.2006.00351.x*

Isengard, B. (2013), ‘"the apple doesn’t live far from the tree": Living distances between parents and their adult children in europe’, *Comparative Population Studies* **38**(2), 237–262.
URL: *https://www.comparativepopulationstudies.de/index.php/CPoS/article/view/44*

Konrad, K. A., Künemund, H., Lommerud, K. E. & Robledo, J. R. (2002), ‘Geography of the family’, *American Economic Review* **92**(4), 981–998.

Maruyama, S. & Johar, M. (2017), ‘Do siblings free-ride in being there for parents?’, *Quantitative Economics* **8**(1), 277–316.

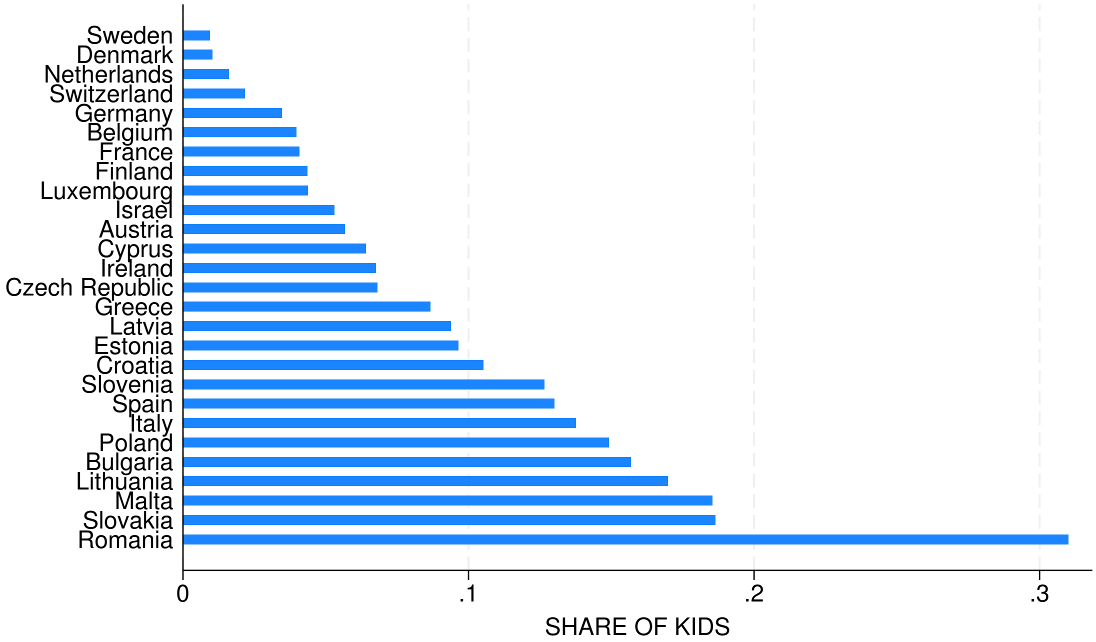
Roca, J. D. L. & Puga, D. (2017), ‘Learning by working in big cities’, *The Review of Economic Studies* **84**(1), 106–142.

Smits, J. (2010), ‘Moving close to parents and adult children in the netherlands: The influence of support needs’, *Demographic Research* **22**(31), 985–1014.
URL: *https://www.demographic-research.org/articles/volume/22/31*

WHO (2022), ‘Health and care workforce in europe: time to act’, *World Health Organization. Regional Office for Europe* .

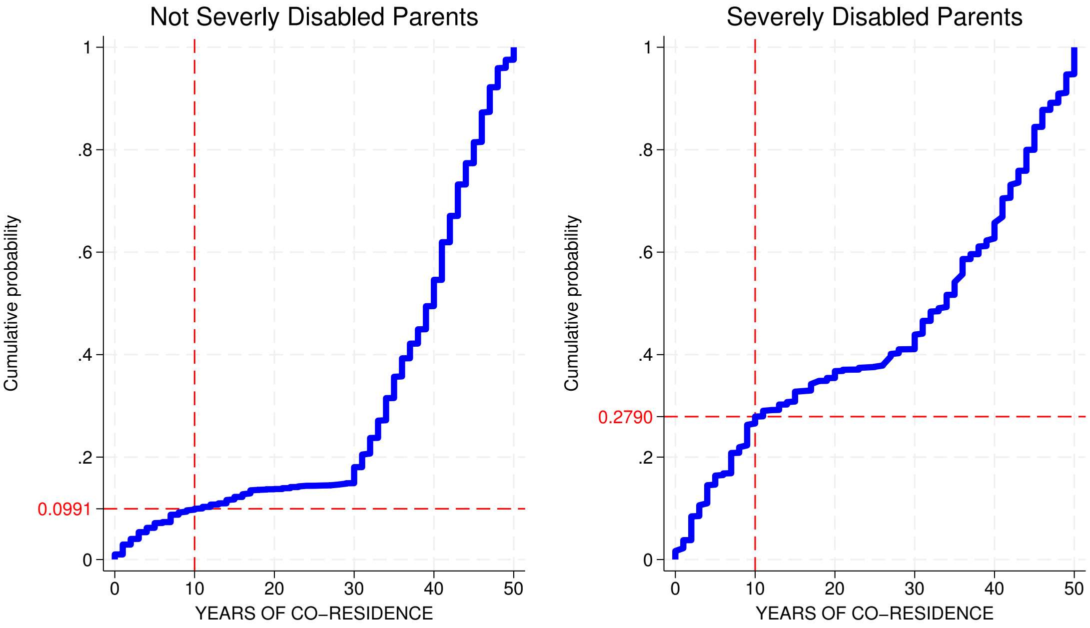
Appendix A Empirical Facts

Figure A.1: Shares of Kids Co-Residing with Parents by Countries



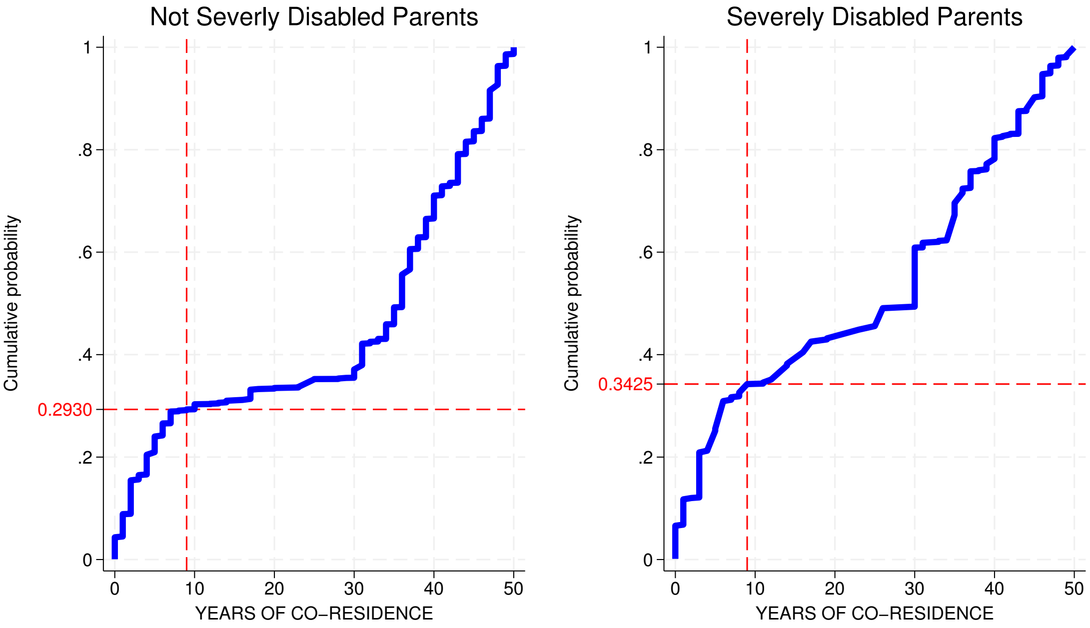
Note: Calculated as the share of kids co-residing with their parents. All kids are $\geq$ 30y.o., all parents are $\geq$ 65y.o. For families with multiple children, we measure distance using the oldest child.

Figure A.2: Distribution of Years a Currently Co-residing Child Lives with Parent. Low LTC Expenditures Countries



Note: Parent is "severely" disabled if the sum of (I)IADLs≥ 2 for that parent. All kids considered are $\geq$30 y.o., and parents are ≥ 65 y.o. Only one parent (family respondent) is considered from each family. Longest years of co-residence are taken in case of multiple co-residing kids. Observations are weighted by SHARE calibrated household weights.

Figure A.3: Distribution of Years a Currently Co-residing Child Lives with Parent. High and Mid LTC Expenditures Countries



Note: See Figure A.2 for details.

Table A.1: SHARE First Interview Data vs. Longitudinal Data

	Dataset	
	First-Time Interviews (N=49,364)	Full Panel (N=170,730)
Parent Age (Years)	74.61 (7.05)	75.10 (7.36)
Gender		
Male	20,444 (41.4%)	71,475 (41.9%)
Female	28,920 (58.6%)	99,255 (58.1%)
N of (I)ADLs	1.33 (2.85)	1.24 (2.76)
Number of Children	2.11 (1.57)	2.20 (1.53)
Nursing Home Resident		
No	46,968 (95.1%)	165,586 (97.0%)
Yes	2,396 (4.9%)	5,144 (3.0%)

Note: The table compares the SHARE data extract that consists of the first-time interviews pooled across waves with the SHARE data that also includes longitudinal observations. For both datasets, included SHARE waves are: 1-2, 4-6, and 8. Values in parenthesis for continuous/count and categorical variables stand, respectively, for standard deviations and percentages calculated within each child location group. The observations in each row of the table are weighted with OECD-SHARE weights adjusting for the under-representation of nursing home residents in SHARE data Barczyk & Kredler (2019).

Table A.2: SHARE First Interview Data. Summary Statistics. SHARE-OECD Weights

	Location of Children			
	At Least 1 Co-Resident Child (N=6,508)	At Least 1 Child Within 25 km (N=21,609)	All Children at least 25 km Away (N=14,528)	Total (N=42,645)
Parent Variables				
Parent Age (Years)	74.40 (7.60)	74.48 (6.74)	74.20 (6.83)	74.38 (6.93)
Gender	1.60 (0.49)	1.59 (0.49)	1.56 (0.50)	1.58 (0.49)
N of (I)ADLs	1.65 (3.15)	1.09 (2.43)	1.05 (2.57)	1.18 (2.63)
Nursing Home Resident				
No	6,437 (98.9%)	20,976 (97.1%)	13,901 (95.7%)	41,346 (97.0%)
Yes	71 (1.1%)	633 (2.9%)	627 (4.3%)	1,299 (3.0%)
Number of Kids	2.87 (1.75)	2.58 (1.35)	2.06 (1.08)	2.46 (1.39)
Family Status				
Single	3,142 (48.3%)	9,335 (43.2%)	6,035 (41.5%)	18,586 (43.6%)
Couple	3,366 (51.7%)	12,274 (56.8%)	8,493 (58.5%)	24,059 (56.4%)
Children Variables				
Avg. N of Own Kids	1.13 (0.94)	1.60 (0.87)	1.48 (0.97)	1.47 (0.93)
Average Age	43.77 (9.76)	45.90 (7.49)	45.66 (7.86)	45.44 (8.10)
Avg. Share of Females	0.46 (0.34)	0.52 (0.34)	0.49 (0.39)	0.50 (0.36)
Avg. Share of College Educated	0.21 (0.34)	0.29 (0.38)	0.43 (0.44)	0.32 (0.40)
Avg. Share Married	0.51 (0.36)	0.76 (0.33)	0.69 (0.39)	0.69 (0.36)
Any Foster/Adopted/ Step-Children				
No	6,353 (97.6%)	20,729 (96.0%)	13,795 (95.0%)	40,904 (95.9%)
Yes	154 (2.4%)	873 (4.0%)	730 (5.0%)	1,729 (4.1%)

Note: The data consists of the first interviews pooled across waves of SHARE. Included SHARE waves: 1-2, 4-6, and 8. Values in parenthesis for continuous/count and categorical variables stand, respectively, for standard deviations and percentages calculated within each child location group. The observations in each row of the table are weighted with OECD-SHARE weights adjusting for the under-representation of nursing home residents in SHARE data Barczyk & Kredler (2019).

Table A.3: Sudden Health Shocks, Disability, and Co-Residence. Intensive Margin

	OLS Estimates			**2SLS Estimates**		
Dep. Var.: I($\geq$1 child living with parent)	(1)	(2)	(3)	(4)	(5)	(6)
Sum of 13 (I)ADLs	0.009***	0.013***	0.005	0.007*	0.018***	0.004
	(0.001)	(0.002)	(0.005)	(0.004)	(0.007)	(0.008)
Constant	1.479***	1.755**	1.872**	1.523***	1.579***	1.902***
	(0.360)	(0.672)	(0.828)	(0.249)	(0.421)	(0.472)
SHARE Weights		✓			✓	
OECD-SHARE Weights			✓			✓
Observations	29540	29540	29540	29513	29513	29513
Adjusted R^2	0.198	0.250	0.240	0.198	0.249	0.239

Note: **Columns 1-3** present results form OLS regressions of a dummy for at least one child living with parent on the sum of 13 (I)ADLs. **Columns 4-6** present results from 2SLS regressions, where in the first stage the sum of 13 (I)ADLs is predicted with the binary variable equal to 1 for those parents who are currently suffering from the consequences of stroke and/or fracture. Standard errors in parentheses are clustered at country level in all specifications. All kids considered in regressions are $\geq$ 30 y.o., and parents are $\geq$ 65 y.o. Only one parent (family respondent) is considered from each family. All specifications feature children controls, parent controls, year & country fixed effect. Children controls include, on family level: *share of those with at least college education, share of females, share of full-time employed, share married, average number of own kids, average age, dummies for any child being adopted/foster-/step-child*. Parent controls include: *age, age squared, number of kids, gender*.