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The effect of parental health shocks on living arrangements and employment

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Abstract

This study investigates the impacts of health shocks among older individuals on the dynamics of their living arrangements in Europe and the United States. Exploiting unpredicted health shocks, we use an event-study difference-in-differences approach to demonstrate that health shocks increase difficulties with activities of daily living and instrumental activities of daily living, thereby increasing the need for care. Our findings indicate that health shocks raise the probability of nursing home residency and co-residence with adult children by 0.7 and 1.4 percentage points in Europe, and by 2.1 and 1.8 percentage points in the U.S., respectively. Further analyses reveal that more generous long-term care public policies correlate with a higher probability of nursing home residency and a lower probability of co-residing with adult children, highlighting the significant role of public policies in household responses to health shocks. Additionally, we find that health shocks negatively impact adult children's labor supply, particularly in the U.S.

KEYWORDS

health shocks, living arrangements, long-term care

JEL CLASSIFICATION

J14, I18

1 | INTRODUCTION

The share of older individuals in the population is increasing in most developed countries. It is also known that, as individuals age, they face increased health risks, decline in cognitive capabilities, and diminished ability to perform daily tasks. Consequently, there is a growing demand for care services, which poses challenges to the sustainability of long-term care (LTC) systems. To address this issue, governments often implement measures to reduce LTC costs by promoting community-based aging and encouraging informal care, both of which are considered cost-effective alternatives to nursing home care (Mazzotta et al., 2018).

Given this context, it is essential to explore the impacts of health risks on the living arrangements of older individuals and how these arrangements evolve over time. The literature identifies several factors influencing the living choices of older adults, including preferences for aging in place, personal financial situations, and the availability of formal and informal caregiving services (Pani-Harreman et al., 2021). However, there is limited evidence on how increased care needs affect living arrangements, especially following sudden health deterioration among the elderly. Moreover, while aging in place can impose significant physical and economic burdens on family caregivers, the impact on the employment of adult children and how this evolves over time remains unclear.

In this study, we first explore the dynamics of living arrangements among older individuals in response to unexpected health shocks that increase their care needs. Our primary outcomes of interest include co-residence with an adult child and living in a nursing home, both serving as potential substitute options for older individuals seeking care (Mommaerts, 2018).[1] We also examine the heterogeneity of our results across various individual, household, and country characteristics. Additionally, we extend our analysis to study the effect of health shocks on co-residence with other relatives and non-relatives. Furthermore, leveraging the richness of our data, we construct a children-panel containing longitudinal information on the employment status and work hours of the children of the survey respondents. This allows us to study how the sudden need for care of a parent affects the labor supply of their children.

Specifically, as a first step we exploit the onset of unpredictable health shocks and show that these trigger an increase in difficulties with Activities of Daily living (ADL) and Instrumental activities of daily living (IADL). Then, we use an event-study difference-in-differences approach (de Chaisemartin & D'Haultfœuille, 2024) to explore the evolution of living arrangements and children's employment over several years after the health shock. A similar strategy has been used by Gonçalves et al. (2023), who examined the long-term trajectories of individuals suffering a health shock compared to individuals not experiencing any health shock. This approach has the advantage that it not only allows for individual fixed effects, but can also be used to assess whether the outcomes follow different trajectories already before the shock. Furthermore, compared to the traditional difference-in-differences model, the event-study design allows us to visualize potential dynamics of the effects (Schiele & Schmitz, 2023).

Our results are based on data from Europe (SHARE) and the United States (HRS), which allows us to explore differences across regions of the world with very different LTC policies. In particular, we first explore the heterogeneity of our results across European countries characterized by varying levels of LTC policy generosity. Such results may stem from differences in LTC policies as well as cultural distinctions, which are challenging to disentangle. To circumvent this issue, we also exploit within-country variability in nursing home bed availability. Finally, we explore heterogeneity within the US, where cultural differences are less pronounced, by exploiting variation in state spending on Medicaid Long-Term Services and Supports (LTSS).

In general, the decision to co-reside with an adult child due to increased care needs has been highly neglected in the literature, despite its potentially significant consequences for both care-givers and care recipients. On the one hand, co-residence with a parent at an adult age might be disruptive as children, who are more likely to be employed or have other obligations within their own households, face higher costs in terms of missed opportunities. Moreover, there is evidence that co-residence is associated with intensive care arrangements, which leads to larger negative effects on care-givers' employment (Heitmueller, 2007; Michaud et al., 2010). On the other, it might help care-givers to better manage domestic care arrangements and to save on housing costs in order to finance formal care.

In the literature on LTC living arrangements (Hays, 2002), economic conditions have emerged as key determinants alongside health factors (Bethencourt & Rios-Rull, 2009; Cheng et al., 2018; Compton & Pollak, 2015; Engers & Stern, 2002; Mutchler & Burr, 1991; Pani-Harreman et al., 2021). However, most studies take a static perspective, merely depicting LTC arrangements at a single moment in time. This overlooks the dynamic nature of such arrangements, which may evolve as individuals age and experience changes in health status. Furthermore, they often fail to address the endogeneity of accommodation choices. This approach has limitations as individuals may choose their living arrangements in anticipation of future care needs, and unobserved factors influencing both living arrangements and health may exist.

Exceptions include Hiedemann et al. (2017) who model LTC arrangements, and not only living arrangements. The authors find evidence of an important inertia in LTC arrangements in the US, such that individuals tend to stick to their first LTC arrangement. Arnault and Juin (2021) used data from the Survey of Health, Aging, and Retirement in Europe and studied the determinant of changes in living arrangements from one wave to the other. They find a limited role of changes in parental disability. Martikainen et al. (2008) find that health conditions associated with functional limitations are determinants of transitions from a private household to a nursing home in Finland.

A much more extensive literature exists on the impact of informal care-giving on care-givers employment (see Bauer and Sousa-Poza (2015), Moussa (2019), and Wen and Huang (2024)). Overall, the vast majority of studies find a null or a negative relationship between care-giving and employment status and work hours of the care-giver, but there is no agreement on the size or even the statistical significance of this effect. The main difficulty in identifying this effect lies in the mutual causation between care-giver employment and care-giving.[2]

Most studies that recognize the endogeneity of the care-giving decision have addressed this issue with strategies based on instrumental variable (IV) regression, where measures of care recipient's care need or the gender composition of children are used as instrumental variables for the involvement in informal care.[3] IV are often subject to criticism given the difficulty to evaluate the assumptions made to identify a causal effect. We adopt a different approach by examining how families adapt to sudden increases in care needs, focusing on changes in living arrangements and caregivers' employment. This strategy allows us to leverage an arguably exogenous event and transparently evaluate our identification assumptions through event-study plots. We believe this approach complements and offers a valuable contribution to the existing literature.

We show that experiencing a health shock increases the likelihood of transitioning into a nursing home or co-residing with a child in both Europe and the US, albeit with variations across different demographic groups and regions. In both settings, older individuals, childless individuals, singles, and those with lower wealth are more prone to nursing home admission post-health shock. Couples are more likely than singles to co-reside with children after a health shock. Notably, the gender composition of children affects co-residence, with the presence of daughters associated with a higher likelihood of co-residence in Europe and the opposite trend in the US. Disparities in public spending on formal care contribute to heterogeneous effects, with European countries and US states with higher spending showing greater nursing home admission rates post-health shock. Lastly, regarding caregivers, we find a general decline in children's employment following a parent's health shock, particularly evident in the US, where a more persistent impact is observed.

The outline of the paper is as follows. In Section 2, we present our empirical strategy. In Section 3, we describe the data, sample selection, and present descriptive statistics on the main variables. Results are presented in Section 4. In Section 5, we conclude and discuss the policy implications of our results.

2 | EMPIRICAL STRATEGY

In our empirical analysis, we will study the effect of experiencing a health shock (due to stroke, heart attack, cancer or hip fracture) on the living arrangements of older individuals, in particular the probability of moving into a nursing home and the probability of co-residence with a child. We carry out event study estimations to analyze the causal effect of health shocks on living arrangements and to check whether these shocks are anticipated (see for instance Schiele and Schmitz (2023)). In order to highlight that living arrangements change as a result of an increased need for care, we will first show the effect of experiencing a health shock on ADL and IADL.

As common in the literature, in our setup the treatment (experiencing a health shock) is binary and staggered, meaning it hits individuals at different points in time, and it is an absorbing state, meaning that once the treatment is switched on, it does not switch off. A common method to estimate dynamic effects is to run a two-way fixed effects (TWFE) event-study regression of the outcome on individual fixed effects, period fixed effects, and indicators for whether the individual started receiving the treatment t periods ago.

Recent advances in econometrics literature, though, have highlighted the issues related to using TWFE models to obtain treatment effects in a staggered treatment adoption setting like ours, where there are more than two periods and units are treated at different points in time. In particular, the TWFE dynamic specification fails to yield sensible estimates of dynamic causal effects when there are heterogeneous dynamic treatment effects across adoption cohorts. The reason is that this specification includes “forbidden comparisons” between sets of units both of which have already been treated (Roth et al., 2022).

For this reason, we will employ the estimation strategy proposed by de Chaisemartin and D’Haultfœuille (2024), which consists of a difference-in-differences (DID) estimator that compares changes in outcomes for units whose treatment status changed to other units whose treatment has not changed yet (i.e., those who will be treated later and those who will never be treated). For simplification, we present the estimation procedure without covariates, but in all regressions, we flexibly control for age by including age fixed affects, given that age is a clear confounder in the estimation of the effect of health shocks on the need for care and living arrangements. In the staggered treatment case, we call “group of treatment” all observations that are treated in the same period. Let us define the group of treatment by g, with $g = 1, \ldots, G$. Each group g is treated in the period F_g. For all groups, the reference period to which the outcome evolution is compared is the last period before treatment, that is $F_g - 1$. The method suggested by de Chaisemartin and D'Haultfœuille (2024) first computes the average treatment effect on the treated for each group g and at each post-treatment period l with the following formula:

$$DID_{g,l} = Y_{g,F_g+l} - Y_{g,F_g-1} - \frac{1}{N_l^g} \sum_{g':F_{g'}>F_g} \left(Y_{g',F_g+l} - Y_{g',F_g-1}\right) \tag{1}$$

where $Y_{g,t}$ is the observed outcome of g at time t. N_l^g is the number of observation of group g still observed at post-period l. This estimator compares the evolution of the outcomes during the period from $F_g - 1$ to $F_g + l$ between group g and groups g' whose treatment has not changed yet at time $F_g + l$. Because effects by groups of treatment are meaningless in our context, we present the average estimated effect at post-period l over all the treated groups for which data are available. This is given by:

$$DID_l = \frac{1}{N_l} \sum_g DID_{g,l} \tag{2}$$

where N_l is the number of observations for which a $DID_{g,l}$ could be estimated. This approach is unbiased under the parallel trends assumption and is robust to heterogeneous treatment effects. To test the parallel trends assumptions, the authors propose placebo estimators comparing the outcome trends of switchers and non-switchers before the switch occurred.

In practice, this approach leads to an event-study graph, with the distance to the first treatment change on the x-axis, the DID treatment effects on the y-axis to the right of zero, and placebo estimators on the y-axis to the left of zero. This event-study graph is useful to test the parallel trends assumption, and to provide reduced-form evidence of whether increasing the treatment for $t+1$ periods increases or decreases the outcome on average (de Chaisemartin & D'Haultfœuille, 2024).

We include two leads before the health shock, that will be used to assess the validity of the common trend assumption, and four lags, leading to the estimation of four dynamic treatment effects.[4]

3 | DATA

In our research, we leverage two distinct data sources: the Survey of Health, Aging, and Retirement in Europe (SHARE), covering European nations; and the Health and Retirement Study (HRS), conducted in the United States. In the subsequent sections, we provide individual introductions to each dataset, followed by a comprehensive account of variable construction, where any notable divergences across surveys will be highlighted.

3.1 | Data sources

3.1.1 | Survey of health, aging, and retirement in Europe

For Europe, we draw data from SHARE, a longitudinal, cross-national European survey. It includes microdata on health, socioeconomic status, and social and family networks of a representative sample of individuals (and spouses) aged 50 and above from 28 European countries and Israel. The baseline SHARE survey was conducted in 2004, with follow-up surveys conducted biennially since then. Questions are asked in the native language and follow a generic questionnaire such that they are comparable across countries. Data collection began in 2004, with 12 countries included in the first wave. Data for the seventh wave were collected in 2017 and contain information from 28 European countries. The third and seventh waves of SHARE, also known as SHARELIFE, differ from the regular panel waves as they focus on retrospective questions about the respondents' childhood and their employment, fertility, marital and health histories. Our analyses are based on data from the regular waves, that is, waves 1, 2, 4, 5 and 6, broadly covering years from 2004 to 2015.

Interviewed individuals report information on their children, including the distance they live from them, their labor supply and family composition. Nonetheless, SHARE does not provide users with a family dataset that links SHARE children across waves,[5] therefore this needs to be constructed using available information. To track children from one wave to the next, we utilized their gender and age, which led to the exclusion from the sample of a very small number of households with multiple children of the same age and gender. This approach allowed us to build a "children panel", with one observation for each respondent's child, containing some basic information on their age, gender, labor market status and the living distance from their parents. Using this, we augmented the baseline respondents' longitudinal dataset with variables about the respondents' children.

3.1.2 | Health and retirement study

For the United States, we use HRS data, a longitudinal panel study that surveys a representative sample of approximately 20,000 people in America aged 50 and above every two years.[6] The study collects information about income, work, assets, pension plans, health insurance, disability, physical health and functioning, cognitive functioning, and health care expenditures.

We integrate information on respondents included in the standard data files with the RAND HRS Family data file, a user-friendly version of HRS family data. The dataset contains a collection of variables related to the respondent's family, including a subset of available characteristics of all children of HRS respondents and spouses, data on children-in-law, and data on grandchildren of the respondent.[7] We use the RAND HRS Family Data 2018 version, which include 14 waves of core interview data across 14 survey years (1992, 1993, 1994, 1995, and biennially 1996–2018).

3.2 | Sample selection

To track respondents' onset of health shocks, we restrict our analysis to respondents who were observed in at least two consecutive waves. As we are interested in the children's living arrangements following a health shock experienced by their parents, we focus on parents with at least one child alive. We will also consider households with no children to study differential nursing home behavior with respect to households with children. We further drop individuals younger than 50 and older than 90.

We construct two samples: one where the unit of analysis is the individual and a second one where the unit of analysis is the household. We use the former to study outcomes measured at the individual level (limitations with ADL and with IADL, living in a nursing home), and the latter to study outcomes measured at the household level (coresidence with children).[8] Additionally, to study adult children's labor supply, we construct individual-level data for each child (employment status and work hours).

3.3 | Variables

3.3.1 | Health shock measure

We define a health shock as the onset of a serious illness between two waves. In the survey, participants indicate whether they have experienced any of the listed medical conditions between the last interview and the current one. These conditions include heart attacks, strokes or cerebral vascular diseases, any type of cancer diagnosis, and hip fractures.[9] With the exception of hip fractures, these conditions are commonly used indicators in research about the economic impact of health shocks (Schiele & Schmitz, 2023). Because the occurrence of specific types of health shock is rare in the sample, similar to the previous literature (Schiele & Schmitz, 2023), we consider respondents to have a health shock if they report that they had any of these four types of health shocks in between two consecutive waves.

3.3.2 | Outcome variables

First, we would like to shed light on the channels driving households decisions about living arrangements when an older family member experiences a health shock. We begin by evaluating the extent to which the need for assistance with daily activities changes as a result of the health shock. All surveys collect information on the number of reported limitations with ADL and IADL. The ADL index (Katz et al., 1963) describes the number of limitations with ADL. It refers to people's everyday self-care activities such as dressing, walking, grooming, eating, transferring bed, and toileting, which are fundamental for maintaining independence. The IADL index (Lawton & Brody, 1969) describes the number of limitations with instrumental activities of everyday life. The modified ADL version used in SHARE includes six activities, resulting in scores ranging from 0 to 6. The modified IADL version used in SHARE includes seven activities, which increased to nine in wave 6. Thus, the score ranges from 0 to 9. The higher the index is, the more difficulties with these activities and the lower the mobility of the respondent. In HRS, both ADL and IADL include five activities. This is not an issue for our analysis given that we only explore the effect of the health shock on limitations to validate their influence on care needs.

To measure the living arrangement of the respondents and their children, we construct a dataset with children who are alive during each wave and track the children across wave. The children panel contains demographic information about the children, including gender, year of birth, and other information such as their labor market status. More importantly, we track the child's current location across all waves. Consequently, for each wave, we are able to observe the current distance between respondents and all their children, as well as any potential changes in their living arrangements across waves.

The survey question on the distance from children presents some differences across surveys. In SHARE, a categorical variable is used to represent the distance between the respondent and each child. This variable adopts a nine-level scale ranging from 1 (in the same household) to 9 (more than 500 km away). Based on the closest distance, we obtain a dummy variable measuring co-residence with a child, which equals one if at least one child lives with the respondent in the same household and zero otherwise. In the HRS, we exploit a generated variable counting the number of children residing with the respondent. As before, we use this information to construct a dummy which equals one if at least one child co-reside with the respondent.

Finally, we study whether the respondent is living in a nursing home in a given wave. We use a dummy variable, which equals one if the respondent lives in a nursing home and zero otherwise. Given that panel attrition problems might be more serious for individuals moving to a nursing home, we exploit another question asking respondents whether they have been in a nursing home or residential care facility overnight in the last 12 months (for SHARE data) or last 24 months (for HRS data). This will also allow us to account for the robustness to temporary stays that are more frequent in the US (Bom et al., 2023).

3.4 | Descriptive statistics

Descriptive statistics are displayed in Table 1. Average ages are relatively close in the US (66.8) and in Europe (66.2). Europeans are half as likely to have ADL limitations compared to American individuals. However, this difference is not necessarily attributed to variations in health between the regions. Indeed, ADL limitations are measured with self-reported measures that should be compared with caution because they capture cultural differences (Jylhä et al., 1998). Nonetheless, Bom et al. (2023) also find that older individuals in the US are more likely to be disabled than in the Netherlands. Regarding IADL limitations, the difference between regions is less pronounced, although individuals in the US still exhibit a higher likelihood of limitations.

The proportion of individuals living in a nursing home in Europe is only 0.5%, and the proportion of individuals who accessed a nursing home over the last 12 months (but are not currently residing in a nursing home at the time of the interview) is rather similar. Regarding the US, the corresponding proportions are 1.5% and 3.1%, respectively. This difference in the US might arise from the fact that older individuals tend to use nursing home on a temporary rather than a permanent basis (Bom et al., 2023). On top of actual differences in the use of nursing home care in the US and in Europe (Bergeot & Tenand, 2023; Bom et al., 2023), the difference between SHARE and HRS could be explained by the fact that not all SHARE countries sample individuals living in nursing homes and HRS may offer better tracking of individuals transitioning into nursing homes (Barczyk & Kredler, 2019).

TABLE 1 Descriptive statistics.

	Europe			US		
	Mean	**Std.dev.**	**Obs**	**Mean**	**Std.dev.**	**Obs**
Panel A: Pooled individual data over waves						
Age	66.195	9.368	177,358	66.829	9.971	227,302
Has any ADL limitation	0.107	0.309	177,358	0.202	0.401	227,302
Has any IADL limitation	0.166	0.372	177,358	0.226	0.418	227,302
Conditional nb of ADL limitation	2.115	1.534	18,951	2.078	1.300	35,523
Conditional nb of IADL limitation	2.315	1.938	29,422	2.085	1.350	31,323
Lives in a NH	0.005	0.073	177,358	0.015	0.122	201,597
Has temporarily lived in a NH last 12 months	0.004	0.062	176,036	0.031	0.174	226,634
Panel B: Pooled household data over waves						
Co-reside with a child	0.270	0.444	107,447	0.302	0.459	153,413
Panel C: Individual data (not pooled)						
Had a health shock	0.125	0.330	62,997	0.349	0.477	34,690
Present two waves	0.456	0.498	62,997	0.165	0.371	34,690
Present three waves	0.352	0.477	62,997	0.082	0.275	34,690
Present four waves	0.112	0.316	62,997	0.092	0.289	34,690
Present at least five waves	0.080	0.271	62,997	0.641	0.480	34,690

Note: this table presents descriptive statistics on the pooled sample across individuals and waves (Panel A), pooled sample across households and waves(Panel B) and at the individual level without pooling (Panel C). Source data are SHARE for Europe, HRS for the US.

The proportion of households co-residing with at least one child is similar in Europe and the US, 27% and 30% respectively. The aggregated statistics at the European level, however, hide important heterogeneity. Following Crespo and Mira (2014), we group countries in our sample into three groups, according to the availability and generosity of public formal care services and LTC benefits, measured as public expenditure on LTC as a percentage of GDP.[10] The resulting grouping broadly corresponds to Northern countries (Netherlands, Denmark, Sweden), Central countries (Switzerland, France, Belgium, Germany, Austria, Czech Republic, Luxembourg), and Southern countries (Slovenia, Spain, Italy, Portugal, Estonia, Israel, Poland, Greece). Co-residence is much more prevalent in Southern Europe (38%) than in Central Europe (23%) and Northern Europe (15%) (Table A1). This might be the result of cultural differences, but also of heterogeneity in LTC and generosity of pension systems. Similarly, we divided the US sample into states with high and low per-beneficiary Medicaid Long-Term Services and Supports (LTSS; see Section 4.3 for details). The descriptive results in Table A2 indicate that nursing home residency is more common in states with high LTSS, whereas co-residence is more prevalent in states with low LTSS.

Regarding our treatment variable, we find that 35% of older individuals experienced a health shock in the US, and 13% in Europe. This is consistent with the literature finding significantly higher disease prevalence in the US than in Europe (Solé-Auró et al., 2015).

Because marital status can influence LTC arrangements, we also conduct sub-sample analyses by splitting the sample by household type (single vs. in a relationship). In Table A3, we show the mean of the main outcomes by household type. Single individuals are much more likely to live in a nursing home, especially in Europe. The difference by marital status is larger in the US when it comes to temporary stays in a nursing home. This result is in line with the literature finding that having a partner reduces the likelihood of entering a nursing home (Engers & Stern, 2002; Hiedemann & Stern, 1999). Interestingly, singles are less likely to co-reside with a child in Europe, while no similar pattern is observed by household type in the US.

One should note that co-residence does not necessarily mean the parent receives informal care from children. In some cases, this can be a way for parents to support their kids who are facing economic difficulties when the co-residing child does not provide care. We nonetheless expect our analysis to capture co-residence where informal care is provided

TABLE 2 Average outcome right before and after the health shock.

	Wave before health Shock ($t = -1$)	Wave after the health Shock ($t = 0$)
Panel A: Europe		
Has any ADL limitation	0.169	0.271
Has any IADL limitation	0.242	0.375
Lives in a NH	0.008	0.019
Has temporarily lived in a NH last 12 months	0.008	0.017
Co-reside with a child	0.205	0.202
Panel B: US		
Has any ADL limitation	0.212	0.291
Has any IADL limitation	0.227	0.301
Lives in a NH	0.010	0.043
Has temporarily lived in a NH last 12 months	0.023	0.101
Co-reside with a child	0.268	0.260

Note: this table presents average outcome computed at the wave right before the outcome ($t-1$ in our regression) and the wave of the treatment ($t = 0$). The sample is composed of observations who faced a health shock (i.e., treated observations).

because we identify changes in co-residence due to a sudden deterioration of the parent capabilities to perform daily life activities.

To provide preliminary evidence for our analysis, we present the average outcomes calculated for the wave immediately before the treatment ($t-1$ in our regression) and the first wave of treatment ($t = 0$). Since the time since treatment is only applicable to treated units, this calculation is limited to individuals who have experienced a health shock. In Table 2, we observe that the probabilities of having limitations and residing in a nursing home increase following a health shock. For co-residence, the proportion of households living with at least one child remains unchanged. While this before-and-after comparison offers descriptive evidence, we refer to our difference-in-differences results for causal evidence on the effects of health shocks (see Section 2).

We finally document the number of observed waves per panel in panel C of Table 1. In Europe, 46% of the respondents are observed for two waves and 35% for three waves. We will therefore have limited power to estimate the effect of health shocks in Europe many years after (and before) the event. Respondents are followed for a longer period of time in the US. We observe 64% of individuals for at least five waves. The lower attrition observed in the HRS sample may be attributed to varying success rates in tracking individuals permanently entering a nursing home with respect to SHARE. One should note that because most SHARE countries do not sample NH residents at baseline and because they appear less able to follow individuals entering a NH, we will underestimate the true effect of health shocks on nursing home use.[11]

Given the attrition previously documented and that the focus is on health shocks, non-random panel attrition is a concern. After a health shock, individuals might be more difficult to follow due to the deterioration of their health capital. In order to test whether attrition bias our estimates, we will follow Schiele and Schmitz (2023) and estimate our models on a sample of individuals present for at least three consecutive waves (four waves in the US) as a robustness test.

4 | RESULTS

4.1 | Effect of health shocks on ADL and IADL

Health shocks might influence the living arrangements of older individuals, and consequently affect their children due to the increased care needs they induce. Therefore, first we provide evidence that health shocks indeed cause an increased need for care. In Figure 1, we show the DID event study plot of the effect of a health shock on limitations with ADL and IADL. Panel A of Figure 1 presents the results for Europe, while Panel B illustrates the effect for the US.

In the graphs, the zero corresponds to the first wave after the health shock and the reference wave (the last wave before the health shock) is −1. The figure clearly shows an increase in the number of limitations with both ADL and IADL reported by the respondent in both Europe and the United States.

Interestingly, the effect only slightly decreases over time, but it remains positive and significant. The effect seems to even increase after four waves, even though we should interpret this effect with caution given that the sample size reduces with the distance from the shock.

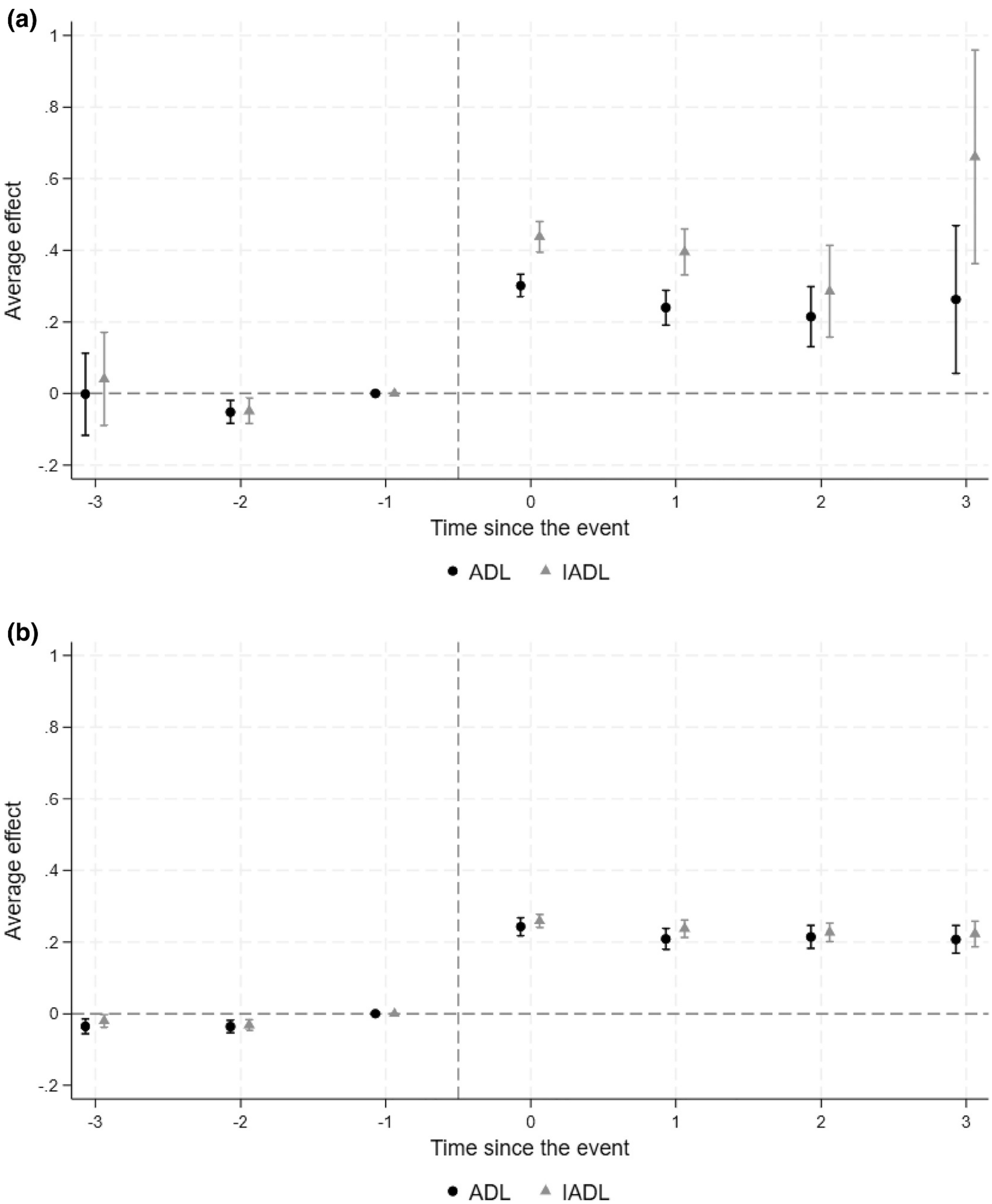

FIGURE 1 Effect of a health shock on the need for care. Panel (a) Europe. Panel (b) United States. This figure displays treatment effects in the form of event-study plots constructed using the de Chaisemartin and d'Haultfoeuille (2024) estimator. This analysis is based on data at the individual level. The time zero corresponds to the first wave after the health shock and the reference wave (the last wave before the health shock) is −1. The bars represent 95 percent confidence interval. Outcomes are the number of limitations in activities of daily living and instrumental activities of daily living activities.

Overall, the average effect of a health shock over the four waves amounts to 0.28 and 0.42 more reported limitations with ADL and IADL, respectively (see Table A4) in Europe. The corresponding average effects in the US are 0.22 and 0.24 (see Table A5). Compared to the sample averages, this amounts to an increase of about 262% and 253% for ADL and IADL, respectively, in Europe, and 109% and 106% in the US. We believe this is evidence that we can interpret our next results as the effect of a very sharp and lasting increase in needs.

We also perform our analysis separately by age. We expect health shocks to have worse consequences for older individuals, who might need more time to recover, or might be less likely to recover at all. In Figure B5 we show the average effect for the two macro-regions ("Baseline"), and the effect by age. As expected, the estimated average effect of a health shock on both ADL and IADL limitations is larger for older individuals.

Although we recognize that the care needs drive the care receipt, we exploit our data to show that individuals experiencing a health shock do in fact receive more care and help from individuals residing within or outside the household.[12] Figure B6 clearly shows that, after a health shock, individuals are more likely to receive help or care. The estimated magnitude in the US on informal care receipt is in line with Gonçalves et al. (2023). Regarding the increase in ADL and IADL limitations, we cannot directly compare the results because their outcome is defined as the probability of having ADL limitations, while we look at the number of limitations. Nonetheless, they also find a sharp increase in the chance of having ADL limitations, which seems in line with our results.

4.2 | Effect of health shocks on living arrangements

In Figure 2, we show the DID event study plot of the effect of a health shock on the probability of being in a nursing home in Europe and the US. In both figures, we do not observe differential trends between the control and treated group before the health shock, which speaks in favor of the common trend assumption. In both cases, we observe a positive and statistically significant effect of the health shock on the probability of living in a nursing home, a trend that seems persistent, particularly in the United States. Moreover, the estimated dynamic effects are larger in the US. The dynamic after the health shock is rather flat, we therefore discuss the magnitude by looking at the average effect over time.

In Table A4 we show the average effect over the four lags, weighted by the number of individuals switching into the treatment state observed in each period.[13] Overall, as shown in Table A4, the average effect over four waves in Europe amounts to a significant (at the 5% level) increase of 0.7% points (pps) in the probability of living in a nursing home, meaning that the probability more than doubles in Europe (the average in the sample is 0.5%, see Table 1). In the US, the effect is much larger given that we estimate a significant increase of 2.1 pps (the average in the sample is 1.5%).

Because attrition problems might be more serious for individuals moving to a nursing home, we show a robustness analysis where the outcome is an indicator variable of whether the respondent is currently living in a nursing home or has been in a nursing home or residential care facility overnight in the last 12 months, or both. Results are displayed in Figures B1 and B2. Overall, we observe similar dynamics, but the estimated average effects are roughly doubled in size in the US. This is an indication of the importance of transitory periods spent in a nursing home after a health shock in the US. One should note that the estimated effect in the US appears lower than the one found by Gonçalves et al. (2023) when looking at the current residency status, while it is similar when also considering transitory NH use. In Europe, transitory use of NH appears relevant only in the first wave of treatment.

In Figure 3, we show the DID event study plot of the effect of a health shock on the probability of co-residing with a child. We observe a positive effect on this probability in both the US and Europe. Interestingly, the effect on the probability to co-reside increases in time in both Europe and the United States. In the first year, we observe an increase of about 1 pps, which continue to increase up to 7 pps in Europe and 3 pps in the US. One potential explanation of this pattern is that some individuals might go live with a child after they leave the nursing home, possibly because they cannot afford it anymore. This seems especially relevant for the US, where spending on LTC is low and individuals are more likely to make transitory use of nursing homes. The average effect over the years is a 1.4 pps higher probability of co-residing with a child in Europe and 1.8 pps in the US (see Table A4), which represent a 5.2% and 6% increase with respect to the sample mean in Europe and the US, respectively. One potential explanation for this difference between European countries and the US could be the higher general rate of transitions to NH in the US than in Europe (Bom et al., 2023).

Because co-residence with other individuals than children might be relevant as well, we complement these results by analyzing the probability of co-residing with another relative (who is not a spouse or child) or with other non-

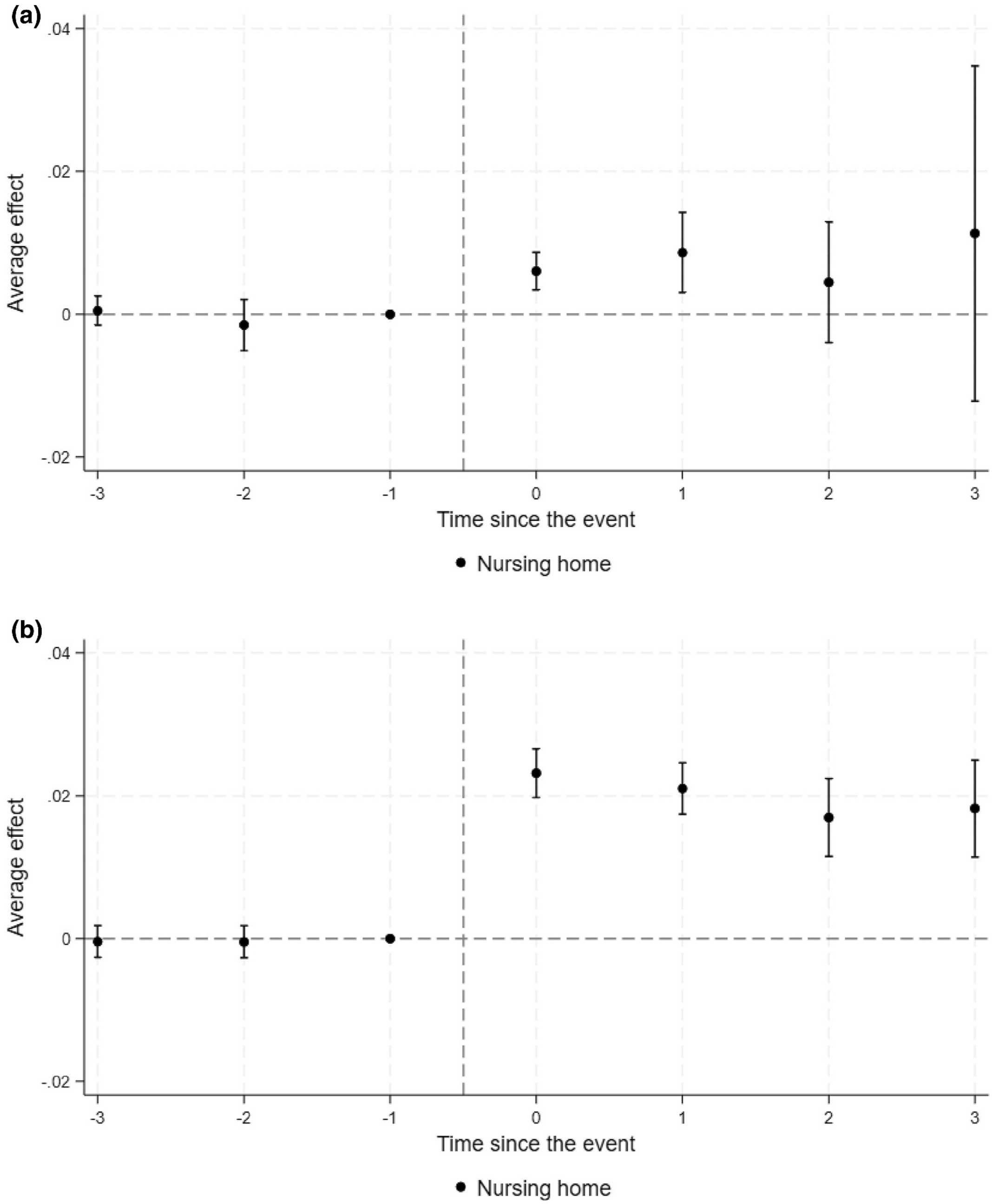

FIGURE 2 Effect of a health shock on nursing home residency. Panel (a) Europe. Panel (b) United States. This figure displays treatment effects in the form of event-study plots constructed using the de Chaisemartin and d'Haultfoeuille (2024) estimator. This analysis is based on data at the individual level. The time zero corresponds to the first wave after the health shock and the reference wave (the last wave before the health shock) is −1. The bars represent 95 percent confidence interval. Outcome is a dummy variable equal to one if the individual lives in a nursing home at the time of the survey.

relatives. Results for "other relatives" are displayed in Figure B3, and show a positive increase in the probability of co-residing with another relative that is statistically significant in Europe. The estimated magnitude over the period after the health shock is as large as for co-residence with children. Results for the probability of co-residence with non-relative, displayed in Figure B4, do not instead show any significant pattern in either Europe or US.

Due to the shorter panel spanned by the SHARE data, we can only include two leads in our event study analysis for Europe. This might cast doubts on the validity of the parallel trend assumption. As we do not face the same limitation with HRS data, we run a robustness check for the US where we include four leads and five lags. Results displayed in the Appendix Figures B7 and B8 confirm the robustness of our analyses to the parallel trend assumption.

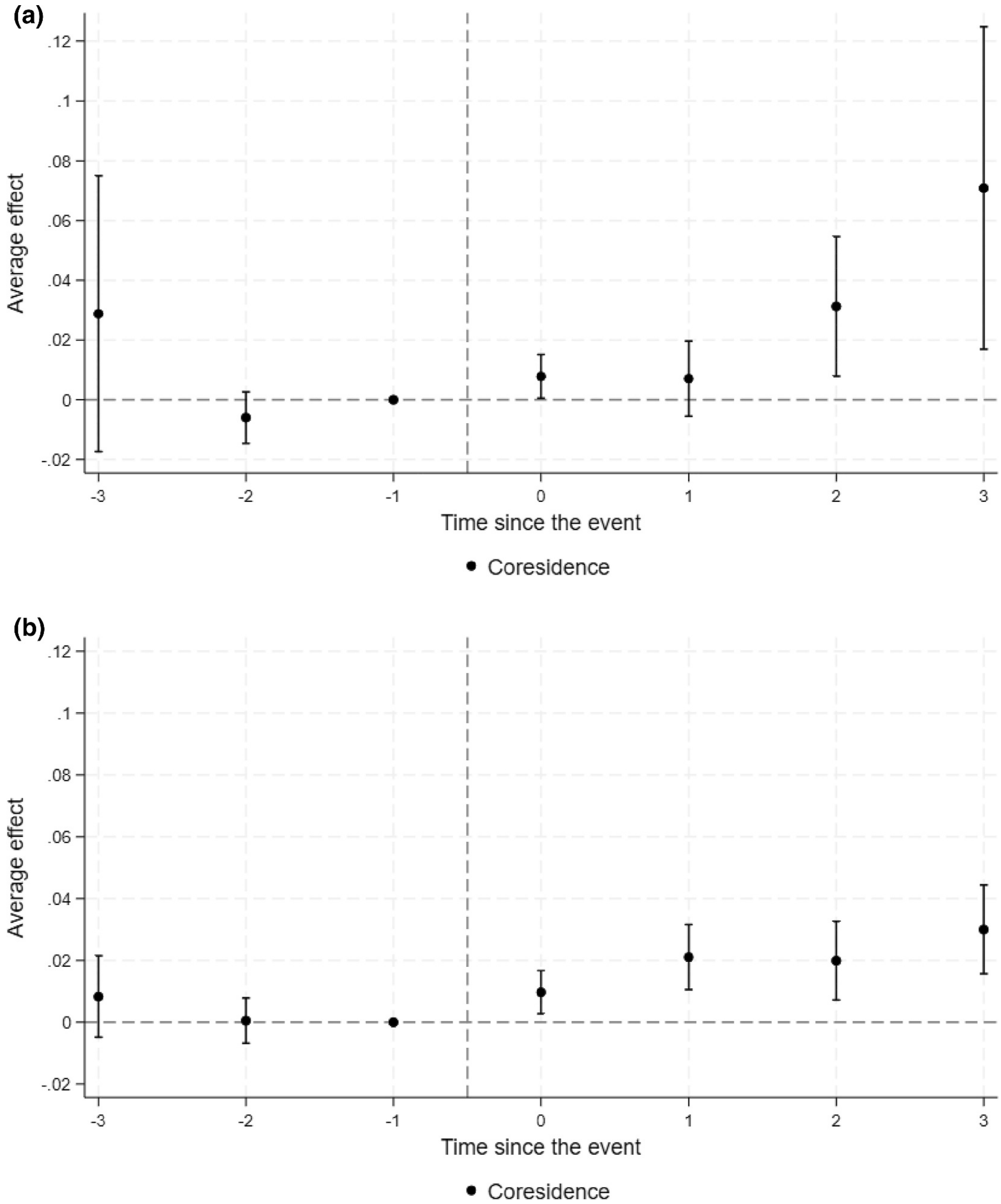

FIGURE 3 Effect of a health shock on co-residence with a child. Panel (a) Europe. Panel (b) United States. This figure displays treatment effects in the form of event-study plots constructed using the de Chaisemartin and d'Haultfoeuille (2024) estimator. This estimation is based on data at the household level. The time variable is the survey wave. The time zero corresponds to the first wave after the health shock and the reference wave (the last wave before the health shock) is −1. The bars represent 95 percent confidence interval. The outcome is a dummy variable equal to one if there is at least one child living in the same household.

Finally, because panel attrition might be a concern in a sample of older individuals affected by health shocks, we follow Schiele and Schmitz (2023) and estimate our models on a sample of individuals present for at least three consecutive waves in SHARE data and four waves in HRS data as a robustness test. Results are shown in the Appendix Figures B9 and B11 for Europe, B10 and B12 for the United States. Overall, the dynamics are highly in line with our baseline results. We conduct an additional analysis to evaluate to what extent attrition may bias our results. For each event-time *j*, we compute the percentage of observations that are treated used to compute the ATT at that date *j*. We use this statistic as a way to assess whether treated observations exit the sample at a faster rate than those in the control group. We can see in Figure B21 that the proportion is rather stable. This is quite reassuring in the sense that our results do not appear to be driven by attrition in the short run. A rather similar pattern is observed for post-treatment waves.

Nonetheless, we can see that the proportion is smaller for the pseudo-ATT in event-time −3. This clearly indicates that treated observations are observed for less periods than controls. We believe this is again in line with Table 1, in which we show that observations from SHARE are observed for fewer periods than those in HRS. Therefore, even if we cannot exclude the presence of some selective attrition, especially in the European sample, this analysis suggests that attrition should not strongly bias our results, reinforcing our confidence in our findings.

4.2.1 | Heterogeneity analyses

Next, we move to a heterogeneity analysis of our results. We present all estimates of the average effects in Figure 4.

First, as a way of comparison, we estimate our model of transition into a nursing home for a sample of individuals with no children. As expected, individuals with no children are more likely to move into a nursing home after a health shock than individuals with at least one child, in both Europe and the United States. This is an indication that having at least one child might operate as way to delay or avoid NH entry.

Second, we study the effect of the health shock on the probability of living in a nursing home and of co-residence by age of the respondent. Older and younger individuals are defined on the basis of the median age in the respective sample.[14] We observe a higher probability of moving into a nursing home after a health shock for older individuals, which is expected given their higher increase in limitations compared to younger individuals. In the US, the effect among the oldest individuals is around four times larger than for the youngest ones. We should note that, in Europe, we even do not detect a significant effect in the younger population. We also observe a higher probability of co-residing with a child for older individuals in the US, while the effect is similar across age groups in Europe.

Third, we study the effect of the health shock on the probability of living in a nursing home and of co-residence with a child, separately by household type (single or couple). On the one hand, the presence of a partner might reduce the need for external help (Byrne et al., 2009; Stern, 1995). This is not the case, however, if the individual hit by the health shock was the primary care-giver in the household. In Figure 4, we show that indeed single individuals are more likely to move into a nursing home after a health shock than individuals in a couple. Single individuals in Europe experience a 1.8 pps increase in the probability of living in a NH, while this number is about 0.3 pps for those in a couple. This difference, although large, does not seem statistically significant possibly due to lack of power. The difference is markedly larger in the US: those living in a couple experience a 4.2 pps increase in the probability of living in a NH, while singles a 1.7 pps increase. With respect to the probability of co-residing with a child, we observe a much less marked difference between singles and couples, but overall there is a slightly higher probability of co-residing with a child for couple households, possibly because single older individuals are more likely to move to a nursing home.

We next move to the characteristics of the children. First, we create two indicators measuring, respectively, whether the share of daughters among the households' children is above or below the median in the sample, and whether the household has any daughter. We observe a slightly lower probability of moving into a nursing home for households with no daughters. We do not observe large differences depending on the share of daughters. On the other hand, we observe that the probability of co-residing with a child is higher for households with many daughters, or any daughter in Europe. Interestingly, in the US we observe the opposite pattern: those with no daughters are more likely to co-reside with a child. One should note that, due to the imprecision of the estimates, our results on co-residency do not seem statistically different by group in spite of rather large difference in point estimates.

We can further leverage the richness of our data to construct an indicator measuring whether the proportion of children working full-time is above or below the median in the sample. Overall, when many children are working full-time, the probability of moving into a nursing home is slightly larger. The probability of co-residing with a child is slightly lower for European households with many children working full-time, but higher for American households with many children working full-time.

Finally, we study the heterogeneity by household's wealth.[15] Interestingly, in both Europe and the US, poorer individuals are more likely to move into a nursing home after a health shock, while richer individuals are more likely to start living with a child, even if in the latter case the difference between poorer and richer households is not large. Regarding nursing home, the difference is statistically significant only in the US. The heterogeneity in transition into nursing home might be explained by the greater capacity of wealthier households to modify their homes and maintain community residence (Diepstraten et al., 2020).

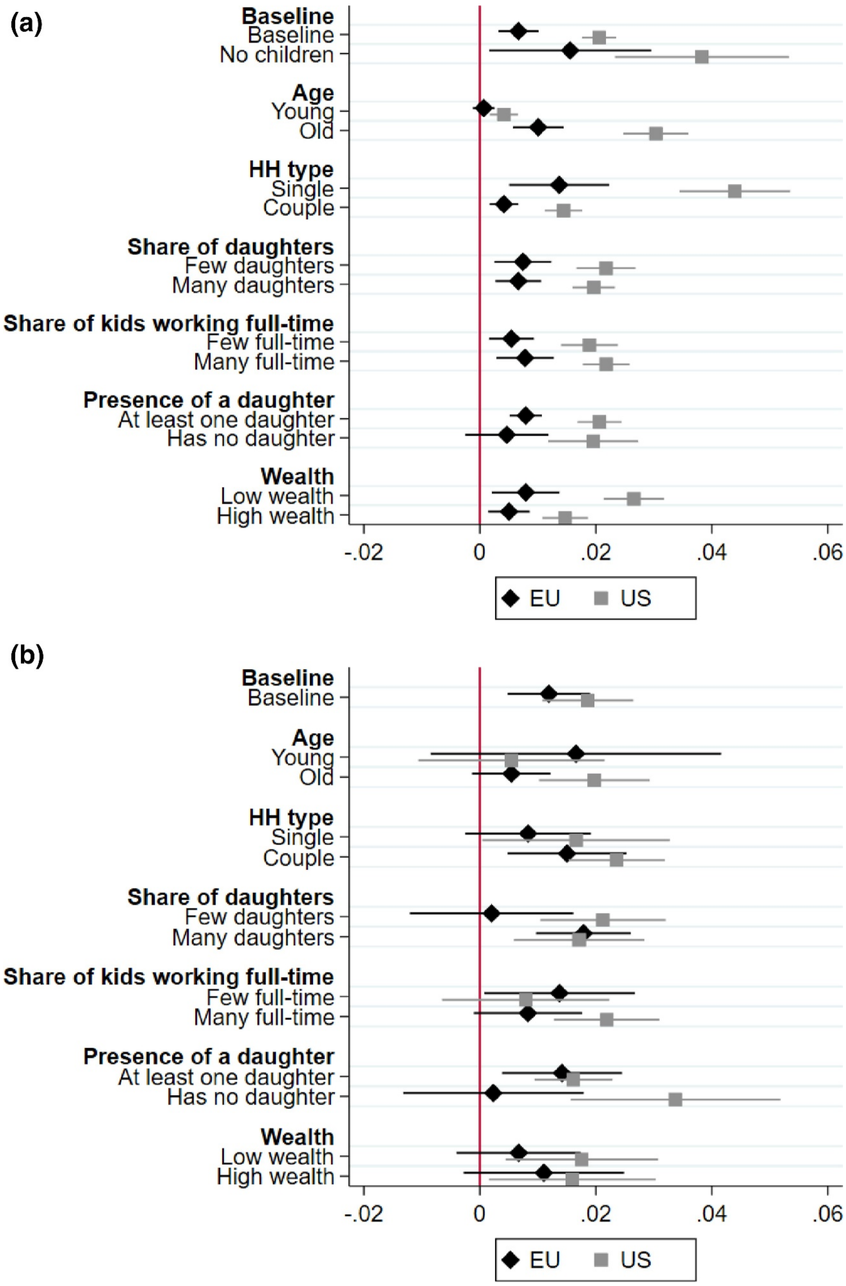

FIGURE 4 Heterogeneity analysis of living arrangements, by individual characteristics. Panel (a) Nursing home residency. Panel (b) Co-residence with a child. This figure displays average treatment effects over the post-treatment period, constructed using the de Chaisemartin and d'Haultfoeuille (2024) estimator. Panel A is based on individual-level data, and Panel B is based on household-level data. The bars represent 95 percent confidence interval. Outcome in Panel A is a dummy equal to one if the individual lives in a nursing home at the time of the survey. In Panel B, the outcome is a dummy variable equal to one if the there is at least one child living in the same household. Individuals are categorized as "Young" if their age at the time of the interview is below the sample median age, and as "Old" if their age is equal to or above the sample median age. Individuals are categorized as having "Few daughters" if the proportion of daughters among their children is less than 0.5, and as having "Many daughters" if the proportion of daughters is 0.5 or more. For the share of kids working full time, we define "Few full-time" if the proportion of children working full-time at the time of the respondent's first survey is below the sample median, and "Many full-time" if it is equal to or above the sample median. For wealth, individuals are classified as "Low wealth" if their household wealth is below the sample median at the time of the first survey, and as 'High wealth' if it is equal to or above the sample median.

4.3 | Heterogeneity by LTC expenditure

Finally, we investigate the geographic heterogeneity of our results within Europe and the United States. This will allow us to explore the potentially mitigating role of LTC policies on living arrangements.

4.3.1 | Europe

There are two points worth mentioning about Europe. First, there are large differences in the baseline probability of co-residence across European countries. As shown in Table A1, this probability is particularly high in Southern European countries (38%, vs. 15% in Northern Europe and 23% in central Europe). Second, there is high heterogeneity across countries in the generosity of LTC policies and in the availability and affordability of nursing homes.

We first follow Crespo and Mira (2014) by grouping countries in our sample into three groups, according to the availability and generosity of public formal care services and LTC benefits, measured as public expenditure on LTC as a percentage of GDP. The resulting grouping broadly corresponds to Northern countries (Netherlands, Denmark, Sweden), Central countries (Switzerland, France, Belgium, Germany, Austria, Czech Republic, Luxembourg), and Southern countries (Slovenia, Spain, Italy, Portugal, Estonia, Israel, Poland, Greece).

In Figure 5, we show the dynamics of the probability of transitioning into a nursing home for the three groups of countries. The pattern is consistent with the expected gradient according to the different levels of generosity of public formal care services and benefits. We estimate an average increase of 12 pps and 6 pps in Northern and Central Europe, respectively (see Table A4). We do not find any statistically significant effect in Southern Europe instead. Results in Figure 5 show larger dynamic effects in the Northern countries.

Results in Table A4 show that the average effect over the four waves on the probability of co-residing with a child (weighted by the number of individuals observed in each period) is 1.3 pps in Southern Europe, only slightly larger than in Northern Europe (1 pps), but considerably larger than in Central Europe (0.5 pps). Because the proportion of older individuals co-residing with a child is much larger in Southern Europe than in Northern countries, the percentage change is much larger in Northern Europe (3.4% vs. 6.8%). The percentage effect is the lowest in Central Europe (2.2%).

We should nonetheless bear in mind that these differences are also driven by cultural differences, and we cannot disentangle the effect of LTC benefits from the cultural norms that also influence living arrangements (Gentili et al., 2017). To tackle this issue, we also exploit within-country, regional disparities in the density of beds per hundred thousand residents within nursing and other LTC facilities. We obtain information on beds availability at the NUTS 2 level from Eurostat. These statistics are available only for a subset of countries and a finite set of years. For the countries with available data in any given year, we compute the mean number of beds across the provided years. Subsequently, we categorize countries based on the median of the mean number of beds to delineate groups with high and low bed availability. In Figure B19, we show, for the available regions, quartiles of the density of beds per hundred thousand residents (on the left), and the regions above and below the country median (on the right).

The event-study findings are illustrated in Figure 6. Once again, the results underscore the significance of resources allocated to LTC in determining nursing home access, as evidenced by its greater prevalence in regions with higher bed availability (Panel A). We also observe a significant effect on co-residence two waves after the health shock only in regions with low beds availability (Panel B). However, despite leveraging within-country variation in availability, observed disparities are rather small and not significant. Several explanations may account for this result. Firstly, it is plausible that the within-country variation is insufficient to yield statistically significant differences. Secondly, it is conceivable that individuals in need of LTC may relocate to regions offering greater bed availability. Finally, bed availability is just one component of the broader spectrum of LTC services.

4.3.2 | United States

We conduct an analysis of the heterogeneity of living arrangements across states with different access to LTC, mirroring our previous analysis conducted for Europe. Given the presumed minimal cultural disparities in family structures across different states within the United States, we anticipate that this investigation will provide valuable insights into the influence of LTC system generosity.

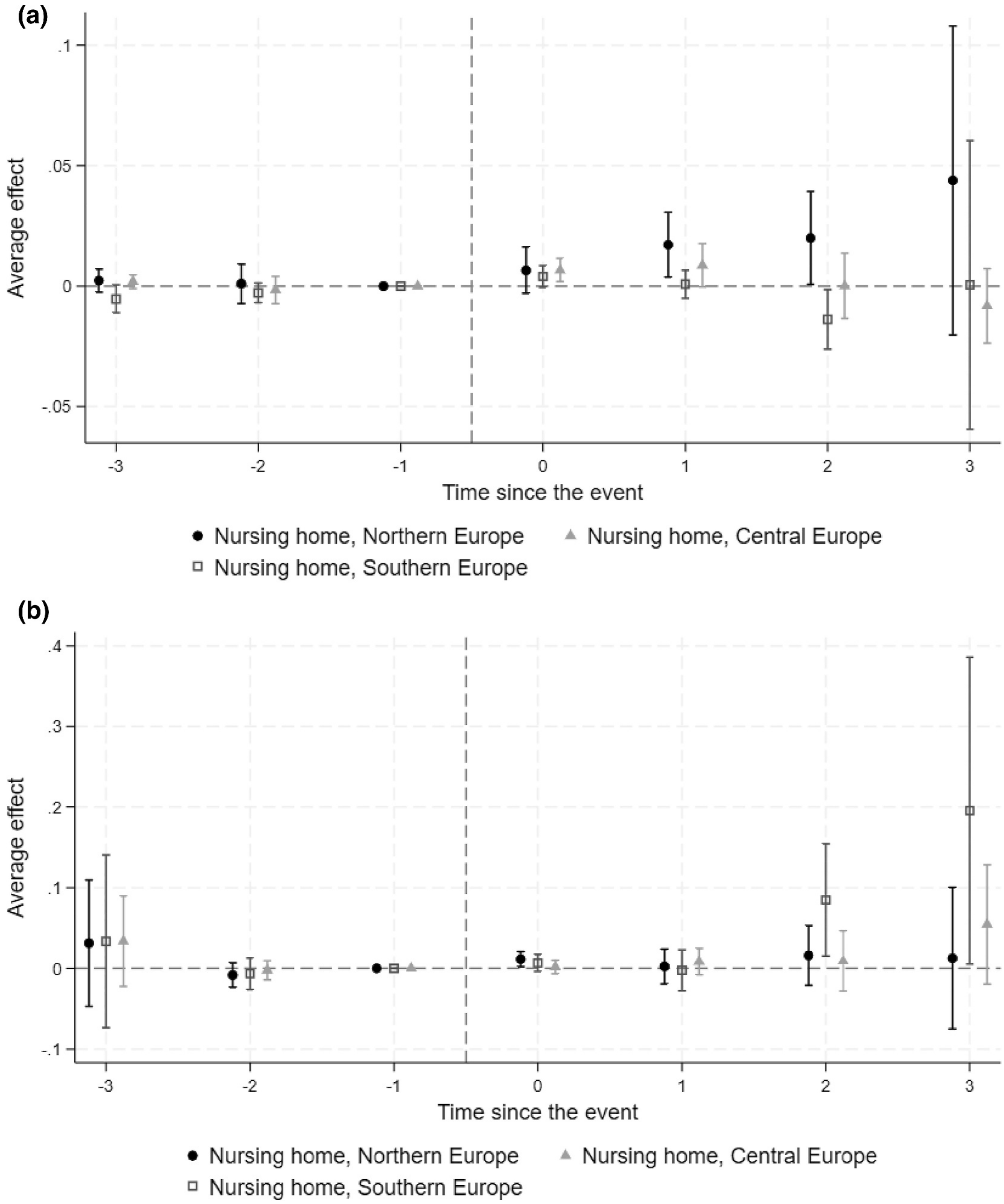

FIGURE 5 Effect of a health shock on living arrangements by public expenditure on long-term care (LTC) as a percentage of GDP in Europe. Panel (a) Nursing home residency. Panel (b) Co-residence with a child. This figure displays treatment effects by region of Europe in the form of event-study plots constructed using the de Chaisemartin and d'Haultfoeuille (2024) estimator. Panel (a) is based on individual-level data, and Panel (b) is based on household-level data. The time variable is the survey wave. Outcome in Panel (a) is a dummy equal to one if the individual lives in a nursing home at the time of the survey. In Panel (b) the outcome is a dummy variable equal to one if the there is at least one child living in the same household. The time zero corresponds to the first wave after the health shock and the reference wave (the last wave before the health shock) is −1. The bars represent 95 percent confidence interval.

For the United States, we exploit variation in state spending on Medicaid LTSS for older individuals. In particular, as in Mellgard et al. (2022), we calculate the LTSS annual expenditure per beneficiary as the state's total annual Medicaid LTSS spending divided by the number of beneficiaries older than 65. We use aggregated Medicaid LTSS Expenditure data to measure State LTSS annual expenditure.[16] Information on the number of beneficiaries aged 65 or older comes from the Medicaid Statistical Information System (MSIS).[17]

Because of data availability, we can construct a measure of LTSS annual expenditure per beneficiary older than 65 only for the years 1999–2010.[18] We then take the average expenditure over the available years, and finally split states

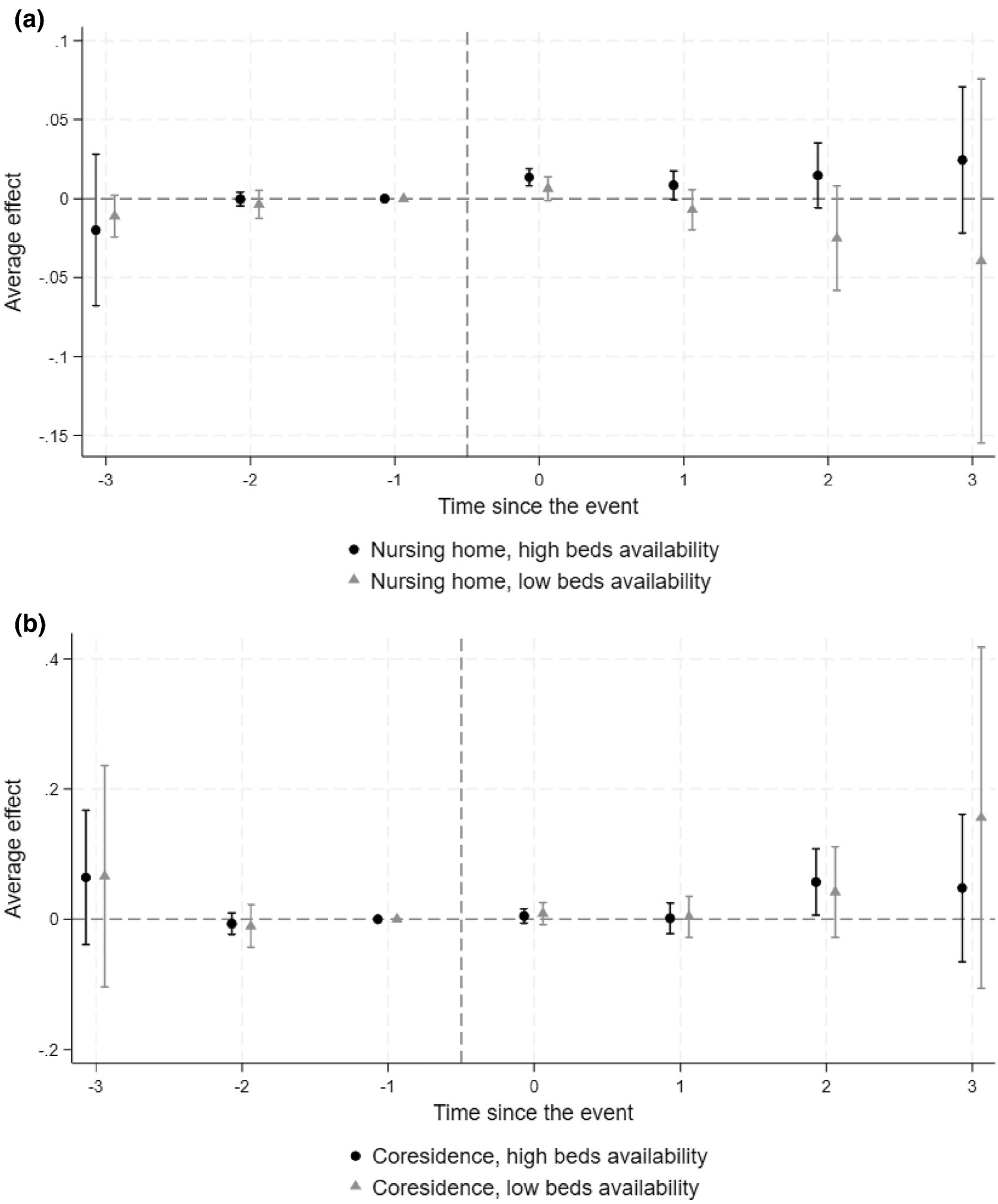

FIGURE 6 Effect of a health shock on living arrangements by density of beds in nursing homes. Panel (a) Nursing home residency. Panel (b) Co-residence with a child. This figure displays treatment effects in Europe by density of beds in nursing homes at the local level, in the form of event-study plots constructed using the de Chaisemartin and d'Haultfoeuille (2024) estimator. Panel (a) is based on individual-level data, and Panel (b) is based on household-level data. Outcome in Panel (a) is a dummy equal to one if the individual lives in a nursing home at the time of the survey. In Panel (b), the outcome is a dummy variable equal to one if the there is at least one child living in the same household. The time zero corresponds to the first wave after the health shock and the reference wave (the last wave before the health shock) is −1. The bars represent 95 percent confidence interval.

into those with median average expenditure above and below the median.[19] Finally, we are able to merge our index of LTSS relative expenditure to our sample using HRS restricted data information on the state of residence of respondents.[20] Figure B20 shows quartiles of Medicaid spending across US states (on the left), and states above and below the US median spending (on the right).

The event-study findings are depicted in Figure 7. These results underscore the significance of LTC expenditure in shaping both nursing home utilization and living arrangements. Notably, states with lower Medicaid spending on LTSS

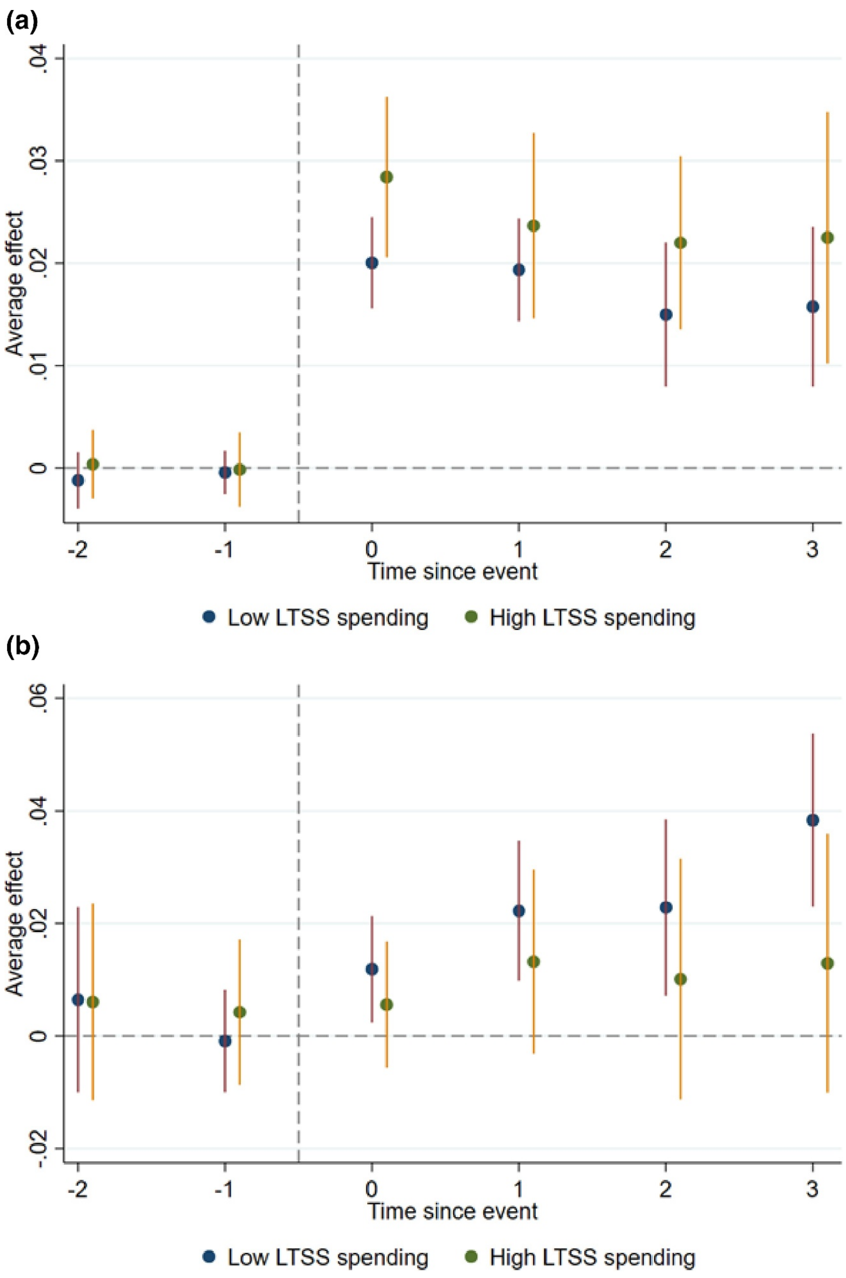

FIGURE 7 Effect of a health shock on living arrangements by per-beneficiary Medicaid spending for LTSS in the United States. Panel (a) Nursing home residency. Panel (b) Co-residence with a child. This figure displays treatment effects by region of US, by LTSS spending, in the form of event-study plots constructed using the de Chaisemartin and d'Haultfoeuille (2024) estimator. Panel (a) is based on individual-level data, and Panel (b) is based on household-level data. Outcome in Panel (a) is a dummy equal to one if the individual lives in a nursing home at the time of the survey. In Panel (b), the outcome is a dummy variable equal to one if the there is at least one child living in the same household. The time zero corresponds to the first wave after the health shock and the reference wave (the last wave before the health shock) is omitted. The bars represent 95 percent confidence interval. LTSS, long-term services and supports.

exhibit a lower increase in the likelihood of nursing home admission following a health shock. Conversely, in these states, there's a higher increase in the probability of co-residing with a child post-health shock.

Our findings on the heterogeneity of LTC systems in Europe and the US are consistent. They indicate a potential substitution between institutional care and co-residence with children, which is in line with Mommaerts (2018).

4.4 | Effect on children's employment

While the literature on this topic is extensive (see Bauer and Sousa-Poza (2015) and Moussa (2019)), most studies either overlook the endogenous nature of care-giving or address it using an IV approach. We contribute to this literature by employing a different identification strategy: an exogenous health shock of the parent. This event study approach offers several advantages over the commonly used IV strategies. First, identification relies solely on the assumption of parallel trends, which can be transparently assessed by visually inspecting pre-trends. Second, it provides a clear presentation of the dynamics of a parent's health shock on employment, a topic that is less explored in the existing literature. A similar identification strategy is used by a small number of recent studies. In the Netherlands, a country with one of the most generous LTC systems, Rellstab et al. (2020) don't find any effect of unexpected parental hospitalization on the children's labor supply. Maestas et al. (2023) study the employment patterns of family care-givers in the US over a long period, starting from when they begin care-giving, and find a negative effect on earnings and employment for women. The only other study exploiting health shocks that suddenly increase care dependency is Frimmel et al. (2020). The authors find for Austria a significant reduction of children's labor supply, but, due to data limitations, they can only observe relatively young individuals, and can follow them only for 3 years after the health shock.

We take advantage of the panel data at child level that is described in Section 3. We will conduct an analysis at the child level, using the same difference-in-differences and event study strategies used before, to estimate the consequences of health shocks on the children's labor supply.

We present our results on employment and work hours in Figure 8, for Europe and the US respectively. In Europe we do not observe any effect on employment, while in the US we observe a negative and statistically significant effect on employment, but limited to the first wave after the health shock. Indeed, we observe a 1% point decrease in the probability of employment in the first wave after the health shock in the US.

Regarding work hours, we find a negative and statistically significant effect on the probability of working full-time in Europe in the first wave after the health shock. In the US, this effect is more pronounced and persistent. The average effect is also statistically significant, and amounts to a reduction in full-time employment of about 1.5% relative to the sample mean.

Our results appear in line with the literature. First, as Schmitz and Westphal (2017), who study the dynamic effect of informal care-giving, we do not find a significant effect on the extensive margin of labor supply but a significant decrease in full-time work. In addition, also in line with the authors' findings, we find that effects start right after the parent's health shock. One difference in our results regard the persistence of the effects. Indeed, authors find lasting reduction on full-time in Germany, while we identify lasting effects only in the US. One should note that differences in the results with Schmitz and Westphal (2017) could also be explained by the use of different identification strategies, and the fact their study concerns the German population only. Our results also contrast with Rellstab et al. (2020) in the Netherlands, which is a country with a very generous LTC system that can offset the potentially negative effect of care-giving on labor supply.

Finally, in the Appendix we show the heterogeneity of these results by gender of the children (see Figures B13–B16). Results point to larger negative effects on the probability of employment for women in the US, and larger negative effects on the probability of working full-time for men in the US, showing up in the longer term. In Europe, we observe similar coefficient across genders, but considering that women are less likely to work, percentage effects on employment are larger for women.

Moreover, considering that men are less likely than women to work part-time, percentage effects are larger for men in both Europe and the US. Overall, women seem to respond more on the extensive margin, while men on the intensive one.

4.5 | Robustness by type of health shock

Gonçalves et al. (2023) find that after a stroke or heart attack, informal care-givers provide the daily support, whereas following a hip fracture, nursing home care is more important. In light of this, we investigate the robustness of our results to the type of health shock. Summary results can be found in Figures B17 and B18.

On the left panel of Figure B17, we show the estimated effect of each health shock on the average number of reported ADLs and IADLs. Having a hip fracture induces an increase of the same magnitude in both ADLs and IADLs limitations, and in both the US and Europe. Having a heart attack seems to induce the lowest increase in ADL and IADL limitations. With respect to having a stroke or a cancer, they both largely increase ADL limitations but have a much smaller effect on IADLs.

On the right panel of Figure B17, we present average estimated effects on living arrangements. We still observe the strongest effects on NH use in the US, especially for hip fractures and cancer. This is line with our result suggesting that these shocks induce the largest increase in limitations in the US. Note that this result is also in line with Gonçalves et al. (2023). The only health shock that does not lead to increased NH admissions is having a stroke. In Europe, on the other hand, only having a stroke or a hip fracture increases NH admissions. The observed differences between the US and Europe might be explained by differences in the medical treatment of these health shocks, or in the use of nursing

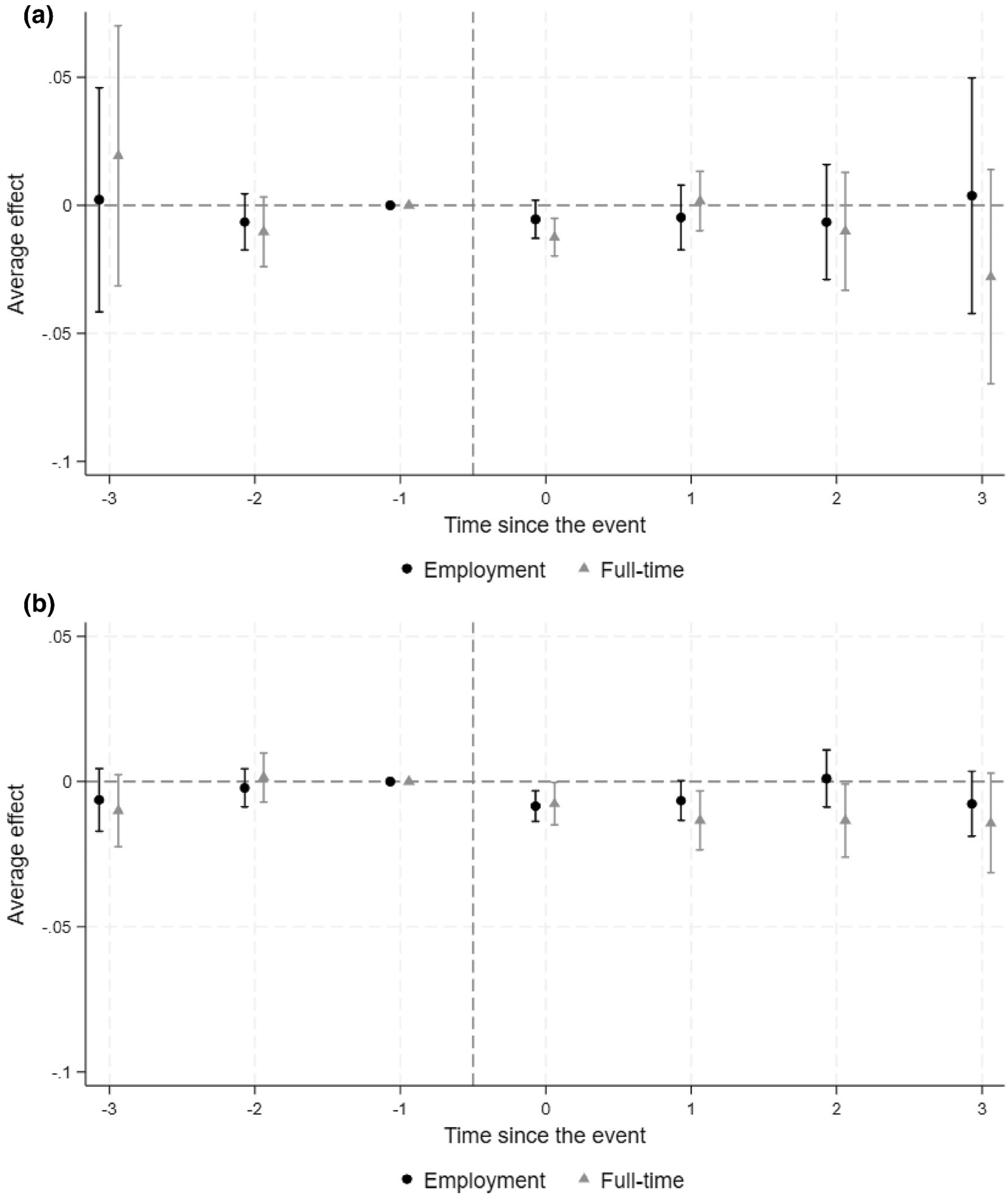

FIGURE 8 Effect of a health shock on children's employment. Panel (a) Europe. Panel (b) United States. This figure displays treatment effects in the form of event-study plots constructed using the de Chaisemartin and d'Haultfoeuille (2024) estimator. This estimation is based on children-level panel data. Outcomes are dummy variables indicating whether the child is employed (with respect to not employed) and whether the child works full-time (with respect to work part-time or not employed). The time zero corresponds to the first wave after the health shock and the reference wave (the last wave before the health shock) is −1. The bars represent 95 percent confidence interval.

home care, which is typically more permanent in Europe than in the US (Bergeot & Tenand, 2023; Bom et al., 2023). With respect to the probability of living with a child, we also detect a significant effect only in the US for hip fractures and cancer.

Results on children's labor outcomes are summarized in Figure B18. Regarding cancer, we find a significant reduction in the probability of working and working full-time in the US. This result is in line with our result that cancer has a strong effect on co-residency, which might reflect an increase in intensive care-giving from children. Having a stroke seems to decrease the children's probability of working in the US. This result is a little puzzling because we did not detect any significant effect of strokes on living arrangements. Finally, in Europe, a parent's heart attack decreases the probability of working full-time for children.

5 | CONCLUSIONS

Previous empirical evidence shows a positive cross-sectional correlation between health deterioration of older individuals and their likelihood of living with their children or being in a nursing home. In this study, we contribute to the literature by estimating the causal link between these variables and the dynamics of LTC living arrangements. Drawing data from Europe (SHARE) and the US (HRS), we first show that the onset of unpredictable health shocks trigger an increase in difficulties with ADL and IADL among middle-aged and older individuals, leading to an increase in their care needs. Then, we use an event-study difference-in-differences approach to explore the evolution of living arrangements even several years after the health shock. Finally, we apply the same methodology to analyze the impact of parents' health shocks on their children's employment status and work hours.

The results indicate that following a health shock, there is an increased likelihood of transitioning into a nursing home or co-residing with a child in both Europe and the US. However, the effects vary across different groups, with some differences observed between the US and Europe. Specifically, we observe that older individuals, those without children, singles, and individuals with lower wealth are more likely to transition into nursing homes after a health shock in both Europe and the US. Although the magnitudes of these effects differ between Europe and the US, the overall patterns of heterogeneous effects remain similar. Regarding co-residence with children, we find a larger effect for couples than singles in Europe and US. Age and household wealth also play significant roles in co-residence patterns: older and wealthier individuals in the US are more likely to co-reside with their children after a health shock, while the opposite is true in Europe.

Furthermore, the gender composition of children does not strongly influence transitions into nursing homes. However, in the US, the absence of daughters is associated with a higher likelihood of co-residence, whereas the opposite is observed in Europe.

Finally, differences in the availability and generosity of public formal care services and LTC benefits contribute to heterogeneous effects. In Europe, Northern countries with higher availability and generosity show larger dynamic effects on transitioning to nursing homes compared to Central and Southern countries. In the US, states with higher Medicaid spending on LTSS exhibit a greater increase in the likelihood of nursing home admission following a health shock. Conversely, a higher probability of co-residence is observed in countries and states with lower levels of LTC generosity.

For the impact of health shocks on care-givers, overall, we observe a decline in children's employment following parent's health shock. In Europe, we observe no significant effect on children's employment status. However, in the US, we find a statistically significant negative effect on employment, limited to the first wave following the health shock. Additionally, at the intensive margins, we note a negative and statistically significant effect on the likelihood of working full-time in Europe during the initial wave after a parent's health shock, with a more persistent effect observed in the US.

We contribute to the literature by studying how families respond to sudden increases in older individuals' care needs, focusing on changes in household living arrangements and the employment of care-givers. Different from existing literature, we exploit an arguably exogenous event and employ a difference-in-differences event study strategy. This approach offers distinct advantages over previously used empirical strategies, allowing us to investigate the dynamics of living arrangements following a health shock.

We conclude arguing that changes in care needs have a causal effect on LTC arrangements and children's employment, and that families adjust relatively fast, as most effects are observed soon after the shock. We also emphasize that LTC systems play a significant role because individuals tend to opt more often for institutions than for co-residence with their children. This can be interpreted as a sign that, despite older individuals may prefer to live in the community (Nieboer et al., 2010), they would prefer to not rely on their children when they have a sudden strong increase in their care needs (Cahill et al., 2009). Finally, given the heterogeneity we find across countries, the role of culture is also important in explaining how families respond to the health shock, which is in line with previous research (Gentili et al., 2017).

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CONFLICT OF INTEREST STATEMENT

All authors declare that they have no conflicts of interest.

DATA AVAILABILITY STATEMENT

SHARE data are openly available and can be accessed, after filling in a user statement, from the following website: https://share-eric.eu/data/data-access. HRS data are openly available and can be accessed after registation from the following website: https://hrsdata.isr.umich.edu/data-products/public-survey-data. HRS data on geograpghic information are restricted and can be accessed through a virtual desktop infrastructure (VDI) system after successful application (https://hrs.isr.umich.edu/data-products/restricted-data/vdi).

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ENDNOTES

[1] In addition, in the US, informal care provided by children appears to delay nursing home entry (Charles & Sevak, 2005; Newman et al., 1990; Sasso & Johnson, 2002; Van Houtven & Norton, 2004).

[2] Any negative link between care-giving and work can be explained in two main ways. Firstly, providing care takes up a significant amount of time, making it challenging to balance with a regular job. Care-givers might need to cut down on their work hours or even resign from their positions to ensure the person in need receives adequate care. Secondly, individuals who are either unemployed or work part-time tend to have more available time, making them more likely to take on care-giving responsibilities. As stressed by Michaud et al. (2010), these two causal pathways can also coexist.

[3] Exceptions are Rellstab et al. (2020), Maestas et al. (2023) and Frimmel et al. (2020).

[4] Due to data limitations, we are unable to include additional leads in the European sample. However, the US data does not have these limitations, allowing us to conduct robustness checks on the US sample with the inclusion of four leads (see Appendix).

[5] Specifically, children have an ID that allows us to identify them within one wave, but the ID of each child is not necessarily the same across waves.

[6] The target population for the original HRS cohort includes all adults in the contiguous United States born during the years 1931–1941 who reside in households, with a 2:1 oversample of African-American and Hispanic populations. The original sample is refreshed with new birth cohorts (51–56 years of age) every six years. The sample has been expanded over the years to include a broader range of birth cohorts as well. The target population for the AHEAD survey consists of United States household residents who were born in 1923 or earlier. Children of the Depression (CODA) recruits households born 1924–1930, War Babies 1942-47, Early Boomers 1948-53, and Mid-Boomers 1954-59.

[7] The files are longitudinal files that link HRS child families within wave and link HRS children across waves, available either at a respondent-child observation level, or at the respondent level, with summary variables about the respondent's children.

[8] We use a household-level sample for these latter outcomes because they are defined at this level. Including an observation for each individual in the analysis would disproportionately weight households with two spouses, effectively counting them twice compared to single-person households. We believe this could bias our analysis, particularly since we observe heterogeneous effects depending on whether the household consists of a single individual or a couple.

[9] Respondents in HRS are asked about hip fractures only if they are older than 65 years.

[10] We obtain this information from OECD (2020).

[11] One potential solution could be to follow Banks et al. (2023), who suggest a re-weighting procedure to account for this under-representation in England when using ELSA. We did not implement this procedure in our sample because it requires having data on NH residents for all SHARE countries and for the age-range we consider. Unfortunately this proved to be rather difficult.

[12] The questions on received help slightly differ across the surveys. In HRS, individuals reporting any limitation are asked whether they received any help and from whom (inside or outside the household). In SHARE, respondents are asked if they received any help from at least one person from outside the household in the last 12 months, and if they reported any limitation they are asked if they received any help from people inside the household in the last 12 months.

[13] Notice that, because we lose observations as the number of lags increases, further lags are given a relatively smaller weight.

[14] In the sample where the unit of analysis is the household, we define age as the age of the older member in the couple.

[15] Given that wealth might be endogenous to the health shock, we use wealth measured in the first observed wave of each panel.

[16] Data comes from reports including Medicaid expenditures for all LTSS, including institutional services and Home- and Community-Based Services, by service category and state (Medicaid, 2024).

[17] Data are obtained from tables publicly provided by the "Centers for Medicare and Medicaid Services", containing high-level aggregated statistics relating to Medicaid eligibility and claims, by US state (Centers for Medicare and Medicaid Services, 2024).

[18] Data on Medicaid beneficiaries cover all states only from 1999 to 2010.

[19] Expenditure data are CPI adjusted.

[20] Specifically, information on state of residence comes from the "Cross-Wave Geographic Information (State) [1992–2020] (v9.0, Early)" dataset.

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APPENDICES

A | Additional tables

TABLE A1 Descriptive statistics by public expenditure on LTC as a percentage of GDP, Europe.

	Northern Europe			Central Europe			Southern Europe		
	Mean	Std.dev.	Obs	Mean	Std.dev.	Obs	Mean	Std.dev.	Obs
Panel A: Pooled individual data over waves									
Lives in a NH	0.009	0.094	50719	0.008	0.089	128762	0.003	0.056	106946
Has temporarily lived in a NH	0.005	0.071	50223	0.004	0.065	127429	0.004	0.061	106411
Panel B: Pooled household data over waves									
Co-reside with a child	0.148	0.355	19428	0.230	0.421	49207	0.381	0.486	38812

Note: Data sources are SHARE for Europe, HRS for the US.

TABLE A2 Descriptive statistics by per-beneficiary Medicaid spending for LTSS, United States.

	Low LTSS spending			High LTSS spending		
	Mean	Std.dev.	Obs.	Mean	Std.dev.	Obs.
Panel A: Pooled individual data over waves						
Lives in a NH	0.014	0.117	136080	0.018	0.132	64919
Has temporarily lived in a NH	0.028	0.166	151996	0.037	0.189	74014
Panel B: Pooled household data over waves						
Co-reside with a child	0.309	0.462	103182	0.284	0.451	49865

Note: Data sources are SHARE for Europe, HRS for the US.

TABLE A3 Descriptive statistics by marital status.

	Europe			US		
	Mean	Std.dev.	Obs	Mean	Std.dev.	Obs
Single: Lives in a NH	0.014	0.117	79552	0.029	0.168	86229
Couple: Lives in a NH	0.003	0.058	206875	0.012	0.110	251614
Single: Has temporarily lived in a NH last 12 months	0.007	0.084	78397	0.051	0.219	97423
Couple: Has temporarily lived in a NH last 12 months	0.003	0.056	205666	0.028	0.164	282104
Single: Co-reside with a child	0.203	0.403	77903	0.317	0.465	97824
Couple: Co-reside with a child	0.293	0.455	204438	0.287	0.452	282891

Note: Data sources are SHARE for Europe, HRS for the US.

TABLE A4 Estimated average effects, Europe.

	Average	SE	CI LB	CI UB	*N*
ADL	0.277	0.014	0.249	0.305	155368
iADL	0.418	0.019	0.380	0.455	155368
Co-residence	0.014	0.004	0.006	0.022	85434
Nursing home	0.007	0.002	0.003	0.010	155368
Co-residence, single	0.011	0.007	−0.004	0.025	32272
Nursing home, single	0.014	0.005	0.004	0.023	35611
Co-residence, couple	0.017	0.006	0.005	0.029	52938
Nursing home, couple	0.004	0.002	0.001	0.007	119757
Co-residence, NE	0.010	0.007	−0.004	0.023	29458
Nursing home, NE	0.012	0.004	0.004	0.021	29689
Co-residence, CE	0.005	0.005	−0.004	0.015	74699
Nursing home, CE	0.006	0.003	0.001	0.011	75635
Co-residence, SE	0.013	0.008	−0.003	0.028	48986
Nursing home, SE	0.002	0.003	−0.003	0.007	50044
Co-residence, high nb beds	0.014	0.012	−0.009	0.037	15062
Co-residence, low nb beds	0.006	0.008	−0.010	0.022	24825
Ever NH, high nb beds	0.012	0.005	0.003	0.003	27705
Ever NH, low nb beds	0.007	0.003	0.001	0.013	27705
NH, high nb beds	0.002	0.002	−0.002	0.006	27869
NH, low nb beds	0.001	0.002	−0.004	0.005	27869
Co-residence with other relatives	0.016	0.006	0.005	0.028	86650
Co-residence with nonrelatives	0.002	0.002	−0.001	0.005	86650

Note: This table reports estimated average treatment effects over the post-treatment periods based on de Chaisemartin and d'Haultfoeuille (2024) estimator. Data source is SHARE. In the list of outcomes, ADL and iADL stand for the number of ADL and IADL limitations the individual has, respectively. Nursing home is a dummy equal to one if the individual lives in a nursing home. Co-residence is a dummy equal to one if at least child lives in the same household at the time of the survey. NE stands for Northern Europe, CE for Central Europe and SE Southern Europe. Co-residence with other relatives is a dummy equal to one if there is a relative other than a child that lives in the same household. Co-residence with non-relatives is a dummy equal to one if there is an individual that is not a family member that lives in the same household.

TABLE A5 Estimated average effects, United States.

	Average	SE	CI LB	CI UB	*N*
ADL	0.222	0.009	0.204	0.240	402269
iADL	0.241	0.010	0.222	0.260	374118
Co-residence	0.018	0.004	0.010	0.026	254144
Nursing home	0.021	0.002	0.017	0.024	360293
Co-residence, single	0.017	0.009	0.000	0.034	80802
Nursing home, single	0.044	0.006	0.033	0.055	73181
Co-residence, couple	0.024	0.005	0.014	0.034	167298
Nursing home, couple	0.014	0.001	0.012	0.017	287112
Nursing home, low LTSS spending	0.018	0.002	0.014	0.022	239055
Co-residence, low LTSS spending	0.022	0.005	0.012	0.032	167880
Nursing home, high LTSS spending	0.025	0.003	0.018	0.032	113510
Co-residence, high LTSS spending	0.010	0.007	−0.003	0.023	80344
Co-residence with other relatives	0.011	0.006	−0.002	0.023	235050
Co-residence with nonrelatives	0.000	0.002	−0.004	0.005	235050

Note: This table reports estimated average treatment effects over the post-treatment periods based on de Chaisemartin and d'Haultfoeuille (2024) estimator. Data source is HRS for the United States. In the list of outcomes, ADL and iADL stand for the number of ADL and IADL limitations the individual has, respectively. Nursing home is a dummy equal to one if the individual lives in a nursing home. Co-residence is dummy equal to one if at least child lives in the same household at the time of the survey. NE stands for Northern Europe, CE for Central Europe and SE Southern Europe. Co-residence with other relatives is a dummy equal to one if there is a relative other than a child that lives in the same household. Co-residence with non-relatives is a dummy equal to one if there is an individual that is not a family member that lives in the same household.

B | Additional graphs

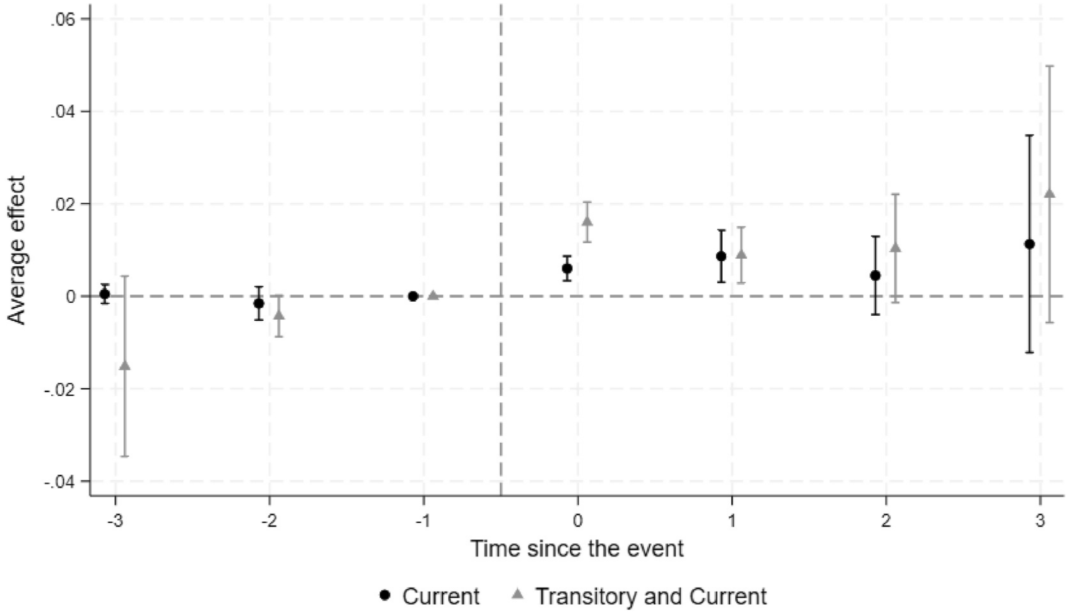


FIGURE B1 Robustness of estimated treatment effects by nursing home use in Europe. This figure displays treatment effects in the form of event-study plots constructed using the de Chaisemartin and d'Haultfoeuille (2024) estimator. This estimation is based on data at the individual level. Outcome for "Current" is a dummy variable indicating whether the individual is living in a nursing home at the time of the survey. The outcome for "Transitory and Current" is a dummy equal to one if the individual lives in a nursing home at the survey or has been temporarily living in a nursing since the last interview. The time zero corresponds to the first wave after the health shock and the reference wave (the last wave before the health shock) is -1. Data source is SHARE, using a sample of individuals with a least one child.

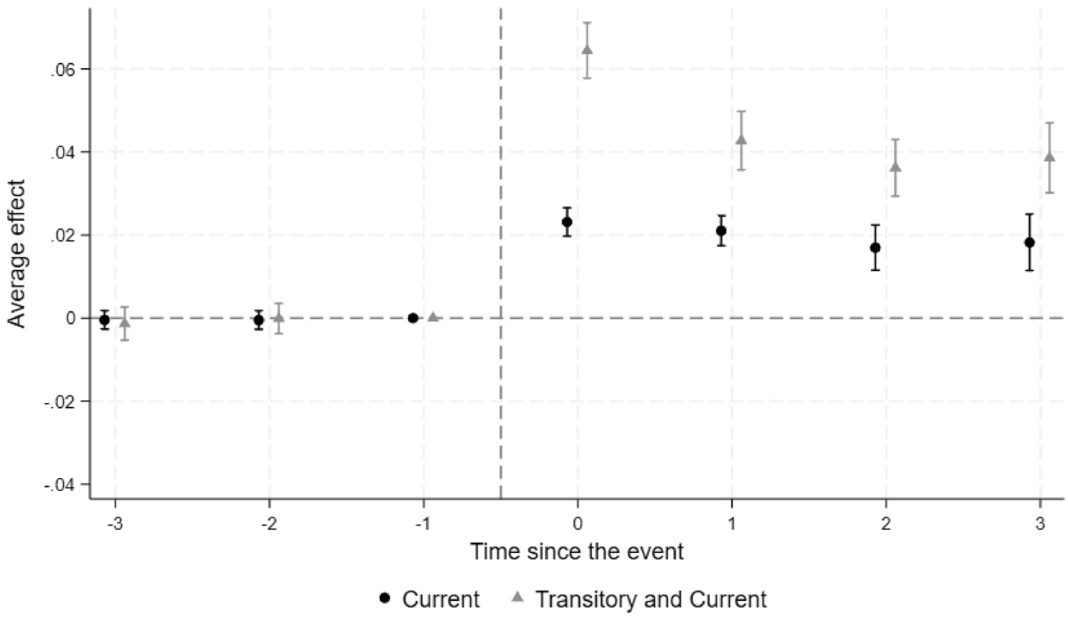


FIGURE B2 Robustness of estimated treatment effects by nursing home use in Unites States. This figure displays treatment effects in the form of event-study plots constructed using the de Chaisemartin and d'Haultfoeuille (2024) estimator. This estimation is based on data at the individual level. Outcome for 'Current' is a dummy variable indicating whether the individual is living in a nursing home at the time of the survey. The outcome for "Transitory and Current" is a dummy equal to one if the individual lives in a nursing home at the survey or has been temporarily living in a nursing since the last interview. The time zero corresponds to the first wave after the health shock and the reference wave (the last wave before the health shock) is -1. Data source is HRS, using a sample of individuals with a least one child.

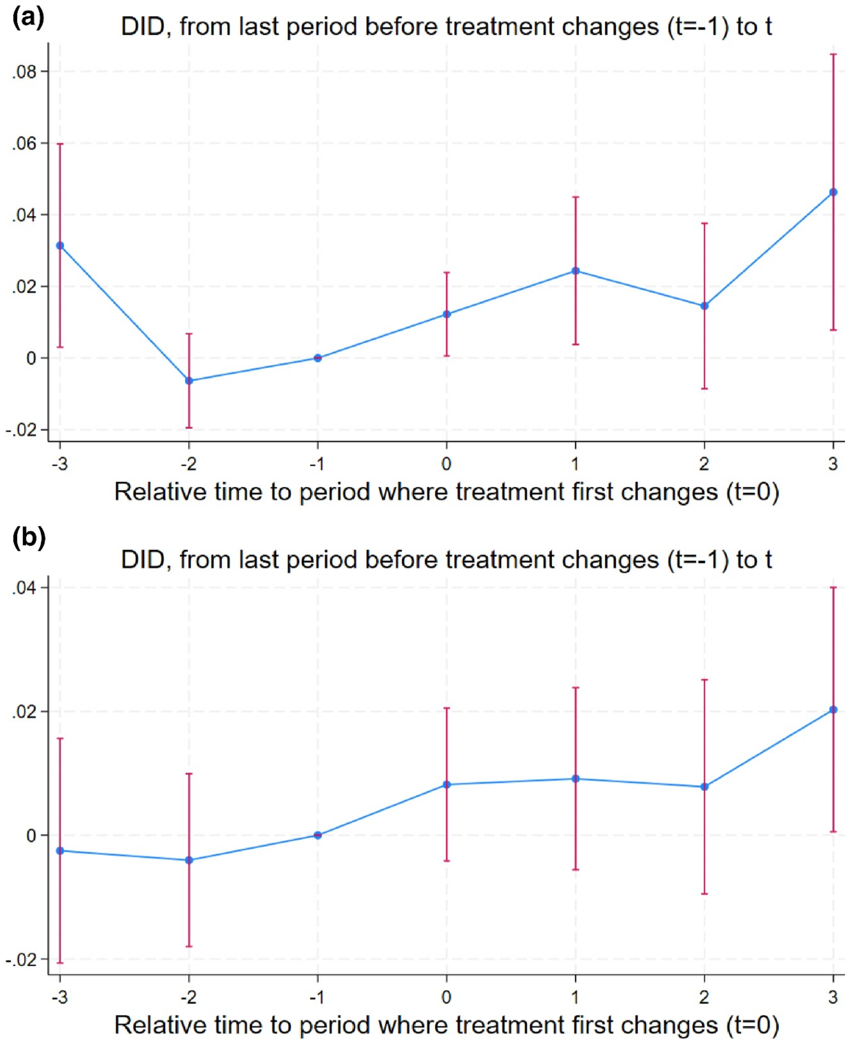


FIGURE B3 Effect of a health shock on coresidence with other relatives. Panel (a): Europe. Panel (b): United States. This figure displays treatment effects in the form of event-study plots constructed using the de Chaisemartin and d'Haultfoeuille (2024) estimator. Outcome is a dummy variable equal to one if there is individual that is a relative other than a child living in the same household at the time of the survey. The time zero corresponds to the first wave after the health shock and the reference wave (the last wave before the health shock) is -1. Data source is HRS in the US and SHARE in Europe, using a sample of households with a least one child. This estimation is based on data at the household level.

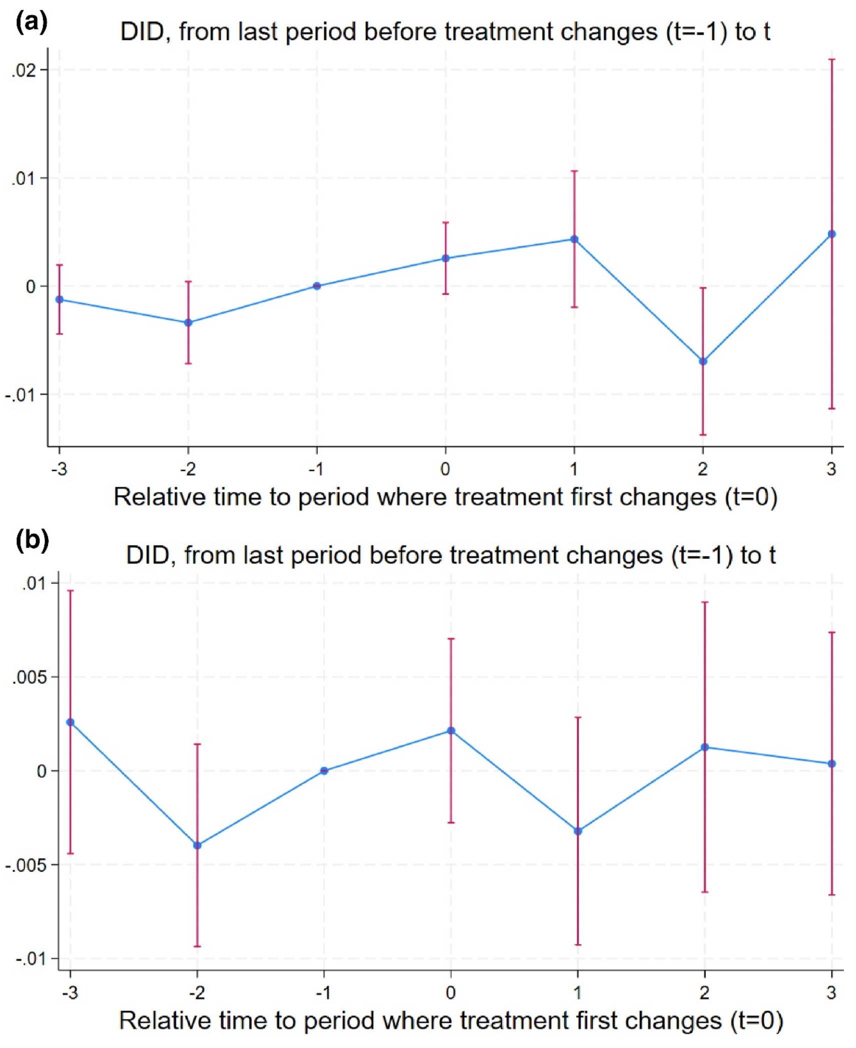


FIGURE B4 Effect of a health shock on co-residence with non-relatives. Panel (a): Europe. Panel (b): United States. This figure displays treatment effects in the form of event-study plots constructed using the de Chaisemartin and d'Haultfoeuille (2024) estimator. Outcome is a dummy variable equal to one if there is individual that is not a family member living in the same household at the time of the survey. The time zero corresponds to the first wave after the health shock and the reference wave (the last wave before the health shock) is -1. Data source is HRS in the US and SHARE in Europe, using a sample of households with a least one child. This estimation is based on data at the household level.

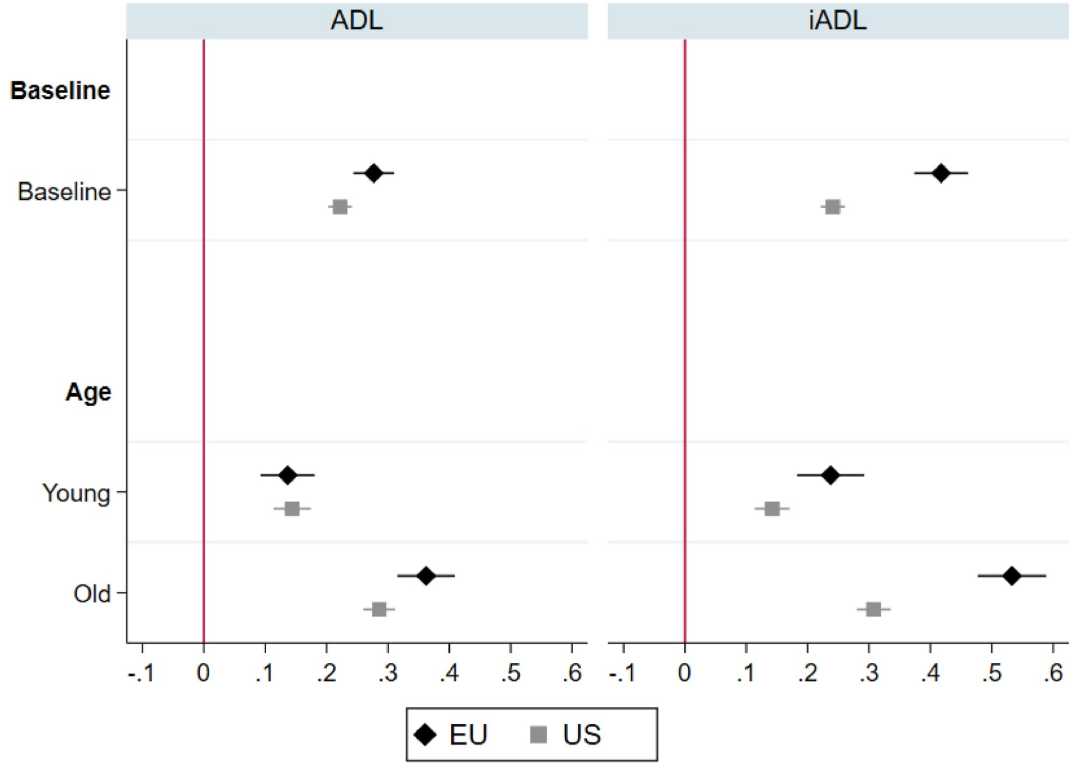


FIGURE B5 Heterogeneity analysis on the number of ADL and IADL limitations, by region and age. This figure displays average treatment effects over the post-treatment period, constructed using the de Chaisemartin and d'Haultfoeuille (2024) estimator. This estimation is based on data at the individual level. The bars represent 95 percent confidence interval. Data sources are SHARE for Europe, HRS for the US. Outcomes are the number of ADL and IADL limitations the individual has at the time of the survey. Individuals are categorized as "Young" if their age at the time of the interview is below the sample median age, and as "Old" if their age is equal to or above the sample median age.

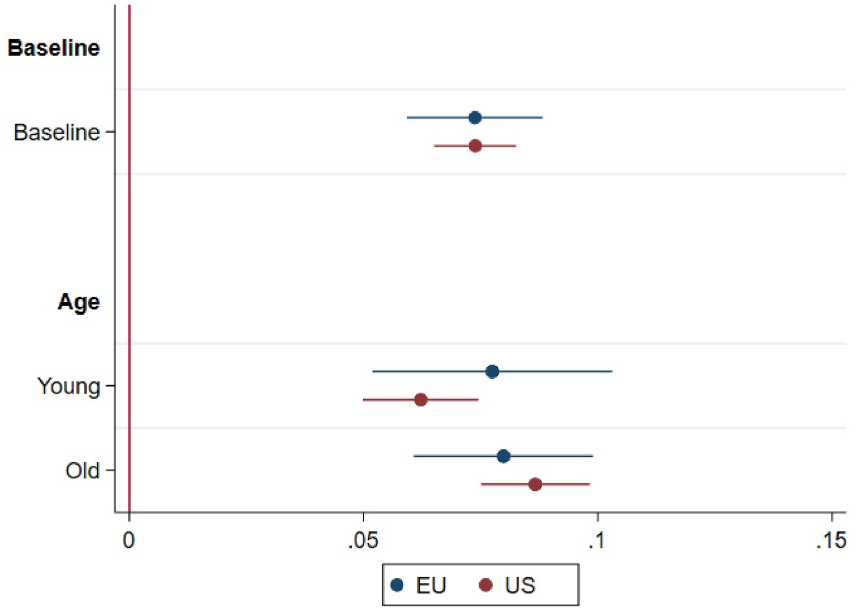


FIGURE B6 Heterogeneity analysis on the probability of receiving care, by region and age. This figure displays average treatment effects over the post-treatment period, constructed using the de Chaisemartin and d'Haultfoeuille (2024) estimator. This estimation is based on data at the individual level. The bars represent 95 percent confidence interval. Data sources are SHARE for Europe, HRS for the US. Outcome is a dummy variable equal to one if the individual receives either informal or formal care at the time of the survey. Individuals are categorized as "Young" if their age at the time of the survey is below the sample median age, and as 'Old' if their age is equal to or above the sample median age.

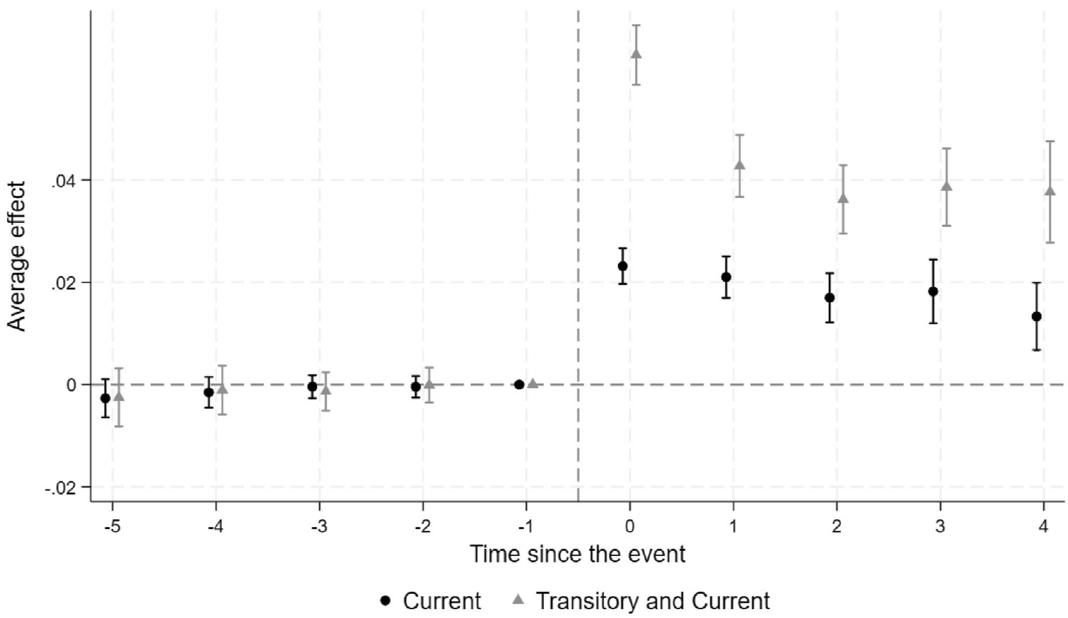


FIGURE B7 Robustness. Effect of a health shock on nursing home residency in the United States with more leads and lags. This figure displays treatment effects in the form of event-study plots constructed using the de Chaisemartin and d'Haultfoeuille (2024) estimator. This estimation is based on data at the individual level. Outcome for 'Current' is a dummy variable indicating whether the individual is living in a nursing home at the time of the survey. The outcome for "Transitory and Current" is a dummy equal to one if the individual lives in a nursing home at the survey or has been temporarily living in a nursing since the last interview. The time zero corresponds to the first wave after the health shock and the reference wave (the last wave before the health shock) is -1. Data source is HRS, using a sample of individuals with a least one child.

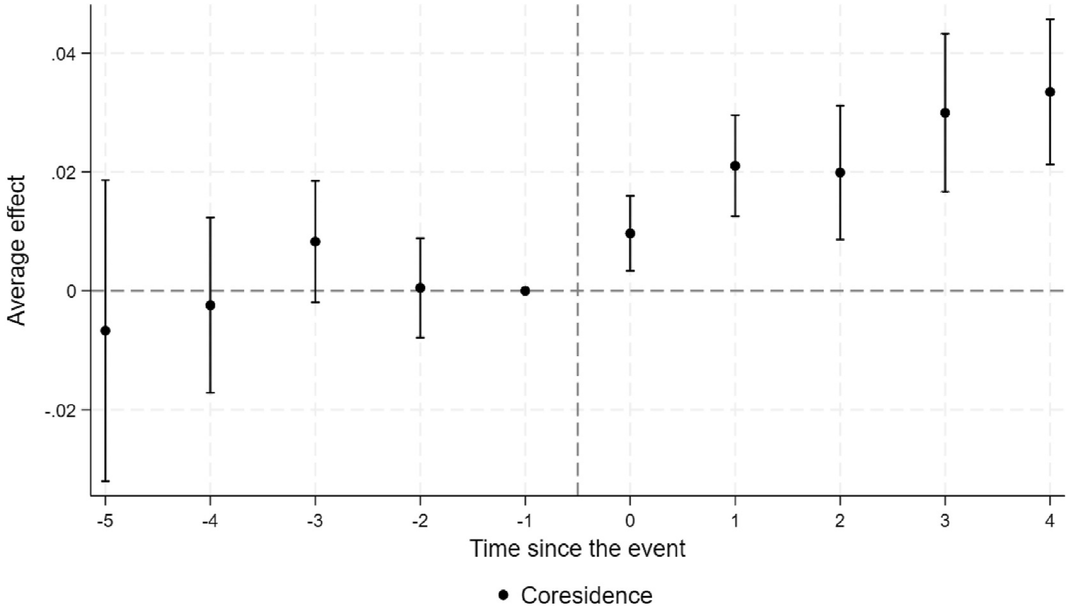


FIGURE B8 Robustness. Effect of a health shock on co-residence with a child in the United States with more leads and lags. This figure displays treatment effects in the form of event-study plots constructed using the de Chaisemartin and d'Haultfoeuille (2024) estimator. This estimation is based on data at the household level. The bars represent 95 percent confidence interval. Outcome is a dummy variable equal to one if at least one child lives in the same household at the time of the survey. Sample is composed of observations present in at least three consecutive waves. Data sources is HRS.

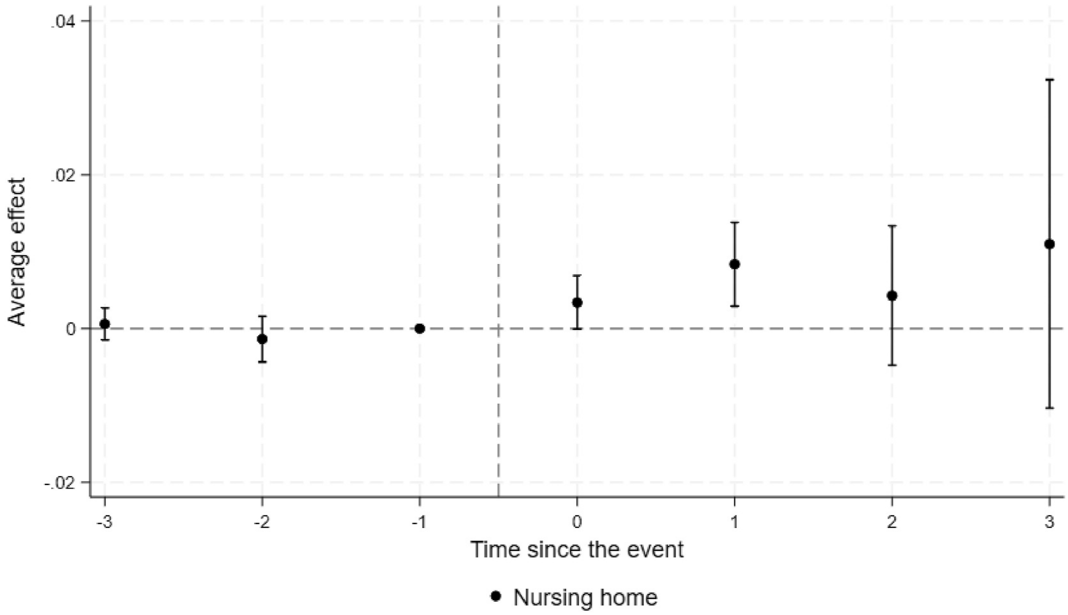


FIGURE B9 Robustness. Effect of a health shock on nursing home residency in Europe with a balanced panel. This figure displays treatment effects in the form of event-study plots constructed using the de Chaisemartin and d'Haultfoeuille (2024) estimator. This estimation is based on data at the individual level. The bars represent 95 percent confidence interval. Outcome is a dummy variable equal to one if the individual lives in a nursing home at the time of the survey. Sample is composed of observations present in at least three consecutive waves. Data sources is SHARE.

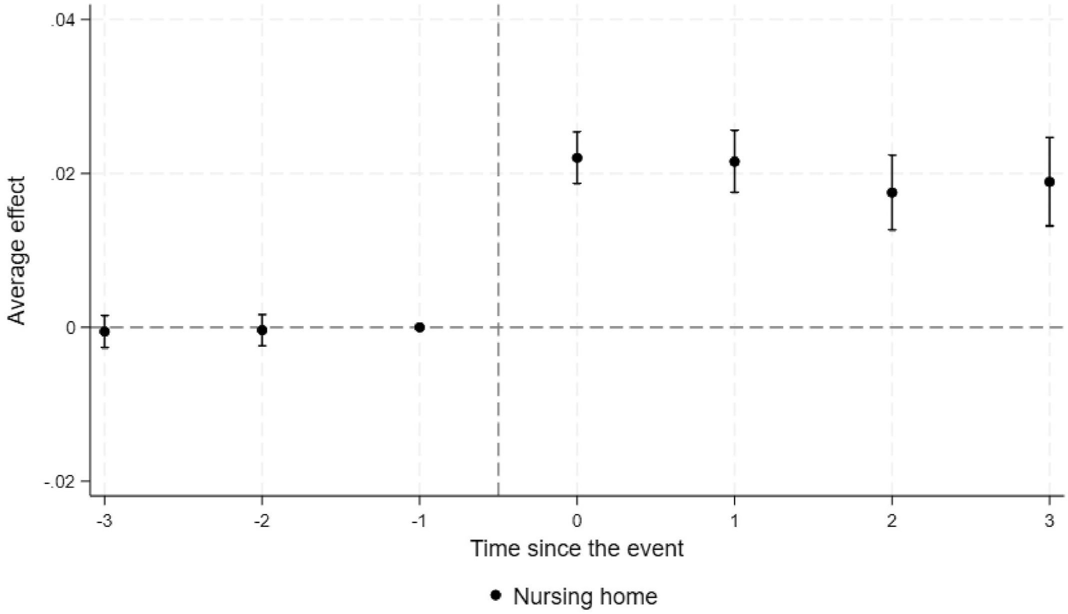


FIGURE B10 Robustness. Effect of a health shock on nursing home residency in the United States with a balanced panel. This figure displays treatment effects in the form of event-study plots constructed using the de Chaisemartin and d'Haultfoeuille (2024) estimator. This estimation is based on data at the individual level. The bars represent 95 percent confidence interval. Outcome is a dummy variable equal to one if the individual lives in a nursing home at the time of the survey. Sample is composed of observations present in at least three consecutive waves. Data sources is HRS.

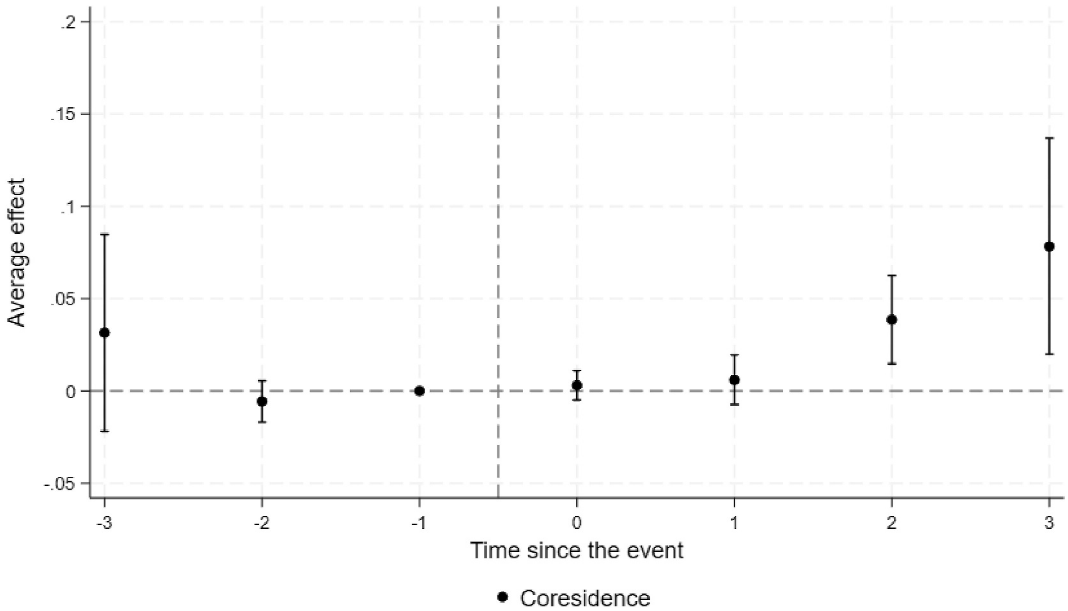


FIGURE B11 Robustness. Effect of a health shock on co-residence with a child in Europe with a balanced panel. This figure displays treatment effects in the form of event-study plots constructed using the de Chaisemartin and d'Haultfoeuille (2024) estimator. This estimation is based on data at the household level. The bars represent 95 percent confidence interval. Outcome is a dummy variable equal to one if at least one child lives in the same household at the time of the survey. Sample is composed of observations present in at least three consecutive waves. Data sources is SHARE.

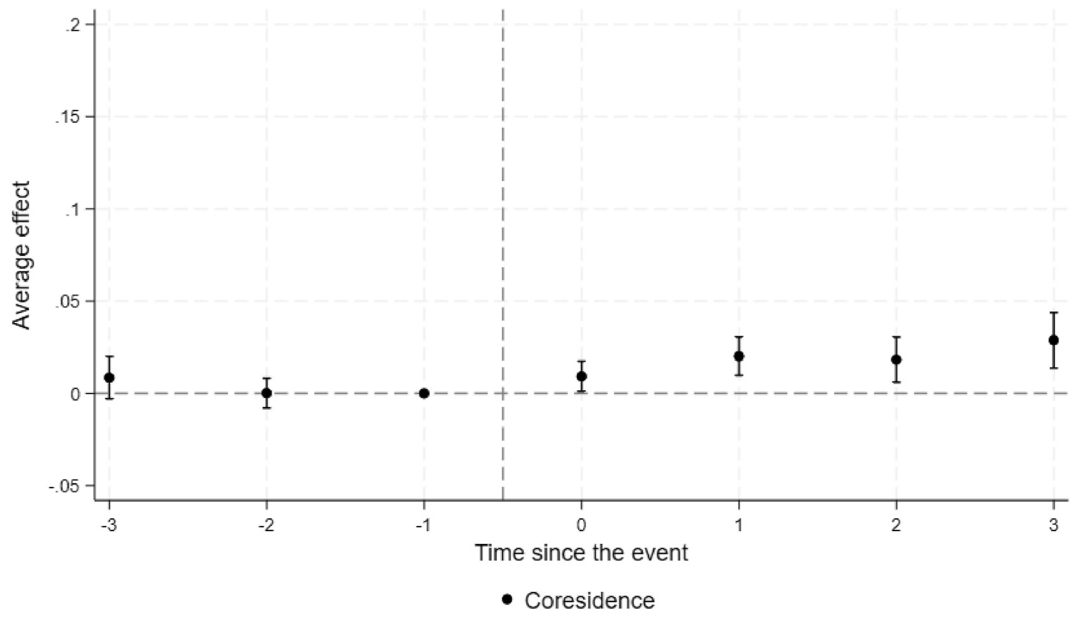


FIGURE B12 Robustness. Effect of a health shock on co-residence with a child in the United States with a balanced panel. This figure displays treatment effects in the form of event-study plots constructed using the de Chaisemartin and d'Haultfoeuille (2024) estimator. This estimation is based on data at the household level. The bars represent 95 percent confidence interval. Outcome is a dummy variable equal to one if at least one child lives in the same household at the time of the survey. Sample is composed of observations present in at least three consecutive waves. Data sources is HRS.

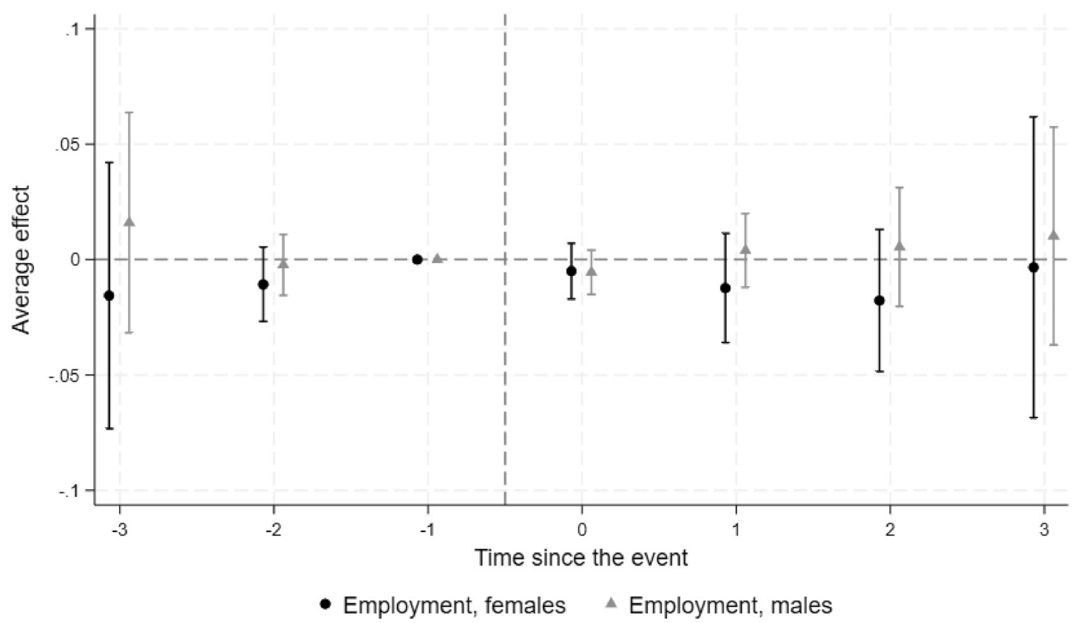


FIGURE B13 Effect of a health shock on children's employment in Europe, by gender. This figure displays treatment effects in the form of event-study plots constructed using the de Chaisemartin and d'Haultfoeuille (2024) estimator. This estimation is based on data at the household level. The bars represent 95 percent confidence interval. Outcome is a dummy variables indicating whether the child is employed (with respect to not employed). Data sources is SHARE.

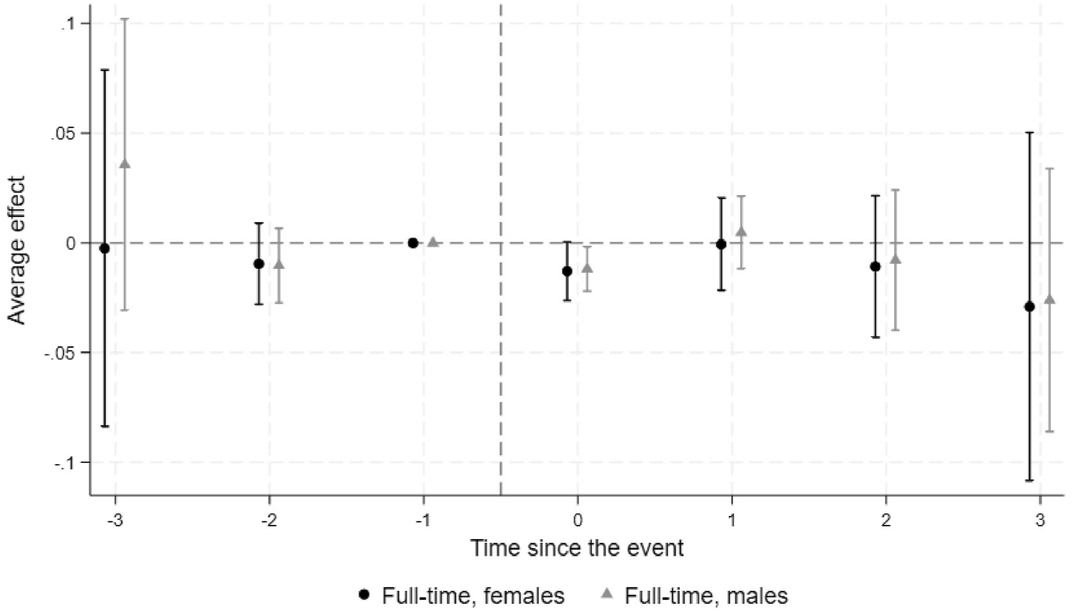


FIGURE B14 Effect of a health shock on children's working hours in Europe, by gender. This figure displays treatment effects in the form of event-study plots constructed using the de Chaisemartin and d'Haultfoeuille (2024) estimator. This estimation is based on data at the household level. The bars represent 95 percent confidence interval. Outcome is a dummy variable indicating whether the child is working full-time (with respect to working part-time and not employed). Data sources is SHARE.

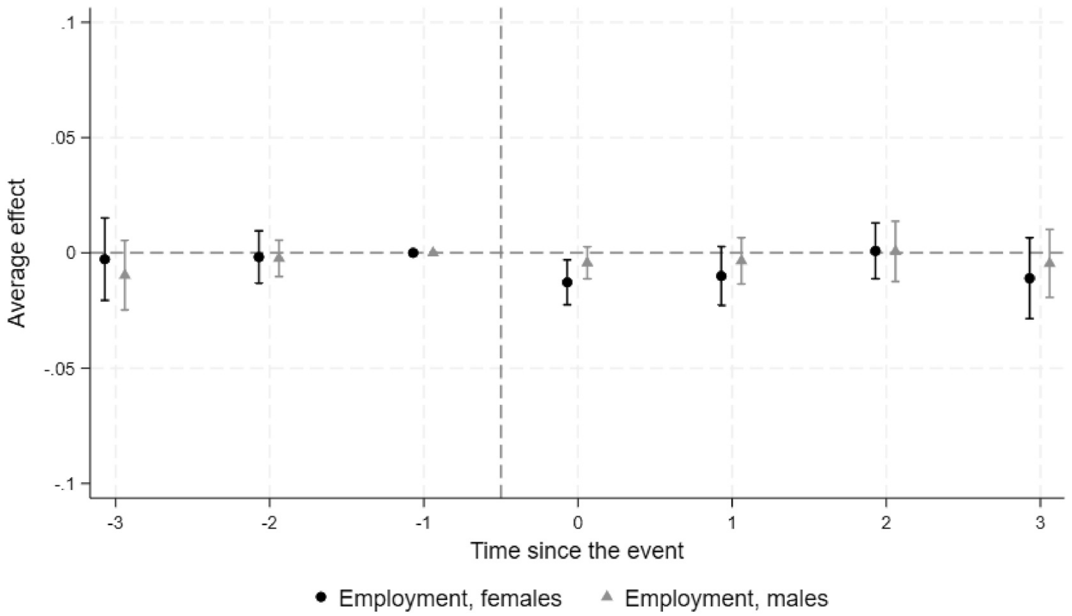


FIGURE B15 Effect of a health shock on children's employment in the United States, by gender. This figure displays treatment effects in the form of event-study plots constructed using the de Chaisemartin and d'Haultfoeuille (2024) estimator. This estimation is based on data at the household level. The bars represent 95 percent confidence interval. Outcomes is dummy variable indicating whether the child is working full-time employed (with respect to not employed). Data sources is HRS.

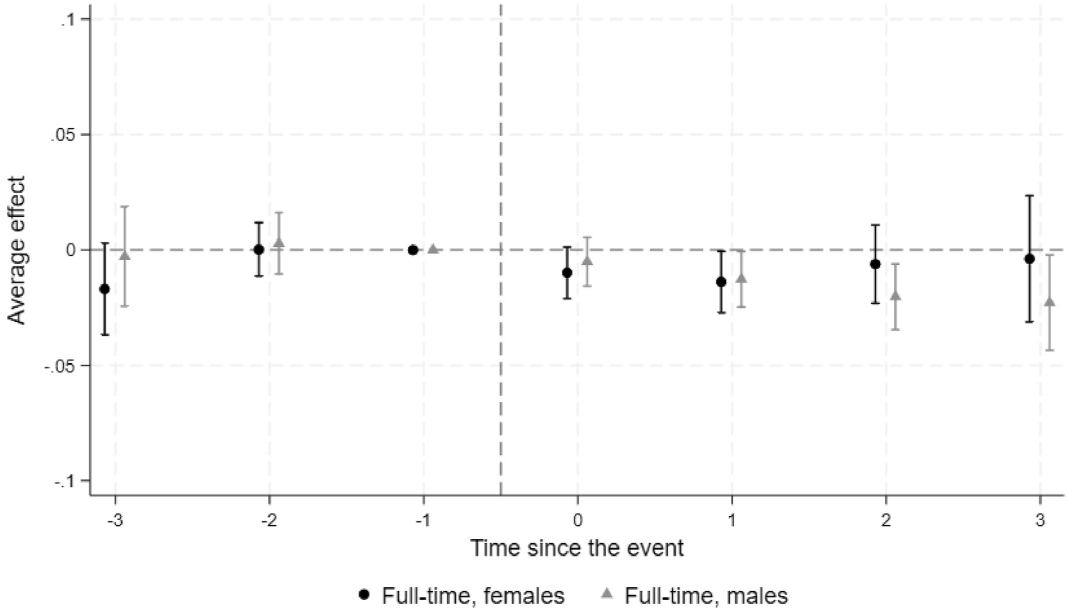


FIGURE B16 Effect of a health shock on children's working hours in United States, by gender. This figure displays treatment effects in the form of event-study plots constructed using the de Chaisemartin and d'Haultfoeuille (2024) estimator. This estimation is based on data at the household level. The bars represent 95 percent confidence interval. Outcome is a dummy variable indicating whether the child is working full-time (with respect to working part-time and not employed). Data sources is HRS.

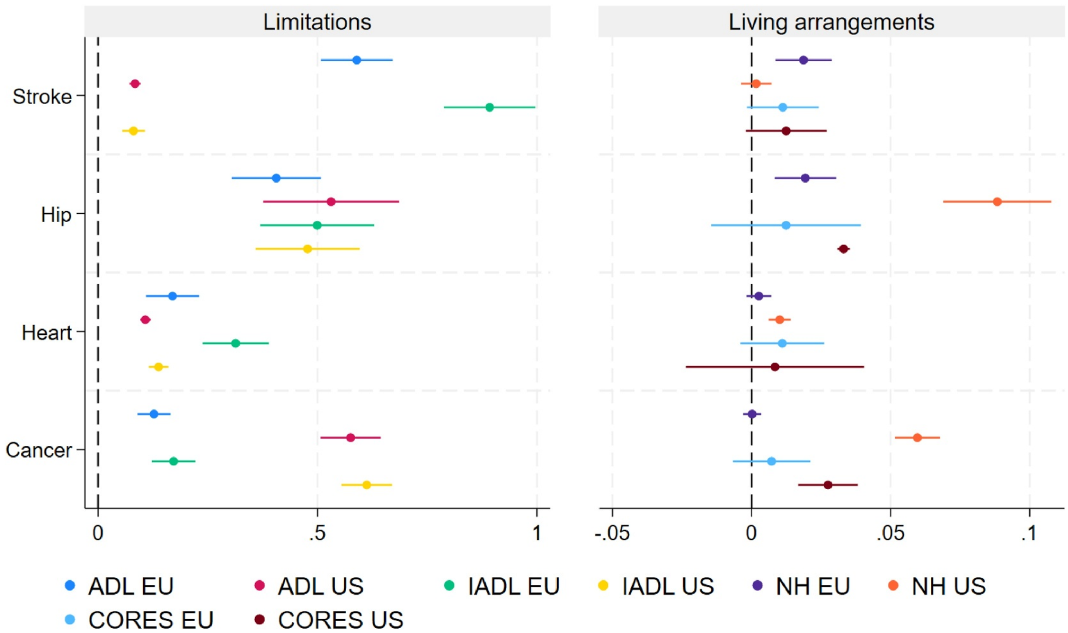


FIGURE B17 Effects by type of health shock on the surveyed individual. This figure displays average treatment effects, by type of health shock, over the post-treatment periods using the de Chaisemartin and d'Haultfoeuille (2024) estimator. The analysis of co-residence is conducted using household-level data, while all other analyses are performed at the individual level. Outcomes on the left panel are the number of ADL and IADL limitations, respectively. On the right panel, NH is a dummy equal to one if the individual lives in a nursing home at the time of the survey. CORES is a dummy equal to one if at least one child lives in the same household at the time of the survey. When indicating EU or US, it means that results are obtained using the sample from Europe (SHARE) or US (HRS), respectively. The bars represent 95 percent confidence interval.

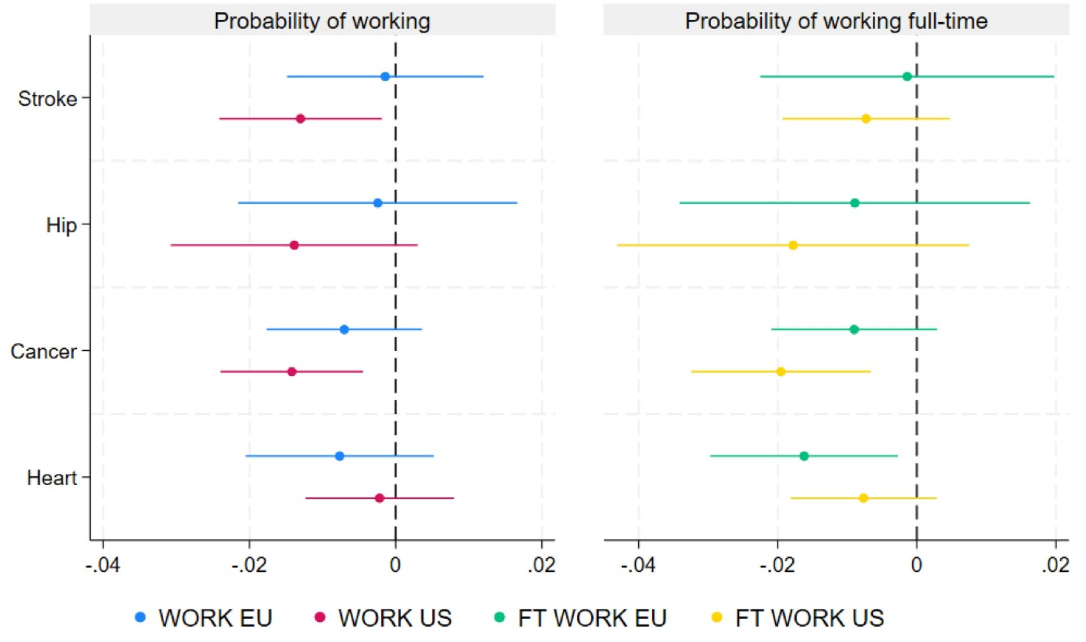


FIGURE B18 Effects by type of health shock on the labor supply of children. This figure displays average treatment effects, by type of health shock, over the post-treatment periods using the de Chaisemartin and d'Haultfoeuille (2024) estimator. This analysis is based on data at the children level. Outcome on the left panel is a dummy equal to one if the child is employed, and zero otherwise. Outcome on the right panel is a dummy equal to one if the child is working full-time, and zero otherwise. When indicating EU or US, it means that results are obtained using the sample from Europe (SHARE) or US (HRS), respectively. The bars represent 95 percent confidence interval.

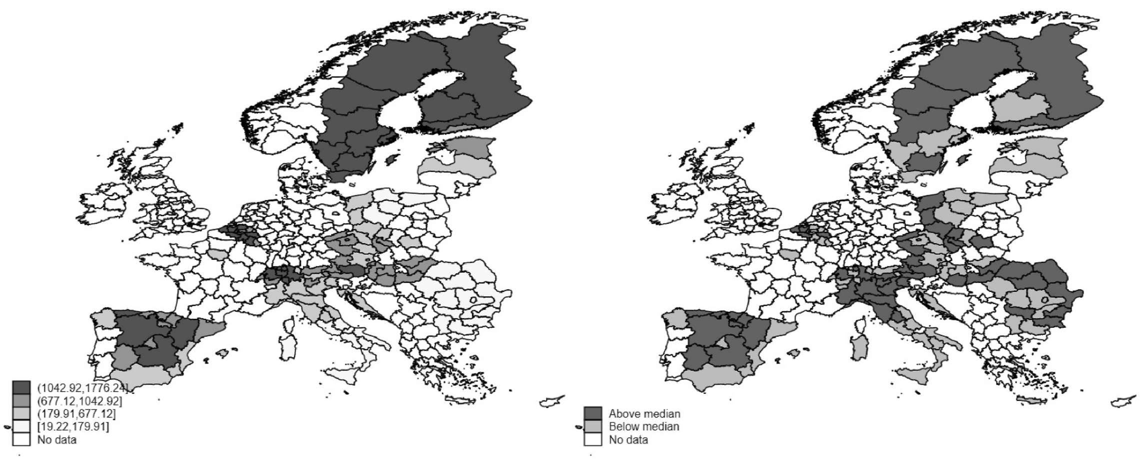


FIGURE B19 Density of beds per hundred thousand residents within nursing homes, Europe. The graph on the left shows quartiles of the number of beds per hundred thousand residents within nursing and other long-term care facilities. The graph on the right shows NUTS2 regions above and below the country median of the number of beds.

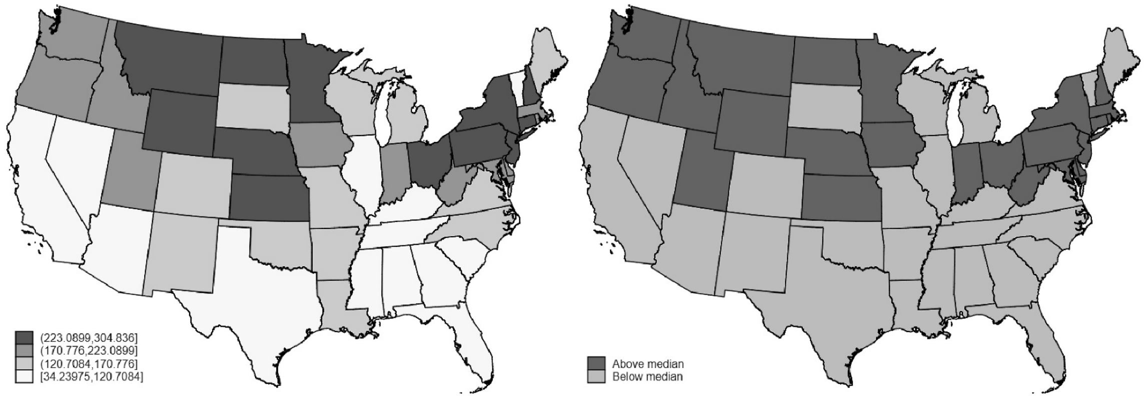
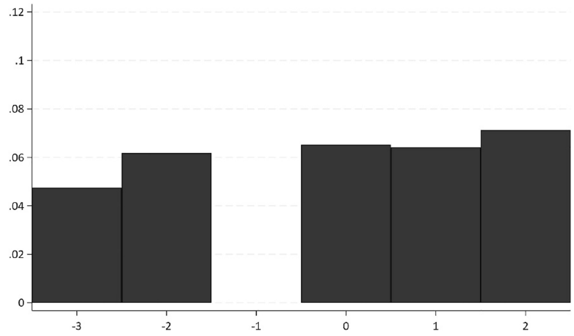
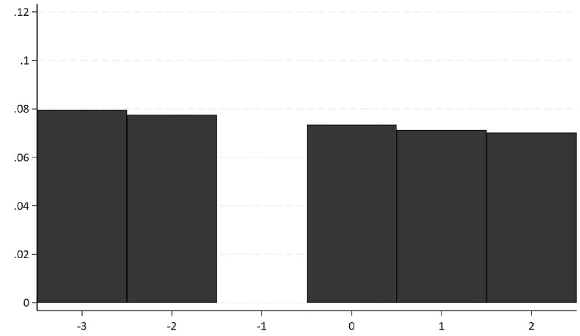


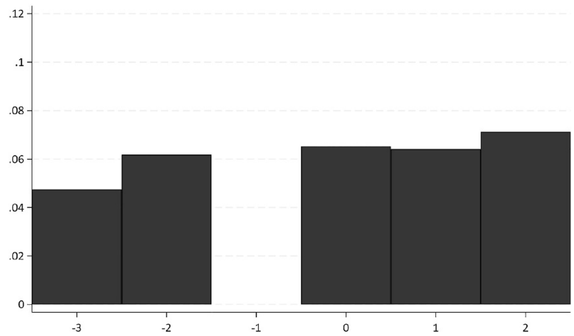
FIGURE B20 Per-beneficiary Medicaid spending for LTSS, United States. The graph on the left shows quartiles of the per-beneficiary Medicaid spending for LTSS. The graph on the right shows states above and below the US median per-beneficiary Medicaid spending for LTSS.



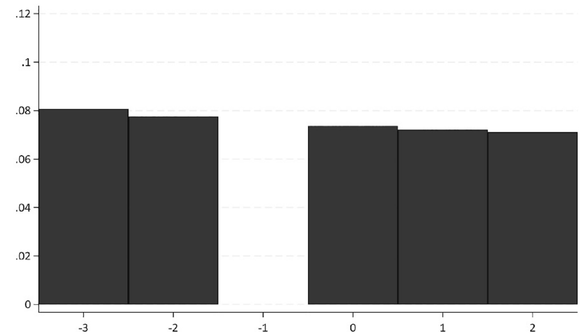
(a) Number of ADL limitations – Europe



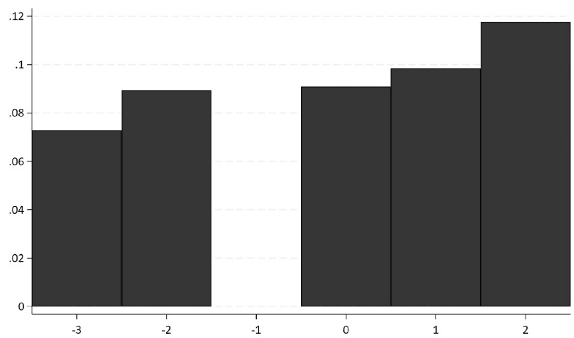
(b) Number of ADL limitations – US



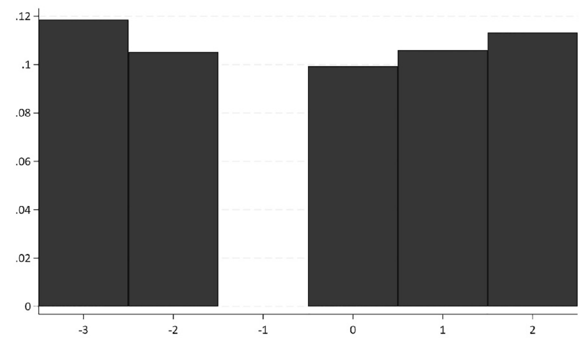
(c) Lives in a nursing home – EU



(d) Lives in a nursing home – US



(e) Co-reside with a child – EU



(f) Co-reside with a child – US

FIGURE B21 Proportion of treated observations used to compute the ATT at each event-time by outcome and region. Proportion of treated observations used to compute the ATT at each event-time in both Europe and in the US, and for different outcomes. It is computed as the number of treated observations used to computed the ATT at a given event-time, divided by the total number of observations used to compute the ATT at this given event-time. It is equal to 0 at time −1 because it is the reference period and not ATT is computed at this period.