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# Informal Care & Mental Health: A Story of Unobserved Heterogeneity

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# Informal Care & Mental Health: A Story of Unobserved Heterogeneity*

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**Abstract**

In most European countries, long-term care systems rely heavily and increasingly on informal care provided by relatives. This work revisits the effect of informal care provision to old-age parents on the mental health of adults aged 50 to 75 using data from the Survey of Health, Aging and Retirement in Europe (SHARE). We apply the marginal treatment effects (MTE) framework, which enables the effect of informal care to be heterogeneous according to both observable and unobservable characteristics. We find a positive average treatment effect of informal care provision on the probability of being depressed. In addition, on average, informal care has no effect (resp. has a large detrimental effect) on the mental health of individuals with a low (resp. large) unobserved resistance to care provision. Hence, according to our results, pushing children who would not become caregivers to provide care might have strong and detrimental consequences. With respect to observed characteristics, the detrimental effect on caregivers' mental health is lower for women and older individuals and is stronger for those living further from their parents. We do not find significant country differences.

**Keywords**: Informal Care, Mental Health, Long Term Care, Marginal Treatment Effects

**JEL codes**: J14; I12; C21.

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# 1 Introduction

Long-term care systems in most countries rely on the provision of informal care, which is mostly provided by family members (i.e., a partner or the children). Indeed, informal care is perceived as a cost-effective way of reducing the use of formal home care and delaying nursing home care (European Commission, 2018), which would help slow governments' increasing long-term care spending. Although this care is received for free by elderly individuals, it has been shown to be costly for caregivers, especially for those providing intensive care, given their potential reduction in labor supply and wages (Bauer and Sousa-Poza, 2015; Lilly et al., 2007). Another potential cost of caregiving can be expressed in terms of physical and mental health because providing care to a relative is often described as a demanding activity with high emotional strain (Pinquart and Sörensen, 2003).

This work revisits the effect of informal care provision to elderly parents on the mental health of adults in Europe. From a theoretical perspective, it is not clear whether the effect of informal care should deteriorate or improve mental health. First, informal care can be an intensive activity that reduces personal time and hence decreases caregivers' mental health. On the other hand, providing informal care can be rewarding, as the caregivers might feel needed, create a close relationship with the care recipient or be proud of their abilities (Heger, 2017). Hence, providing care could also have some beneficial effects on the mental health and well-being of caregivers.

There is a vast literature on the consequences of informal care provision on mental health or depression (Eibich et al., 2021; Heger, 2017; Do et al., 2015; Coe and Van Houtven, 2009; Schmitz and Westphal, 2015). According to the systematic literature review of 15 papers conducted by Bom et al. (2019) on the causal effect of informal care on health and mental health, all contributions reach the conclusion that informal care has no effect or deteriorates the mental health of caregivers.[1] The magnitude of the effect can vary with respect to some individual observable characteristics, such as gender (Heger, 2017; Bom and Stöckel, 2021). Differences by country can also be expected due to differences in long-term care systems (Bom and Stöckel, 2021). Despite the fact that several articles in the psychological field suggest that health benefits

[1] There are more papers studying the effect of informal care on health and/or well-being, but this literature review focus on studies aimed at estimating the causal effect. Therefore, they disregarded all other studies that did not respect their criteria. More recent papers find no effect (Eibich et al., 2021) or a negative effect.

might also be derived from informal caregiving (Brown and Brown, 2014; Fredman et al., 2008; Roth et al., 2015), we did not find any causal analysis conducted with a representative sample supporting this claim.

There are several reasons why the current literature could only provide a partial picture of the effect of informal care on mental health. Indeed, to identify a causal effect, the existing papers use either matching techniques or instrumental variable techniques - coupled with a two-stage least squares estimator - and therefore only identify the average treatment effect on the treated (ATET) or a local average treatment effect (LATE), respectively. These treatment parameters only concern specific groups of individuals and do not completely capture the full heterogeneity of the treatment effect across individuals with different characteristics. Even if these methods allow the treatment effect to be heterogeneous with respect to *some* observed characteristics, they do not relate the heterogeneity in the treatment effect to unobserved heterogeneity in the propensity to provide care.

This latter heterogeneity might be important because the way informal care shapes mental health is likely to vary with individuals' unobserved heterogeneity in their propensity to provide informal care. For example, we might expect that an individual with a high degree of altruism, high preferences for informal caregiving or particular family values might suffer less from care provision than an individual who is less altruistic or with lower preferences for caregiving or different family values. These preferences are almost always unobserved and determine the propensity to provide informal care, which might therefore be a source of heterogeneity. Our argument is supported by Brouwer et al. (2005), who use a sample of informal caregivers and study the process utility of caregiving, which is defined as the difference between current well-being and the well-being an individual would have in a hypothetical situation in which he or she would not provide care (because it would be fully provided by someone else). They find that the process utility of caregiving is positive among individuals with a strong preference for informal caregiving and among those who provide care because they find it pleasant. Another source of unobserved heterogeneity is whether providing care is a choice. Al-Janabi et al. (2018) find that when providing informal care is a choice, care provision is positively associated with caregivers' well-being. We can relate the choice of providing care with an unobserved heterogeneity in the propensity to provide informal care. Indeed, individuals with a (potentially very) low propensity of providing care and who provide care might not have chosen to become caregivers.

Our goal is to provide a more complete picture of the heterogeneous effect of informal caregiving on mental health. Specifically, we apply the marginal treatment effects (MTE) framework that relates heterogeneity in the treatment effect to unobserved heterogeneity in the propensity for caregiving (Heckman and Vytlacil, 1999, 2005, 2007). Such a framework produces a more complete picture of effect heterogeneity than the conventional instrumental variable (IV) or matching techniques usually adopted in the literature. In addition, this framework allows us to explore the heterogeneity with respect to observed characteristics. In particular, we are able to explore the heterogeneity across countries without having to group countries by region and to conduct subsample analyses and therefore provide a more complete picture of geographical differences.

We use a pooled sample of individuals aged 50–75 years from the fifth, sixth and eighth waves of the Survey of Health, Aging and Retirement in Europe (SHARE). Our measure of informal care behavior is a dummy variable indicating whether the individual provides at least care on a weekly or daily basis to at least one parent, and the dependent variable is a dummy variable equal to one if the Euro-D depression scale is higher or equal to four and 0 otherwise. To estimate a causal effect, we use the number of sisters as an instrumental variable. Finally, we use a likelihood estimator of the endogenous switching model, with copula functions that model the correlation of unobserved random terms, to estimate the marginal treatment effects (MTE) as well as the average treatment effect (ATE).

To our knowledge, this paper is the first in which the marginal treatment effect framework is used in the context of informal caregiving. The main contributions of this work can be summarized as follows. First, we estimate the average treatment effect of informal care country by country, while the literature usually splits the sample by region (North, South, East and West). We do not find a significant difference by country; this might be explained by the fact that providing care on a weekly or daily basis is such an intensive activity that its effect on mental health is not shaped by LTC systems. Some observed heterogeneity is found with respect to education, gender, age and geographical distance from the parents. In particular, we observe that informal care provision reduces the depression score for individuals with a low unobserved reluctance to provide care, while it increases the probability of being depressed for highly reluctant individuals. This result implies that informal care can be beneficial for individuals with higher preferences for caregiving. In contrast, it is detrimental for individuals with a lower preference for caregiving, for whom providing informal care is potentially not a free choice.

The main policy implication is that trying to encourage potentially reluctant children – e.g., those who would not have freely decided to become caregivers or have a low preference for caregiving – to provide care to their parents is inefficient since it would increase their risk of mental health issues; this could, in turn, have deleterious effects on their parents' health or well-being.

# 2 Empirical Model

## 2.1 Econometric framework

We study the effect of informal care provision on depression, which is measured by a dummy variable equal to one if the individual is depressed and 0 otherwise. Let $Y_{i1}$ be the individual potential depression status of individual $i$ when providing care ($D_i = 1$) and $Y_{i0}$ when not providing care ($D_i = 0$). These potential outcomes are defined for everyone, but since we do not observe the individuals in each state, we can only observe the outcome $Y_i$, which is defined as:

$$Y_i = Y_{i0}(1 - D_i) + Y_{i1}D_i \qquad (1)$$

We assume that our dummy outcomes are generated by a latent variable index as follows (for $j = 0,1$):

$$Y_{ij} = \begin{cases} 1 \; if \; Y_{ij}^* = X_i\beta_j + U_{ij} > 0 \\ 0 \; if \; Y_{ij}^* = X_i\beta_j + U_{ij} \leq 0 \end{cases} \qquad (2)$$

where $Y_j^*$ is the latent variable that captures the (rescaled) depression score of the individual when in state $j$, $X_i$ is a vector of covariates, $\beta_0$ and $\beta_1$ are the parameters to be estimated and $U_{i0}$ and $U_{i1}$ are unobserved random terms. We assume that the assignment or decision rule for the indicator $D_i$ is generated by a latent variable $D_i^*$ such that:

$$D_i = \begin{cases} 1 \; if \; D_i^* = Z_i\delta - V_i > 0 \\ 0 \; if \; D_i^* = Z_i\delta - V_i \leq 0 \end{cases} \qquad (3)$$

where $D_i^*$ is the latent net utility of providing care, $Z_i$ is composed of the observed characteristics $X_i$ and an instrumental variable, and $V_i$ is an unobserved random term. Note that the unobserved component determining the decision to provide care, $V_i$, enters here as a cost because individuals are less likely to provide care when it is higher. This unobserved component that captures the degree of altruism and preferences for caregiving will be lower (higher) for an individual with high (low) preferences for caregiving such that the propensity to provide care is increased (reduced).

One should note that the decision process can be equivalently represented using a propensity score representation. If $F_V$ is the cumulative distribution function $V$, then (3) can be reformulated as follows:

$$D_i = \begin{cases} 1 \; if \; P(Z_i) > U_{D,i} \\ 0 \; if \; P(Z_i) \leq U_{D,i} \end{cases} \quad (4)$$

where $P(Z_i) = F_V(Z_i\delta)$ is the propensity score of individual $i$, and $U_{D,i} = F_V(V_i)$ is his or her unobserved resistance to the treatment or the quantile of the distribution of $V$. When $U_{Di}$ is higher, this means that the individual has a higher resistance to the treatment or is more reluctant to provide care according to his or her unobserved characteristics. In Section 2.2, we use this representation to compute the marginal treatment effect, which is the treatment effect computed at each quantile of the distribution of V (or equivalently different values of $U_D$).

We have three equations in our econometric framework, one for each of the two potential outcomes (Eq. 1 and 2) and one for the selection into caregiving (Eq. 3 or equivalently Eq. 4). We want to account for the potential endogeneity of the caregiving decision. Therefore, we use an endogenous switching model (Maddala and Nelson, 1975) in which we estimate the three equations simultaneously. To estimate the model, further assumptions must be made regarding i) the marginal distribution of the unobserved random terms $(V_i, U_{i0}, U_{i1})$, ii) the joint distributions of $(V_i, U_{i0})$ and $(V_i, U_{i1})$ and iii) the instrumental variable. Note that the joint distribution of $(U_{i0}, U_{i1})$ cannot be identified because we do not observe individuals in both states (treated and untreated) at the same; hence, we do not make an assumption on this joint distribution. We further discuss the instrumental variable in the Data section (Section 3).

Regarding the marginal distribution of the unobserved random terms, we assume a univariate normal distribution with mean 0 and variance equal to 1. We want to use the most flexible joint distributions of $(V_i, U_{i0})$ and $(V_i, U_{i1})$ as possible and avoid wrongly assuming a given multivariate distribution. Therefore, these joint distributions are modeled by different copula functions: Gaussian, Frank, Clayton, Gumbel and Joe. Let $\eta_j = F_j(U_j)$, for $j \in \{1,2\}$, and $u_D = F_V(V)$ be the marginal cumulative distribution functions of $U_j$ and $V$, respectively. The formulas for the joint distribution of the random variables $\eta_j$ and $u_D$ when using the copula $C(\eta_j, u_D; \theta_j)$ are provided in Table 1. The parameter $\theta_j$ captures the degree of dependence between the two random variables.

Table 1: Copula functions

| Copula | $C(\eta_j, u_D; \theta_j)$ |
|---|---|
| Gaussian | $\Phi_2\{\Phi^{-1}(\eta_j), \Phi^{-1}(u_D); \theta_j\}$ |
| Frank | $-\theta_j^{-1}\log\left\{1 + \frac{(e^{-\theta_j\eta_j} - 1)(e^{-\theta_j u_D} - 1)}{e^{-\theta_j} - 1}\right\}$ |
| Gumbel | $\exp\left[-\left\{(-\log\eta_j)^{\theta_j} + (-\log u_D)^{\theta_j}\right\}^{\frac{1}{\theta_j}}\right]$ |
| Joe | $1 - \left\{(\widetilde{u_D})^{\theta_j} + (\widetilde{\eta_j})^{\theta_j} - (\widetilde{\eta_j}\widetilde{u_D})^{\theta_j}\right\}^{\frac{1}{\theta_j}}$ |
| Clayton | $\left(\eta_j^{-\theta_j} + u_D^{-\theta_j} - 1\right)^{-\frac{1}{\theta_j}}$ |

Notes: Let $\eta_j = F_j(U_j)$, for $j \in \{1,2\}$, and $u_D = F_V(V)$ be the marginal c.d.f of $U_j$ and $V$. For the Joe copula, $\widetilde{u_D} = 1 - u_D$ and $\widetilde{\eta_j} = 1 - \eta_j$.

The properties of these copula functions are discussed in Trivedi and Zimmer (2007). Each of them exhibits different dependence structures. The Gaussian copula, combined with a univariate normal distribution for the marginal distributions, is equivalent to assuming a bivariate normal distribution. The Frank copula, as the Gaussian copula, can model either a positive or a negative dependence structure and is symmetric; it exhibits lower-tail dependence, and it is better suited than the Gaussian copula when the probability of both variables taking extreme values is low. The remaining three copulas are asymmetric and can only exhibit positive dependence. The Clayton copula exhibits strong lower-tail but weak upper-tail dependence, while the Gumbel and Joe copulas have weak lower-tail but strong upper-tail dependence. To allow for a negative dependence with these last three copulas, we can rewrite Equation (1) with the unobserved random term entering as a cost (i.e., negatively). We will call these specifications "negative-Clayton", "negative-Gumbel" and "negative-Joe" later in the paper. To summarize, for each pair $(V_i, U_{ij})$, we have height potential joint distributions (Gaussian, Frank, Clayton, Gumbel, Joe, Negative Clayton, Negative Gumbel, Negative Joe), and we estimate a model for each potential combination. Thus, we estimate 64 models by maximum likelihood Hasebe (2022) and retain the one that best fits the data in terms of likelihood, AIC and BIC.

## 2.2 Treatment parameters

In this paper, we estimate different treatment parameters. The first is the average treatment effect (ATE), which is the average effect in the population given by:

$$E(Y_1 - Y_0|X) = P(Y_1 = 1|X) - P(Y_0 = 1|X)$$

We are also interested in how heterogeneous the effect of informal care is. By taking the derivative of this ATE with respect to a given covariate $x_s$, we can also explore how it is heterogeneous with respect to this given observed characteristic. When the latter is continuous, the derivative of the ATE is computed as follows:

$$\frac{\partial ATE}{\partial x_s} = \beta_{s1}\phi(X\beta_1) - \beta_{s0}\phi(X\beta_0)$$

where $\beta_{s1}$ (resp. $\beta_{s0}$) is the estimated coefficient of the variable $x_s$ when being a caregiver (resp. not a caregiver), and $\phi()$ is the univariate normal density function. It corresponds to the difference of the marginal effect of $x_s$ when treated with the one when not treated. The ATE is heterogeneous with respect to $x_s$ when these two quantities are significantly different. The exact formula is different for discrete or polytomous control variables, and we adapt it in our computations, but the reasoning is very similar.

The second treatment effect we are interested in is the marginal treatment effect (MTE), which is given by:

$$E(Y_1 - Y_0|X = \bar{x}, U_D = u) = P(Y_1 = 1|X = \bar{x}, U_D = u) - P(Y_0 = 1|X = \bar{x}, U_D = u)$$

where $U_D = F_V(V)$ corresponds to the quantile of the distribution of $V$ and is a random variable uniformly distributed between 0 and 1; it represents the individual's unobserved resistance to informal care provision. MTE corresponds to the average treatment effect for an individual whose observed characteristics are at the mean, and unobserved resistance to treatment is $U_D = u$. Therefore, MTE measures the treatment effect at each quantile of the distribution of unobserved resistance to informal care provision. The MTE curve, obtained from the computation of the MTE at different values of $U_D$, is therefore informative on the heterogeneity in treatment effect with respect to unobserved determinants of the propensity to provide informal care (preferences for caregiving, for example). Notice that when $U_D$ is equal to 0.9 (0.1), we are therefore computing the effect of informal care provision for individuals with unobserved characteristics such that they are very likely (unlikely) to provide care. This treatment parameter informs how individuals self-select based on their unobserved characteristics that should capture their preferences (preferences for caregiving, altruism or family norms), i.e., their expected chance to be depressed by their caregiving role according to their unobserved characteristics.

Another treatment parameter we are interested in is the average treatment on the treated (ATT). ATT is the average treatment effect among individuals who effectively self-selected into caregiving. This parameter allows us to compare our findings with those from the literature using matching techniques, which identifies an ATT. This parameter is given by:

$$\begin{aligned} ATT &= E(Y_1 - Y_0|X, D = 1) \\ &= P(Y_1 = 1|X, D = 1) - P(Y_0 = 1|X, D = 1) \\ &= \frac{P\left(Y_1 = 1, D = 1 \mid X\right) - P(Y_0 = 1, D = 1|X)}{P(D = 1|X)} \end{aligned}$$

Finally, we estimate the average treatment on the untreated (ATUT), which is the average treatment effect among individuals who are not treated and did not self-select into caregiving. ATUT is given by:

$$\begin{aligned} ATUT &= E(Y_1 - Y_0|X, D = 0) \\ &= P(Y_1 = 1|X, D = 0) - P(Y_0 = 1|X, D = 0) \\ &= \frac{P(Y_1 = 1, D = 0 \mid X) - P(Y_0 = 1, D = 0|X)}{P(D = 0|X)} \end{aligned}$$

Note that the ATT and ATUT are related to the marginal treatment effect. Individuals who are treated are more likely to have a low resistance to treatment ($U_D$ is low). Conversely, untreated individuals are more likely to have strong unobserved resistance to informal care provision ($U_D$ is high). Hence, the ATT (resp. ATUT) identifies the average effect among individuals with a high (resp. low) unobserved preference for informal care provision. In addition, if there is no heterogeneity with respect to unobserved characteristics, the MTE curve would be flat, and the ATT and ATUT should be very similar.

The formulas for the empirical estimation of the probabilities reported below are given in Appendix A.

# 3 Data

We use pooled data from the release 8.0.0 of the fifth, sixth and eighth waves of the SHARE survey, which concerns individuals aged 50 years or over in 17 countries (Bergmann et al., 2017; Börsch-Supan, 2022). SHARE is a multidisciplinary database of microdata on health, socioeconomic status, and intergenerational transfers. These surveys were conducted in 2013 (w5), 2015 (w6) and 2019/2020 (w8). We do not include waves 3 and 7 because they were part of the SHARELIFE survey, which collects retrospective data at the individual level and does not include regular questions about informal care. Waves 1 and 2 were excluded because information on parents' health is not available for adults coresiding with their parents. Wave 4 is excluded because information on parents is missing for a large proportion of observations due to routing issues related to the introduction of the social network module.

We make few sample restrictions. We focus on individuals aged 75 or younger with at least one parent alive and no missing information on both variables of informal care provision and mental health.[2] We thus obtain a pooled sample of 25,128 observations.

### 3.1 Informal care

Our measure of informal care behavior is a dummy variable indicating whether the individual provides care to at least one parent on a weekly basis. This variable is constructed using two sets of information. First, individuals reporting whether they provide care to parent(s) living outside their household, at least on a weekly basis. Second, adults living with their parents are asked whether they regularly provide personal care to their coresident parents, but not the frequency. We followed Mira and Crespo (2014) and considered that intrahousehold care is made at least on a weekly basis. One should note that we did not consider that children living with their parents are caregivers; we decided to do so because coresidency with parents can also be the result of intergenerational support from the parent to the child. Indeed, individuals can live their parents due to their own economic and family difficulties.

### 3.2 Mental Health

We use the EURO-D scale (Prince et al., 1999), which measures depression symptoms from various dimensions: explicit depression, pessimism, suicidality, guilt, sleep, interest, irritability, appetite, fatigue, concentration (on reading or entertainment), enjoyment, and tearfulness. This measure is widely used, especially by Heger (2017), de Zwart et al. (2017) and Brenna and Di Novi (2016), in the most related literature. Note that the score is constructed such that its values range from 0 to 12, with 12 corresponding to the most depressed. Because we want to focus on the probability of being clinically depressed, our outcome is a dummy equal to one when the Euro-D score is greater than or equal to four and zero otherwise (Prince et al., 1999). This threshold of four was recommended in the literature (Prince et al., 1999), and we also conduct robustness tests by considering thresholds of three and five.

[2] We exclude individuals older than 75 years old because they are more likely to be care recipients than caregivers.

### 3.3 Control variables

When studying the effect of informal care provision on mental health, the literature has shown that it is crucial to control for the health of the parent due to the so-called "family effect". This family effect implies that parental health is correlated to the decision of informal care provision but also to the mental health of the potential caregivers because the latter care *about* the parent. Hence, if we did not control for the parent's health, we would obtain a biased estimate of the effect of informal care provision on mental health. To account for this potential bias, for each parent, we construct a polytomous variable that takes different values according to the health of the parent with the worst health status (as declared by the child): i) excellent or very good, ii) good, iii) fair iv) poor. We also control for the number of parents alive.

With respect to the individual characteristics of the child, we control for age with a polytomous variable, gender, a dummy variable indicating whether the person has a partner in the household, income in quartiles, education, number of children and distance from the parent(s). For all covariates, a "missing" category is introduced to address missing values and avoid losing observations.

### 3.4 Instrumental variables

As explained in Section 2, at least one instrumental variable is required to identify the causal effects we aim to estimate. This variable must satisfy the exclusion restriction assumption and be a strong predictor of caregiving behavior. We use the number of sisters as an instrument for informal care provision. Daughters are more likely to provide care, and siblings – irrespective of their gender – free-ride more on their sisters than on their brothers (Bergeot and van Soest, 2021). We can therefore expect that the number of sisters is a strong predictor of the decision to provide informal care.

We conduct two tests to assess the validity of this instrument. First, we estimate an OLS regression and compute the F-statistic of our instrument to assess the relevance. Regarding the randomness of the instrumental variable (IV) and the exclusion restriction, we use the nonparametric test proposed by Kédagni and Mourifié (2020). Kédagni and Mourifié (2020) derive generalized instrumental inequalities and propose a test to detect all observable violations of the instrumental variable assumption. Their test particularly evaluates the statistical independence assumption, which states that the instrument is independent of the potential outcomes ($Z \perp (Y_O, Y_1)$). We obtain an F-statistic for the excluded instrument equal to 64, which supports the relevance condition. Regarding the nonparametric test, the negative value does not exhibit any violation of the IV assumptions. The results for our main outcome are presented in Table 1. Note that a negative value indicates that the test did not detect violations from the IV assumptions. The test supports that the number of sisters is as good as random at the level of confidence.

Table 2: Test statistics obtained from the generalized instrumental variable test

| | |
|---|---|
| 90% level of confidence | -0.192 |
| 95% level of confidence | -0.199 |
| 99% level of confidence | -0.208 |

Source: SHARE survey. Authors' calculations based on Kédagni and Mourifié (2020). Notes: The table reports the statistics obtained from their test. A negative value indicates that no violation of the instrumental variable assumption is detected.

# 4 Results

## 4.1 Descriptive statistics

In our sample, 19% of the respondents provide informal care to at least one parent on a weekly basis (Table 3). The proportion of individuals declaring at least four depressive symptoms was 26% among caregivers and 22% among noncaregivers; this is descriptive evidence of a potential detrimental effect of informal care provision. Women are overrepresented among informal caregivers (70% versus 56% among noncaregivers). Caregivers declare more often than noncaregivers that the health status of their parent(s) is "poor" (34% versus 21%). This is coherent given that the parent's health status is an important determinant of the decision to provide informal care.

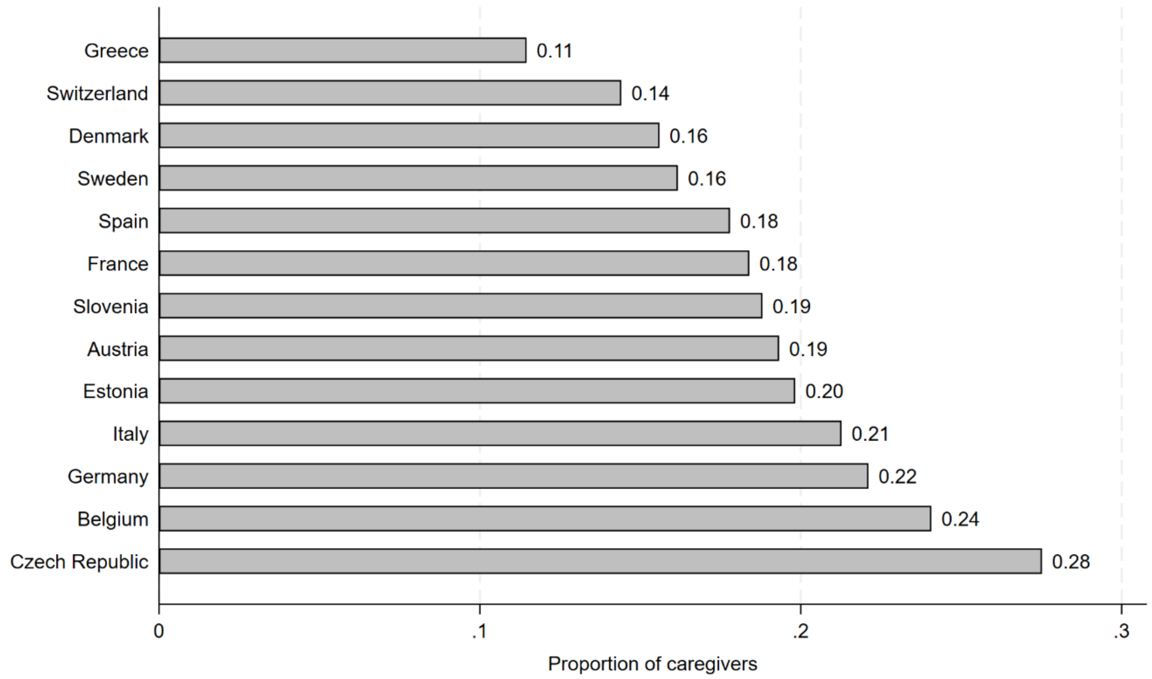
In Figure 1, we display the share of caregivers by country in our sample. This share is higher in France (32%), Belgium (28%), Italy (28%) and Estonia (28%) than in Austria (16%), Slovenia (18%), Sweden (18%) or Denmark (18%).

**Table 3**: Descriptive statistics

| Variables | All sample (N=25,128) Mean (1) | Std (2) | Caregivers (N=4,874) Mean (3) | Std (4) | Non caregivers (N=20,254) Mean (5) | Std (6) |
|---|---|---|---|---|---|---|
| *Variable of interest* | | | | | | |
| Informal care | 0.19 | | | | | |
| *Outcome* | | | | | | |
| Eurod ≥ 4 | 0.23 | | 0.26 | | 0.22 | |
| *Instrument* | | | | | | |
| Nb sœurs | 1.02 | 1.15 | 0.84 | 1.03 | 1.07 | 1.18 |
| *Characteristics of the child* | | | | | | |
| Age 50-54 | 0,26 | | 0,21 | | 0,27 | |
| Age 55-59 | 0,34 | | 0,33 | | 0,34 | |
| Age 60-64 | 0,25 | | 0,29 | | 0,25 | |
| Age 65+ | 0,15 | | 0,17 | | 0,14 | |
| Has a partner | 0.76 | | 0.73 | | 0.77 | |
| Is a woman | 0.58 | | 0.70 | | 0.56 | |
| Number of children | 2.03 | 1.20 | 1.92 | 1.12 | 2.05 | 1.22 |
| Income Q1 | 0.15 | | 0.14 | | 0.16 | |
| Income Q2 | 0.16 | | 0.17 | | 0.16 | |
| Income Q3 | 0.16 | | 0.17 | | 0.16 | |
| Income Q4 | 0.16 | | 0.17 | | 0.16 | |
| Income Q5 | 0.17 | | 0.16 | | 0.17 | |
| Income is missing | 0.19 | | 0.19 | | 0.19 | |
| Secondary education or less | 0.24 | | 0.23 | | 0.25 | |
| Higher secondary education | 0.39 | | 0.41 | | 0.39 | |
| Post secondary education | 0.36 | | 0.36 | | 0.37 | |
| Has a chronic condition | 0.41 | | 0.44 | | 0.41 | |
| *Characteristics of the parent(s)* | | | | | | |
| Two parents are live | 0.23 | | 0.19 | | 0.24 | |
| Excellent health | 0.03 | | 0.02 | | 0.03 | |
| Very good health | 0.08 | | 0.05 | | 0.09 | |
| Good health | 0.27 | | 0.21 | | 0.29 | |
| Fair health | 0.38 | | 0.37 | | 0.38 | |
| Poor health | 0.24 | | 0.34 | | 0.21 | |
| In the same household | 0.06 | | 0.11 | | 0.04 | |
| Less than 1 km | 0.19 | | 0.32 | | 0.16 | |
| Between 1 and 5 kms | 0.19 | | 0.24 | | 0.18 | |
| Between 5 and 25 kms | 0.23 | | 0.22 | | 0.24 | |
| Between 25 and 100 kms | 0.15 | | 0.08 | | 0.16 | |
| More than 100 kms | 0.18 | | 0.03 | | 0.22 | |

Source: SHARE survey. N = 25,128 observations.
Lecture: Among the 4,874 respondents who declare that they provide informal care, 33% are aged between 50 and 55.

**Figure 1**: Proportion of informal caregivers by country




Source: SHARE w5, w6 and w8. N = 25,128 observations of individuals who have at least one parent alive at the time of the survey.
Lecture: Among the respondents from Greece, 11% provide informal care to their parent at least on a weekly basis.

## 4.2 Average treatment effects

We present the likelihood, AIC and BIC for all models we have estimated in Table B.1 (Appendix B). Models are ranked based on their goodness of fit based on the AIC score. All eight models with a Frank copula for $(U_1, V)$ have very similar AIC and BIC values. When we use a model with a different copula for $(U_1, V)$, there is a jump in the AIC score. This result highlights that a Frank copula is the most suited to model the joint distribution of $(U_1, V)$. With respect to $(U_0, V)$, all models have similar AIC and BIC as long as we use a Frank copula for $(U_1, V)$. This might be because all models estimate a low degree of dependance between $(U_0, V)$. For the model we retain, with a negative Joe copula for $(U_0, V)$ and a Frank copula for $(U_1, V)$, we find that Kendall's degree of dependance is -0.06 for $(U_0, V)$ and 0.4 for $(U_1, V)$.

We first present the estimated average treatment effects in the first three lines of Table 4. On average, providing informal care significantly increases the probability of being depressed. We observe a significant 36 percentage point increase in the probability of declaring at least four depressing symptoms; given a baseline probability of being depressed of 23 in the sample, this implies that it is more than doubled when providing care (there is an increase of 150%). We find similar results when changing the threshold at three or five depressive symptoms. These results suggest that providing informal care has a strong causal effect on the probability of being depressed.

Interestingly, the average effects of providing informal care on mental health are different depending on whether they refer to the group of individuals who actually provide informal care (ATT) or those who do not (ATUT). Providing informal care increases the probability of being depressed by 43.2 percentage points on average for those who are not informal caregivers but has no significant impact on those who do provide informal care. These results suggest that the effect of informal care on mental health is not homogeneous; in particular, it differs according to the actual caregiving status, and there should be some self-selection based on unobserved determinants of informal care provision. We further discuss this result in the next section.

**Table 4**: Average treatment effect of informal care provision on depression

| | Eurod-D ≥ 3 | Eurod-D ≥ 4 | Eurod-D ≥ 5 |
|---|---|---|---|
| | (1) | (2) | (3) |
| ATE | 0.328*** | 0.359*** | 0.328*** |
| | (0.059) | (0.063) | (0.106) |
| ATT | 0.132* | 0.054 | 0.047 |
| | (0.068) | (0.080) | (0.048) |
| ATUT | 0.375*** | 0.432*** | 0.428*** |
| | (0.071) | (0.075) | (0.133) |

Source: SHARE survey. Authors' calculations.

Note: ATE stands for average treatment effect, ATT for average treatment effect on the treated and ATUT for average treatment effect on the untreated.

Our results appear robust to the threshold we use to define an individual as depressed. When using at least three or at least five depressive symptoms, the conclusions are qualitatively similar. The estimated ATE is remarkably stable. As an additional robustness test, we present the estimated ATEs, ATTs and ATUTs for models that provide a very close fit from the one we have retained (see Appendix B for the AIC and BIC of each model) in Table 5. The results appear robust given the stability of the estimated ATE and ATUT from one model to another. The ATT appears to be slightly less stable across models, but the difference across models is rather small. One should note that few models suggest a significant (at the 10% level) impact of care provision of approximately 1.5 percentage points.

**Table 5**: Treatment effects on the probability of having at least for depressive symptoms when using copulas with a very similar fit

| $(U_0,V)$ ; $(U_1,V)$ | ATE | ATT | ATUT |
|---|---|---|---|
| n-gumbel ; frank | 0.355*** | 0.033 | 0.433*** |
| | (0.063) | (0.084) | (0.075) |
| n-clayton ; frank | 0.352*** | 0.014* | 0.433*** |
| | (0.061) | (0.007) | (0.076) |
| joe ; frank | 0.352*** | 0.014* | 0.433*** |
| | (0.061) | (0.007) | (0.075) |
| gumbel ; frank | 0.352*** | 0.014* | 0.433*** |
| | (0.061) | (0.007) | (0.075) |
| clayton ; frank | 0.352*** | 0.014* | 0.432*** |
| | (0.061) | (0.007) | (0.075) |
| frank ; frank | 0.352*** | 0.018* | 0.433*** |
| | (0.062) | (0.067) | (0.075) |
| Gaussian ; frank | 0.353*** | 0.022 | 0.433*** |
| | (0.063) | (0.076) | (0.075) |

Source: SHARE Survey. N = 25,128. Outcome is a dummy variable for having at least 4 depressive symptoms. ATE stands for average treatment effect, ATT for average treatment effect on the treated and ATUT on the untreated. It includes all regressions for which BIC or AIC whose distance from the best fitting model is not larger than 2.

We conduct an additional robustness analysis using partial identification. The additional analysis allows us to estimate the bounds of the ATE without parametric assumptions. We follow Acerenza et al. (2023), who propose two different methods; the first only relies on the instrumental variable assumption tested by Kédagni and Mourifié (2020). We provide the bounds for the ATE at the 95% level of confidence in Table 5. The bounds are very large and do not allow us to infer the sign of the marginal treatment effect. Nonetheless, one should note that the bound I not empty, and the authors proved that it can be interpreted as a validation of the instrumental variable assumption tested by Kédagni and Mourifié (2020). To tighten the bounds, Acerenza et al. (2023) suggest further assuming the monotonicity of the outcome in the treatment, which means that either $Y_1 \geq Y_0$ a.s. or $Y_1 \leq Y_0$ a.s; in other words, it assumes that the treatment effect is either positive or negative, but it is not imposed that the sign is known. The results show that the ATE is positive (Table 5), and the ATE obtained with our main methodology belongs to the bounds. We interpret this result as a validation that providing informal care has a positive effect on the probability of being depressed with minimal assumption and that estimates from our main model are not completely driven by formal form assumptions.

**Table 5**: Bounds on the average treatment effect

| Assumption | Bounds on the ATE |
|---|---|
| Instrument validity | [-0.323 ; 0.545] |
| Instrument validity and monotonicity of Y in D | [0.034 ; 0.563] |

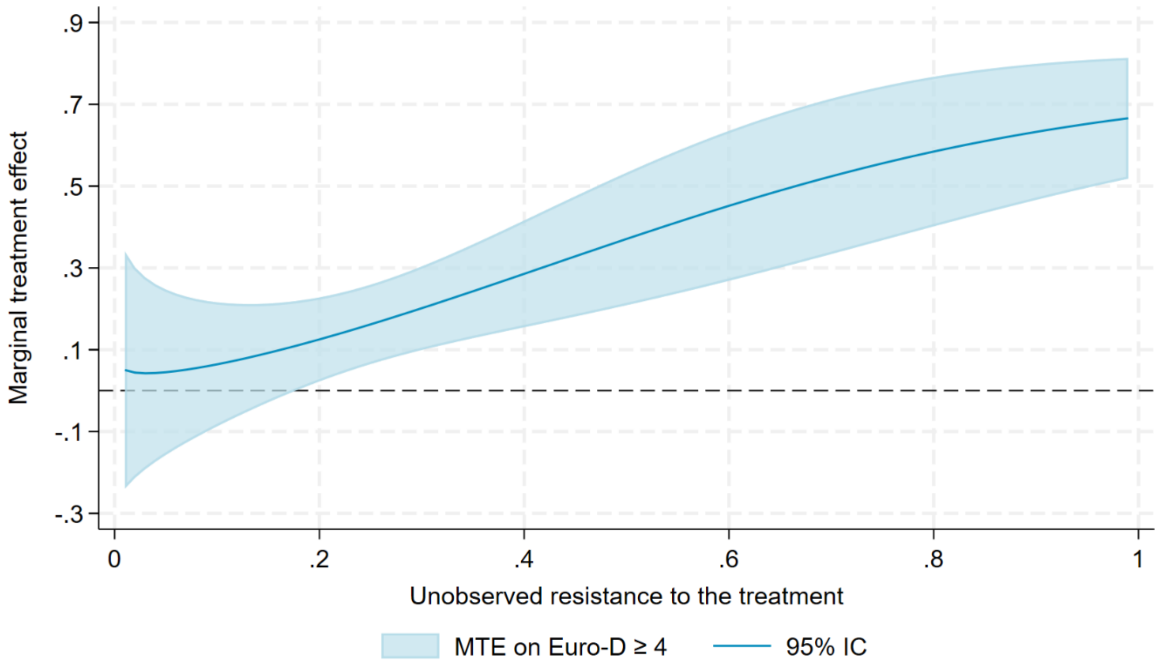
Note: This Table report the estimated bounds following the methodology suggested by Acerenza et al. (2023). Computation is done using *clrbound* Stata package.

### 4.3 Marginal treatment effect

The marginal treatment effect of informal care provision on the probability of having a score of depression greater than or equal to four is presented in Figure 2. The effect of informal care provision on the risk of depression is increasing with respect to the unobserved resistance to treatment. That is, the higher the unobserved resistance to provide care is, the higher the effect of informal care on the risk of depression. Hence, the effect is significantly positive for individuals with $U_D$ higher than 0.18. These individuals would have such strong preferences against informal care provision that pushing them into care would increase their depression score. Conversely, the effect is not significant and near zero among individuals with a low resistance to the treatment. This result suggests that there is no increase in the probability of being clinically depressed for those who have high preferences for care provision. This result is also in line with a small and nonsignificant ATT and a large and significant ATUT. Indeed, individuals who are treated are more likely to have a low resistance to treatment and hence to not experience detrimental effects of informal care provision on their mental health, while untreated individuals are more likely to have a strong unobserved resistance to informal care provision and to feel more depressed by providing care. We do not present the estimated marginal treatment effects from models with a similar fit because the similarity – and stability – of the ATTs and ATUTs suggest that the MTE curves will also be similar.

In Figure 3, we present the marginal treatment effect for the two other thresholds (three and five). The results provide a similar picture, irrespective of the threshold value. The marginal treatment curve is increasing, and the effect is strongly positive for those with a high resistance to the treatment. As the threshold value decreases (from five to three), so does the slope of the MTE curve. For those with a low resistance to the treatment, the treatment effect goes from zero (when the threshold value is five) to almost 0.2 (when the threshold value is three). This result might explain why we find a positive and significant ATT for the probability of reporting at least three depressive symptoms (see Table 3). On the opposite side of the graph, for highly reluctant individuals, the treatment effect decreases from approximately 0.7 (when the threshold is five) to approximately 0.5 (when the threshold is three).

**Figure 2**: Marginal treatment effect on the probability of having at least 4 depressive symptoms.

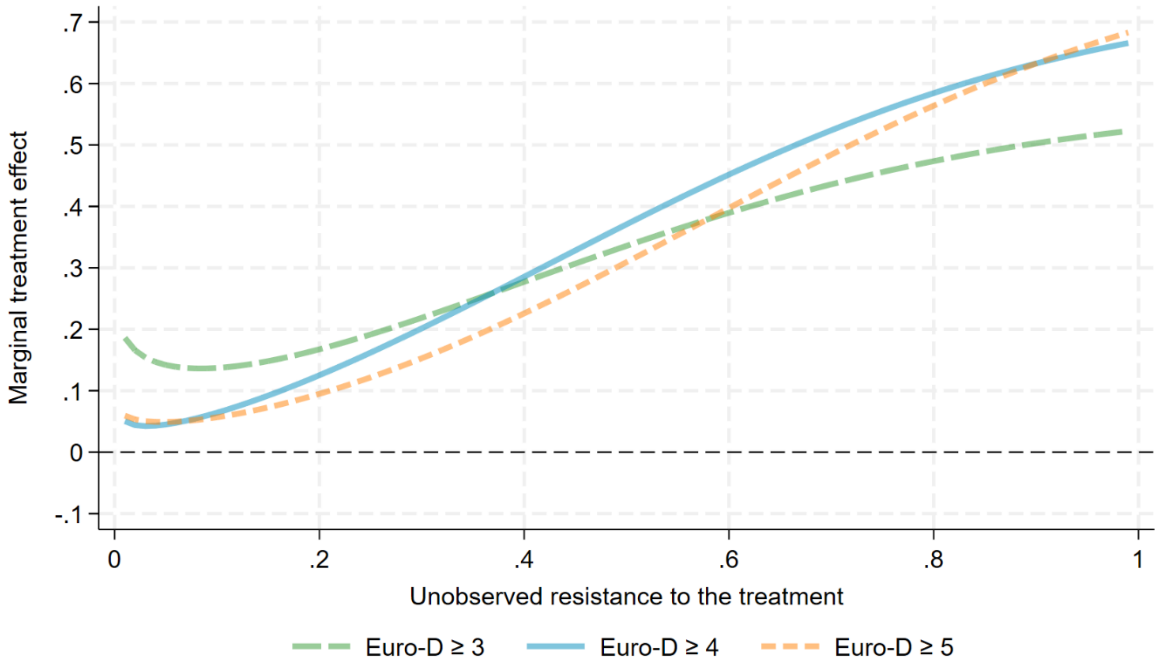



Source: SHARE survey (authors' calculations). Individuals aged between 50 and 75, with at least one living parent.

Note: This graph shows the marginal treatment effect of informal care provision on the probability of having a Euro-D score higher than or equal to four.

These latter results provide important information on the heterogeneity and nonlinearity of the causal effect of informal care. For those with a strong preference for informal care provision, care has no significant effect on their probability of being depressed. Regarding those with low preferences for caregiving, there is a sharp increase in the probability of reporting at least four depressive symptoms. Therefore, we can argue that, on average, there is a detrimental effect on the mental health of the whole population and that it is driven by those who would prefer not to provide care. These results could explain why the literature using matching techniques identified smaller or no effects. Indeed, the average treatment effect on the treated (ATT) – which corresponds to the treatment parameter that can be identified with matching – is null in our main specification.

**Figure 3**: Marginal treatment effect on all thresholds.




Source: SHARE survey (authors' calculations). Individuals aged between 50 and 75, with at least one living parent.

Note: This graph shows the marginal treatment effect of informal care provision on the probability of having a Euro-D score higher than or equal to four.

### 4.4 Observed heterogeneity.

We previously argued that individuals positively self-select into caregiving based on their unobserved characteristics. We now explore the heterogeneity with respect to observable characteristics while focusing on the probability of reporting at least four depressive symptoms (Table 6). Column 1 reports the average marginal effect of the covariates on the probability of providing informal care. The average marginal effect of the observed characteristics when not treated and when treated can be found in Columns 2 and 3, respectively. Column 4 is the derivative of the ATE with respect to the considered observed characteristic; when it is significant, it indicates that the ATE is heterogeneous with respect to this characteristic.

We first describe how individuals self-select into caregiving based on their observed characteristics. A simple way to do so is to compare how observed characteristics affect selection in informal caregiving (Column 1) and the heterogeneity in the ATE (Column 4). We can see that the observed characteristics that decrease (increase) the ATE are positively (negatively) associated with informal care provision, indicating that there is also a mechanism of selection based on observable characteristics. To further investigate this potential selection, we compute $cov(X\beta_1, \delta Z) = -0.391$ and $cov(X\beta_0, \delta Z) = 0.138$. The former equality indicates that observable characteristics that encourage (resp. discourage) the provision of informal care, on average, are also associated with a lower (resp. higher) risk of depression among carers. Conversely, the latter means that observables that encourage (resp. discourage) the provision of informal care, on average, are associated with an increased (resp. lower) risk of depression among noncaregivers. The link that appears to be the strongest (in magnitude) is the one observed among carers; this simply suggests that those who behave play in the opposite way to what their observable characteristics would lead them to do, and in particular those who provide care when their observables should lead them not to do, are more at risk of depression. Therefore, selection on observables seems to play in the same direction as selection based on unobserved characteristics.

When we look more closely at the observable characteristics concerned, we first observe that the effect of informal care on depression is lower when individuals are older and when they are more educated. It is difficult to interpret to what extent age decreases the detrimental effect of informal care provision. One potential reason could be that we do not account for labor market participation, which is likely endogenous, and that older individuals are more likely to be retired. Therefore, this result could capture the fact that older individuals do not face the double burden of working and caring (Schmitz and Stroka, 2013). Regarding education, this result may be related to social differences in the content of care provided (type of care, care intensity) or in the support received by caregivers (use of respite care, support from professionals, etc.) even if we do not find heterogeneity with respect to income. Another explanation could come from the potential correlation between the educational level of children and that of their parents and illustrate the greatest resources available to parents from highly educated children to finance formal care.

We also observe that the effect is lower for women. All other things being equal, among noncaregivers, women have a higher probability of being depressed than men, but this gap is no longer significant among caregivers, which be explained by different factors. First, women can be more productive in the provision of informal care, as suggested by Byrne et al. (2009). If so, providing care could be less time-consuming, and women would observe a more important increase in their parent's well-being than men from their caregiving; this could translate into a more protective impact on their probability of being depressed and, therefore, on a reduced gender gap among caregivers. Second, women are found to be more altruistic toward their parent (Byrne et al., 2009), which could explain why they suffer less from providing care than men, *ceteris paribus*. Third, the effect of social norms could also lead women to be more compliant with their caregiving role than men and to live it better than men. Conversely, among those who do not provide care, women may feel greater social pressure than men to become involved.

Finally, the ATE strongly increases with distance from the parent, meaning that distance potentiates the deleterious effects of care provision on mental health. Among noncaregivers, living close to the parent is associated with a lower risk of depression than coresidence, which suggests a protective effect of intimacy on the mental health of children. Among caregivers, this protective effect tends to decrease and instead reveals a strong deleterious effect of living far away from the parent(s) on the risk of depression. Those living further suffer more from providing care on a weekly basis to their parent(s), which might be due to the accumulation of two components: the burden related to travel to the parent(s) and the burden of caregiving.

To summarize, we have found some heterogeneity with respect to both observed and unobserved characteristics. Being younger, male, having a low level of education or living away from parents reduces the likelihood of providing care while increasing the effect of providing care on the risk of depression. However, selection on observable characteristics appears smaller in magnitude than selection on unobservable characteristics, given the very large difference in treatment effect for those with a low and a high unobserved resistance to the treatment. This result suggests that individuals with a high "preference" (resp. reluctance) for informal care provision have a larger (resp. lower) probability of providing care and a reduced (resp. stronger) deleterious effect of informal care provision on their risk of depression.

**Table 6**: Observed heterogeneity

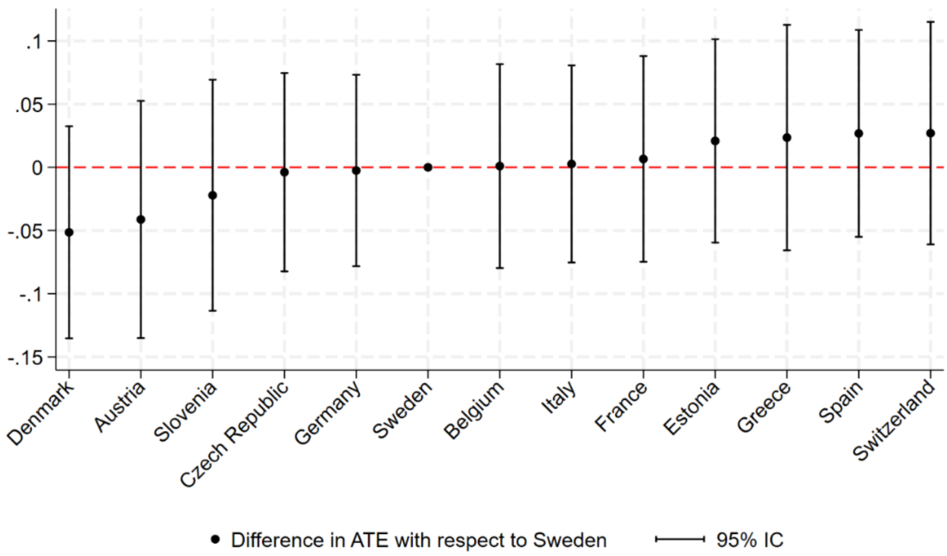
| | Marginal effect on IC (1) | Marginal effect when untreated (2) | Marginal effect when treated (3) | $\frac{\partial ATE}{x_k}$ (4) |
|---|---|---|---|---|
| *Characteristics of the child* | | | | |
| Age 50-54 | ref | ref | ref | ref |
| Age 55-59 | 0.028*** | -0.016** | -0.056*** | -0.039** |
| | (0.006) | (0.007) | (0.018) | (0.019) |
| Age 60-64 | 0.058*** | -0.058*** | -0.106*** | -0.047** |
| | (0.007) | (0.007) | (0.019) | (0.021) |
| Age 65+ | 0.070*** | -0.071*** | -0.123*** | -0.052** |
| | (0.009) | (0.009) | (0.022) | (0.024) |
| Has a partner | 0.003 | -0.053*** | -0.039*** | 0.013 |
| | (0.006) | (0.007) | (0.015) | (0.017) |
| Is a woman | 0.097*** | 0.103*** | 0.029 | -0.073*** |
| | (0.005) | (0.012) | (0.021) | (0.024) |
| Two parents are live | -0.035*** | -0.040*** | -0.013 | 0.028 |
| | (0.006) | (0.007) | (0.017) | (0.019) |
| Has a chronic condition | 0.003 | 0.156*** | 0.158*** | 0.002 |
| | (0.005) | (0.011) | (0.023) | (0.025) |
| Income Q1 | ref | ref | ref | ref |
| Income Q2 | 0.026*** | -0.041*** | -0.054** | -0.013 |
| | (0.008) | (0.009) | (0.021) | (0.023) |
| Income Q3 | 0.034*** | -0.068*** | -0.072*** | -0.005 |
| | (0.009) | (0.009) | (0.022) | (0.024) |
| Income Q4 | 0.033*** | -0.086*** | -0.088*** | -0.003 |
| | (0.009) | (0.009) | (0.024) | (0.026) |
| Income Q5 | 0.032*** | -0.088*** | -0.111*** | -0.024 |
| | (0.009) | (0.009) | (0.025) | (0.027) |
| Income is missing | 0.021 | -0.069*** | -0.056*** | 0.013 |
| | (0.008) | (0.009) | (0.022) | (0.024) |
| Number of children | -0.009*** | 0.004 | 0.013** | 0.009 |
| | (0.002) | (0.002) | (0.006) | (0.006) |
| Secondary education or less | ref | ref | ref | ref |
| Higher secondary education | 0.032*** | -0.025*** | -0.069*** | -0.045** |
| | 0.006) | 0.007) | 0.018) | 0.019) |
| Post secondary education | 0.045*** | -0.048*** | -0.089*** | -0.040** |
| | (0.007 | (0.007) | (0.019) | (0.021) |
| *Characteristics of the parent* | | | | |
| Excellent health | ref | ref | ref | ref |
| Very good health | -0.008 | 0.002 | 0.005 | 0.003 |
| | (0.013) | (0.016) | (0.053) | (0.056) |
| Good health | 0.014 | 0.019 | 0.005 | -0.013 |
| | (0.013) | (0.015) | (0.048) | (0.050) |
| Fait health | 0.057*** | 0.048*** | 0.002 | -0.045 |
| | (0.015) | (0.018) | (0.048) | (0.051) |
| Poor health | 0.146*** | 0.097*** | 0.045 | -0.052 |
| | (0.018) | (0.024) | (0.052) | (0.057) |
| In the same household | ref | ref | ref | ref |
| Less than 1 km | -0.031** | -0.055*** | -0.046* | 0.009 |
| | (0.014) | (0.014) | (0.024) | (0.028) |
| Between 1 and 5 kms | -0.137*** | -0.052*** | 0.021 | 0.074** |
| | (0.012) | (0.017) | (0.027) | (0.032) |
| Between 5 and 25 kms | -0.202*** | -0.029 | 0.069** | 0.099*** |
| | (0.010) | (0.018) | (0.028) | (0.033) |
| Between 25 and 100 kms | -0.276*** | -0.012 | 0.087** | 0.099** |
| | (0.008) | (0.023) | (0.035) | (0.042) |
| More than 100 kms | -0.354*** | -0.016 | 0.184*** | 0.200*** |
| | (0.004) | (0.029) | (0.039) | (0.048) |
| *Instrument* | | | | |
| Number of sisters | -0.017*** | | | |
| | 0.002 | | | |

Source: SHARE survey. Authors' calculations.

### 4.4 Country differences

Given the differences in LTC systems among countries, we also explore the differences in the average treatment by country. In Figure 4, we present differences between the average treatment effect in Sweden, the country of reference and one with one most of the most generous LTC systems in our sample, and the average treatment effect in each considered country. Countries are ranked from the one with the lowest effect to the one with the highest. We do not identify significant country differences, indicating that the average effect of providing informal care regularly on the risk of depression is homogenous among these countries, which is in line with Bom and Stöckel (2021), who find rather similar effects in the Netherlands and in the UK. One potential explanation for this result could be that providing care on a weekly basis is rather intensive such that individuals suffer from caregiving irrespective of the LTC system.

**Figure 4**: Heterogeneity in average treatment effect by country




Source: SHARE survey. Authors' calculations. Note: This figure displays the estimated difference in the average treatment effect with respect to the country of reference (Sweden). Vertical bars are confidence intervals at 95%. Lecture: All other things being equal, the average treatment effect of informal care on the probability of being depressed is 5 percentage points lower in Denmark than in Sweden (country of reference).

## 6 Discussion

In this paper, we revisit the literature on the causal effect of informal care provision to parents on mental health using the marginal treatment effect framework, which allows us to explore heterogeneity with respect to observed and unobserved characteristics. We find that on average, providing informal care has a strong causal effect on the probability of being depressed: it increases the probability of declaring at least four depressing symptoms by 36 ppt.

We also observe some heterogeneity with respect to the observed characteristics. In particular, being younger, a man, having a low level of education or living further away from parents increases the effect of providing care on the risk of depression. We find some evidence of positive selection based on observable characteristics. Observable characteristics that discourage (resp. encourage) the provision of informal care, on average, are also associated with a higher (resp. lower) effect of care provision on the risk of depression; this suggests that those whose observables should lead them to not provide care are more at risk of depression when they provide care. In contrast, we do not find country differences in the effect of informal care on the probability of being depressed.

With respect to unobserved characteristics, we highlight that informal care has no effect on the mental health of individuals who have a low unobserved resistance to care provision, i.e., people for whom providing care is likely to be a choice and have stronger preferences for caregiving. Conversely, providing informal care is detrimental for individuals with a large unobserved resistance to informal care provision, for whom care provision is likely to be a constrained choice. Hence, according to our results, pushing children who would not have to provide their parents with informal care might affect their mental health. This result also suggests a positive selection based on unobserved characteristics and is coherent with a null ATT and a strongly positive ATUT.

The main policy implications of all our results are that policies with the goal of triggering care provision by family members, especially children, could have a large and detrimental effect on the mental health of these new caregivers. These individuals who would have not become caregivers if they were not pushed or constrained to do so have a strong risk of depression. One should also note that a negative externality on the health and well-being of parents can occur if this increase in depression score leads to lower quality informal care provision.

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## Supplementary Material

# Informal Care & Mental Health: A Story of Unobserved Heterogeneity

**Appendix A**: Estimation of treatment parameters

Table A.1: Formulas for the empirical estimation of the treatment effects

| | |
|---|---|
| $P(Y_j = 1)$ | 1-$F_j(-X\beta_j)$ |
| $P(D = 1)$ | $F_V(Z\delta)$ |
| $P(Y_j = 1, D = 1)$ | $F_V(Z\delta) - C_j\{F_j(-X\beta_j), F_V(Z\delta); \theta_j\}$ |
| $P(Y_j = 0, D = 1)$ | $C_j\{F_j(-X\beta_j), F_V(Z\delta); \theta_j\}$ |
| $P(Y_j = 1, D = 0)$ | $1 - F_V(Z\delta) - F_j(-X\beta_j) + C_j\{F_j(-X\beta_j), F_V(Z\delta); \theta_j\}$ |
| $P(Y_j = 0, D = 0)$ | $F_j(X\beta_j) - C_j\{F_j(-X\beta_j), F_V(Z\delta); \theta_j\}$ |
| $P(Y_j = 1 \vert U_D = u)$ | $1 - \left.\frac{\partial C_j\{F_j(-X\beta_j), F_V(U_D); \theta_j\}}{\partial F_V}\right\vert_{U_D=u}$ |

Note: This Table reports the formulae we use to estimate each probability that is used for the computation of the treatment parameters.

**Appendix B**: Bayesian information criteria of each model.

Table B1: Information criterion for each estimated model

| $(U_0,V),(U_1,V)$ | Likelihood | AIC | BIC |
|---|---|---|---|
| n-joe,frank | -22666,811 | 45573,623 | 46549,432 |
| n-gumbel,frank | -22666,886 | 45573,772 | 46549,581 |
| Gaussian,frank | -22666,908 | 45573,816 | 46549,625 |
| Frank,frank | -22666,911 | 45573,822 | 46549,630 |
| Clayton,frank | -22666,913 | 45573,827 | 46549,635 |
| n-clayton,frank | -22666,913 | 45573,827 | 46549,635 |
| Joe,frank | -22666,913 | 45573,827 | 46549,635 |
| Gumbel,frank | -22666,913 | 45573,827 | 46549,635 |
| n-joe,n-clayton | -22668,694 | 45577,389 | 46553,198 |
| n-gumbel,n-clayton | -22668,768 | 45577,536 | 46553,344 |
| Gaussian,n-clayton | -22668,789 | 45577,579 | 46553,388 |
| Frank,n-clayton | -22668,793 | 45577,586 | 46553,394 |
| Gumbel,n-clayton | -22668,795 | 45577,591 | 46553,400 |
| Clayton,n-clayton | -22668,795 | 45577,591 | 46553,400 |
| n-clayton,n-clayton | -22668,795 | 45577,591 | 46553,400 |
| Joe,n-clayton | -22668,795 | 45577,591 | 46553,400 |
| n-joe,joe | -22669,646 | 45579,292 | 46555,101 |
| n-gumbel,joe | -22669,730 | 45579,461 | 46555,270 |
| Gaussian,joe | -22669,749 | 45579,499 | 46555,308 |
| Frank,joe | -22669,750 | 45579,500 | 46555,309 |
| Gumbel,joe | -22669,750 | 45579,500 | 46555,309 |
| Joe,joe | -22669,750 | 45579,500 | 46555,309 |
| n-clayton,joe | -22669,750 | 45579,500 | 46555,309 |
| Clayton,joe | -22669,750 | 45579,500 | 46555,309 |
| n-joe,gumbel | -22669,835 | 45579,670 | 46555,478 |
| n-gumbel,gumbel | -22669,919 | 45579,839 | 46555,647 |
| Gaussian,gumbel | -22669,939 | 45579,878 | 46555,687 |
| Frank,gumbel | -22669,940 | 45579,880 | 46555,688 |
| Clayton,gumbel | -22669,940 | 45579,880 | 46555,689 |
| Gumbel,gumbel | -22669,940 | 45579,880 | 46555,689 |
| n-clayton,gumbel | -22669,940 | 45579,880 | 46555,689 |
| Joe,gumbel | -22669,940 | 45579,880 | 46555,689 |
| n-joe,gaussian | -22670,272 | 45580,544 | 46556,353 |
| n-joe,n-gumbel | -22670,330 | 45580,660 | 46556,468 |
| n-joe,clayton | -22670,330 | 45580,660 | 46556,468 |

Note: This table reports the value of the likelihood function, the BIC and AIC criteria for each estimated model.

Table B1: Information criterion for each estimated model

| $(U_0,V),(U_1,V)$ | Likelihood | AIC | BIC |
|---|---|---|---|
| n-gumbel,gaussian | -22670,345 | 45580,690 | 46556,499 |
| Gaussian,gaussian | -22670,366 | 45580,733 | 46556,541 |
| Frank,gaussian | -22670,369 | 45580,739 | 46556,547 |
| Clayton,gaussian | -22670,371 | 45580,743 | 46556,551 |
| n-clayton,gaussian | -22670,371 | 45580,743 | 46556,551 |
| Gumbel,gaussian | -22670,371 | 45580,743 | 46556,551 |
| Joe,gaussian | -22670,371 | 45580,743 | 46556,551 |
| n-gumbel,n-gumbel | -22670,402 | 45580,804 | 46556,613 |
| n-gumbel,clayton | -22670,402 | 45580,804 | 46556,613 |
| Gaussian,n-gumbel | -22670,423 | 45580,847 | 46556,655 |
| Gaussian,clayton | -22670,423 | 45580,847 | 46556,655 |
| Frank,n-gumbel | -22670,426 | 45580,853 | 46556,661 |
| Frank,clayton | -22670,426 | 45580,853 | 46556,661 |
| Clayton,clayton | -22670,426 | 45580,853 | 46556,661 |
| Clayton,n-gumbel | -22670,428 | 45580,857 | 46556,666 |
| n-clayton,n-gumbel | -22670,428 | 45580,857 | 46556,666 |
| gumbe,n-gumbel | -22670,428 | 45580,857 | 46556,666 |
| Joe,n-gumbel | -22670,428 | 45580,857 | 46556,666 |
| n-clayton,clayton | -22670,428 | 45580,857 | 46556,666 |
| Gumbel,clayton | -22670,428 | 45580,857 | 46556,666 |
| Joe,clayton | -22670,428 | 45580,857 | 46556,666 |
| n-joe,n-joe | -22680,263 | 45600,526 | 46576,335 |
| n-gumbel,n-joe | -22680,342 | 45600,685 | 46576,494 |
| Gaussian,n-joe | -22680,360 | 45600,721 | 46576,529 |
| Frank,n-joe | -22680,361 | 45600,722 | 46576,530 |
| Joe,n-joe | -22680,361 | 45600,722 | 46576,530 |
| Gumbel,n-joe | -22680,361 | 45600,722 | 46576,530 |
| n-clayton,n-joe | -22680,361 | 45600,722 | 46576,530 |
| Clayton,n-joe | -22680,361 | 45600,722 | 46576,530 |

Note: This table reports the value of the likelihood function, the BIC and AIC criteria for each estimated model.