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The Impact of COVID-19 Pandemic on Informal and Formal Care Disruption and Older Adults' Psychological Distress: Evidence from the Household Longitudinal Study-Understanding Society

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The Impact of COVID-19 Pandemic on Informal and Formal Care Disruption and Older Adults' Psychological Distress: Evidence from the Household Longitudinal Study-Understanding Society*

Cinzia Di Novi[1], Gianmaria Martini[2], Caterina Sturaro[3]

Abstract

This paper exploits individual-level data from the U.K. Household Longitudinal Study (U.K.HLS), Understanding Society, to investigate how formal and informal caregiving disruptions, due to the U.K. government's non-pharmaceutical interventions (NPIs) aimed at reducing transmission of the SARS-CoV-2 virus, may have affected the likelihood of psychological distress among older individuals. We model the association between disruption of formal and informal care and mental health of the elderly during the first wave of the COVID-19 pandemic using a recursive simultaneous equation model for binary variables. Our findings reveal that public interventions, most essential for reducing the pandemic spread, influenced the provision of formal and informal care. The burden of formal and informal care disruption has mainly fallen on older adults with underlying medical conditions and therefore at higher risk of COVID-19 complications and related death. The lack of adequate social care following the COVID-19 outbreak has had a negative repercussion on the psychological well-being of these adults.

JEL Classification: I10; I18; C26

Keywords: informal care, formal care, mental health, elderly, disruption, COVID-19

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Introduction

During the 2019–2020 fall and winter, a new coronavirus emerged in Wuhan, China that quickly spread globally reaching pandemic proportions. At the beginning of the pandemic crisis when no medicines or vaccines were available, governments implemented different forms of non-pharmaceutical interventions (NPIs) such as lockdown policies including isolation, quarantine, travel restrictions, and closures of schools, universities, workplaces, and public spaces (Van Bavel *et al*., 2020) to tackle the spread of the virus. Although effective in preventing a further dissemination of the coronavirus, these interventions have disrupted people's social connections with potential repercussions on mental health, especially in more vulnerable groups. Older people, in particular, have encountered unique and remarkable challenges in coping with health and care needs without leaving their homes (Age U.K., 2020).

In the U.K., as in other European countries, elderly support received is dependent upon a combination of informal and formal care: statutory-source community care and social services, privately paid care workers, neighbors, friends, and, in particular, family members (Vlachantoni *et al*., 2015; Maplethorpe *et al*., 2015). The strict restrictions introduced by the U.K. government, together with the reorganization of the healthcare system at all levels, produced a disruption in both of these types of care activities.

The first national lockdown to mitigate the transmission of COVID-19 in the U.K. was introduced on March 23, 2020 and remained in place until July 4, 2020. The government required all those who could to work from home, closed all but essential shops, and advised the population to stay at home and limit contact with other people outside their household, with the exception of caring for a relative in the neighborhood. Moreover, the U.K. NHS identified specific "clinically vulnerable" individuals thought to be at higher risk of severe COVID-19 complications and related deaths and strongly advised them to stay home and avoid all face-to-face contact. The entire elderly population, regardless of individual medical conditions, was also considered clinically vulnerable and advised to stay home as much as possible (Public Health England, 2020; Cabinet Office, 2020).

Relying on data from the Understanding Society COVID-19 Survey (April, 2020) during first the COVID-19 wave across the U.K, Evandrou *et al*. (2020) provided the first descriptive evidence on informal care disruptions affecting the elderly during this time. They investigated the extent of support received by older people from family, friends and neighbors in the first period of the lockdown. According to their findings, a significant proportion of older people received an increased level of help (ranging from shopping, dressing, meal preparation, assisting with online or internet access, gardening or house repairs, and so on) from those who had provided care to them before the outbreak or from new caregivers. This was especially the case among those living alone or with a partner aged 70 and over. However, Evandrou *et al*. (2020) also showed that a smaller group of frail elderly people with difficulties performing key activities of daily living suffered from an informal care disruption and received less care and support during the lockdown compared to the pre-COVID-19 outbreak period. This evidence raised the specter that a group of older vulnerable individuals might not have received an adequate level of social care.

Although it lacked a specific focus on older individuals, another stream of research focused on the effect of COVID-19 mitigation measures, including lockdown restrictions, on the mental health of the British population, (Proto & Quintana-Domeque, 2021; Chandola *et al.*, 2020; Jia *et al*., 2020; Niedzwiedz *et al*., 2020). The findings showed an increased incidence of common mental disorders (CMD) among groups affected by loneliness, unemployment, financial problems, and workers. Women, young adults, ethnic minorities, and those recognized as clinically vulnerable were the groups most adversely affected.

To the best of our knowledge, no studies have been conducted in the U.K. on the connection between disruption of formal care and its potential impact on the elderly population's mental health, nor on the inter-relationship between formal and informal care disruptions due to lockdown restrictions, and older on adults' mental health deterioration. This paper aims to fill this gap by providing additional insights regarding the short-term consequences of mental health care disruptions during the COVID-19 outbreak and contributes to the body of research on the negative associations between such disruptions and the psychological well-being of the elderly.

For the purposes of our study, we used data from the U.K. Household Longitudinal Study (U.K.HLS) Understanding Society (wave #9 and #10) and the COVID-19 Survey (wave #1, April 2020). To study the complex relationship between informal and formal care disruption and elderly psychological well-being, we used a simultaneous equation model for binary variables. Through a recursive probit model estimation, we constructed a joint model of informal care and formal care disruption and mental health conditions that takes into account an individual's unobserved heterogeneity that may characterize this relationship.

According to our results, lockdown restrictions and the reassessment of the U.K.'s NHS to face the healthcare emergency significantly influenced both formal care and informal care provisions for the elderly. The burden of disruption has mainly fallen on older adults with underlying medical conditions and thus more vulnerable to COVID-19 complications and COVID-19-related death. Our findings show that the disruption of informal and formal support represents a significant risk factor for psychological wellbeing in this population group and increases their risk of depression.

The remainder of the paper is organized as follows. We describe the data and the empirical model in Section 2 and in Section 3, we present and discuss the results. Concluding remarks are made in Section 4.

2. Empirical Strategy

2.1 Data

This study uses individual-level data from the U.K. Household Longitudinal Study (U.K.HLS), Understanding Society, a nationally representative panel study of the British population. Sample members living in the U.K. have been interviewed annually since 2009 with the aim of recruiting over 100,000 individuals in 40,000 households. The first wave of the study and data collection period spanned two years and thus wave #1 ran from 2009 to 2011, wave #2 from 2010 to 2012, and so on. Since April 2020, a subsample of participants from the U.K. HLS survey have been interviewed each month and completed short web surveys that focus on the impact of the COVID-19 pandemic. The short web-surveys cover the changing impact of the pandemic on the welfare of British individuals and households. Each month participants completed one survey that included core content designed to track changes alongside variable updated content as the coronavirus situation developed. Core modules included detailed information on household composition, coronavirus illness, long-term health conditions management, mental health measures, loneliness, and employment. Individuals were identified by a personal unique identifier that remained for all waves could be used to link respondents' information across different waves (Institute for Social and Economic Research, 2020).

The integrated data set used for this analysis is the result of matching wave #9 (2017-2019) and #10 (2018-2020) of the main survey and the first monthly COVID-19 wave (April 2020). This data set provides us with the possibility of gathering information related to the COVID-19 outbreak and the years before it.

After correcting for missing values, the sample included 3,721 individuals. In this paper, we focus specifically on those individuals aged 65 and over. Indeed, the COVID-19 pandemic took a heavy toll on their physical as well as mental health. The measures adopted by the U.K. government regarding social distancing and isolation to protect the elderly from the risk of infection often resulted in social isolation and loneliness (to which older adults are more vulnerable because of their functional dependency) that in turn might have increased their likelihood of depression (Banerjee, 2020).

2.2 Dependent Variables

As previously discussed, the main aim of this study is to investigate the potential effects of informal and formal care disruptions on the deterioration of mental health of older people in the U.K during lockdown restrictions intended to curb the COVID-19 spread.

The first step toward a full understanding of this effect requires a complex model that considers the simultaneous relationships between informal and formal care disruption and older individuals' psychological well-being. In our study, we employ a simultaneous equation model for binary variables. We construct a joint model of informal and formal care disruption and mental health outcomes that we estimate through a recursive multivariate probit model that takes into account individuals' unobserved heterogeneity that may characterize these relationships. Thus, we identify two classes of dependent variables: informal and formal care reception and mental health outcomes—i.e., older individuals' psychological distress.

The measure of individuals' psychological distress that we used in this analysis is the 12-item Generalised Health Questionnaire (GHQ-12), which is one of the most widely used screening tools for psychological distress that has been validated for epidemiological studies (Goldberg *et al.*, 1997). The GHQ-12 are collected in all waves of the U.K. HLS Understanding Society to date and included in the Understanding Society COVID-19 Survey. Each one of its 12 items regarding symptoms, feelings, or behaviors is answered on a four-category Likert scale: categories 1 and 2 were scored as 0, and categories 3 and 4 were scored as 1.[4] Finally, the scores from the 12 items were added together to obtain an overall score. The measure attained in this way is called GHQ Caseness and respondents scoring 3 or more (out of a possible total of 12) are likely to be experiencing anxiety and/or depression (Cox *et al.,* 1987).[5] In line with the literature, Caseness GHQ-12 > =3 is used as the threshold to define our dichotomous outcome variable (Lindkvist and Feldman, 2016; Aalto *et al.*, 2012; Holi *et al.*, 2003).

To generate a variable that accurately measures the disruption of informal care, we consider the following two questions included in the first wave of the Understanding Society COVID-19 Survey: "*Thinking about the last 4 weeks, did you receive support from family, neighbours or friends who do not currently live in the same house/flat as you*?" (*Yes=1; No=0*); and "*Thinking back to*

[4] The GHQ-12 items refer to difficulties with sleep, concentration, problems in decision making, feeling overwhelmed, and other indicators of distress.

[5] A different measure is GHQ-12 Likert that converts answers to the 12 questions of GHQ Questionnaire to a single scale by recoding individual variables from 0 to 3 instead of 1 to 4 and uses a scale from 0 (least distressed) to 36 (most distressed) (Cox *et al.,* 1987).

earlier this year, before the outbreak of the coronavirus pandemic. How has the help and support you receive from family, friends or neighbours who do not live in the same house/flat as you changed?" To capture a potential disruption in informal care, we constructed a binary variable that takes value of 1 if respondents, who reported they had not received informal care in the last four weeks before the interview from non-cohabiting family members, neighbors or friends also answered to the second question with respect to the period before the outbreak and 0 otherwise (i.e., if they have received support in the last four weeks before the interviews, and if they have not received support in the last four weeks before the interviews, but there has been no change with respect to the period before outbreak).

In reference to formal care (i.e., community health and social care services), the Understanding Society COVID-19 Survey asked respondents "in need" of formal care to report whether they received help with personal care/medications/shopping/cooking/cleaning/wound dressing/injections from someone visiting them at home regularly. In this question, "in need" meant those who had reported at least one health condition or were having/waiting for treatment at the time of the interview. The answers ranged from one to four, specifically: "1. Yes, as before; 2. Yes, but with reduced support; 3. Yes, with increased support; 4. No." We construct a binary indicator that takes a value 1 if respondents that needed formal care reported they had experienced a reduction in community health and social care services in 2020 or did not receive them at all compared to the pre-pandemic period and 0 otherwise.

According to Evandrou *et al*., (2020) a relatively low proportion of the elderly reported a disruption in informal care and formal care received during the first wave of COVID-19—i.e., about 4% of our sample experienced a disruption of informal care received while about 3% reported on formal care.

2.3 Estimation Method

Identifying an association between formal and informal care disruption and the mental health of the elderly may be complicated by the presence of endogeneity. Older individuals' isolation, resulting from the U.K. government restrictions to contain the virus, might have increased the risk of depression while simultaneously influencing access to formal and informal support (Cacioppo *et al*., 2006; Holt-Lunstad *et al*., 2010). In this application, the situation is further complicated because informal care and formal home care may be simultaneously determined as necessary (van Houtven and Norton, 2004). Indeed, receiving informal care may be correlated to unobserved health characteristics or to unobserved preferences for care that are likely to influence the demand for formal care (Charles and Sevak, 2005; Bonsang, 2009). Moreover, the probability of accessing formal care may have been influenced by the reception of informal care, and access to both may have been influenced by the pandemic. As such, we estimated the model using a recursive multivariate probit design. The recursive structure of the multivariate probit model builds on a first structural-form equation that determines the probability of the onset mental health conditions; a second structural equation for the potentially endogenous dummy measuring the disruption of formal care received; and a third reduced-form equation for the potentially endogenous dummy measuring the disruption of informal care.

Hence, we identified two classes of dependent variables: care disruption—namely, formal and informal care—and health outcome (i.e., the dummy indicator for individuals' mental health as measured by the GHQ score). In the structural equation for mental health, formal and informal care disruption are included as regressors. In the structural equation for formal care disruption, informal care disruption is included as explanatory variable. Inclusion of the indicator of informal care disruption in the formal-care equation allows us to test whether a simultaneous relationship exists between formal and informal care disruption, and whether informal care can be considered a substitute or complement for formal care and thus influence its disruption.

We constructed and estimated a system of three equations with one reduced form and two structural equations. One of the two structural equations was represented by the mental health equation and the other by the formal care disruption equation. Thus:

$$\begin{aligned} y_{1i}^* &= \beta_1' \boldsymbol{x}_{1i} + \varepsilon_{1i} = \delta_1 y_{2i} + \delta_2 y_{3i} + \alpha_1' \boldsymbol{z}_{1i} + \varepsilon_{1i} \\ y_{2i}^* &= \beta_2' \boldsymbol{x}_{2i} + \varepsilon_{2i} = \gamma_2 y_{3i} + \alpha_2' \boldsymbol{z}_{2i} + \varepsilon_{2i} \\ y_{3i}^* &= \beta_3' \boldsymbol{x}_{3i} + \varepsilon_{3i} = \alpha_3' \boldsymbol{z}_{3i} + \varepsilon_{3i}, \end{aligned} \tag{1}$$

where $\boldsymbol{x}_{li}$ (with l = 1, 2, 3) and z_{hi} (with h = 1, 2, 3) are vectors of exogenous variables, β_l and α_h are parameter vectors, and δ_o (with o = 1, 2) and γ_2 are scalar parameters. The error terms distributed as multivariate normal are ε_{hi} , each with a mean zero, and variance covariance matrix Σ. Σ has values of 1 on the leading diagonal and correlations $\rho_{jk} = \rho_{kji}$ on the off-diagonal elements (where ρ_{jk} is the covariance between the error terms of equation j and k).

In the abovementioned setting, the exogeneity condition is stated in terms of the correlation coefficients, which can be interpreted as the correlation between the unobservable explanatory variables of the different equations. All equations in system (1) can be estimated separately as single probit models only in the case of independent error terms (i.e., the coefficient ρ_{jk} is not significantly different from zero).[6] The parameters of the first and second equations are not identified if z_{3i} includes all variables in z_{1i} and z_{2i}.

The estimation of the abovementioned multivariate probit model requires some considerations for the model parameter identification. Maddala (1983) proposed that at least one of the reduced-form exogenous variables (z_{3i}) is not included in the structural equations as an explanatory variable. Following Maddala's approach, we imposed exclusion restrictions. For the reduced form (i.e., the disruption equation for informal care), we included a variable assumed to directly affect the disruption of informal care and only indirectly affect the probability of formal care disruption and a deterioration in mental health. Specifically, to determine an appropriate instrument to predict the reduced form equation, we used information on the geographic proximity between aging parents and their children.

The emergence of COVID-19 and the measures implemented by the U.K. government to curb its spread forced frail older people indoors reduced opportunities to remain socially connected. In March 2020, a stay-at-home order was issued that banned all non-essential movement and contact with other people outside the household. This had important repercussions on the continuity of the informal care provision mainly because (non-cohabiting) caregivers faced difficulties coming to the homes of recipients. In a period characterized by stringent mobility restrictions, traveling a small geographical distance to provide help might have represented an important barrier to caregiving. Wave #9 of the Understanding Society Survey contains a question on which non-coresident relatives respondents have "*alive at the moment*." Respondents with children living outside the household were then asked how long it takes them—door to door—to get to where their sons/daughters' live (aged 16 or over). If respondents reported they have more than one non-coresident child aged 16 or over, they were asked to think about the one with whom they have the most contact. Thus, we create a binary variable that takes value 1 if respondents live within 30 minutes travel time of their children and 0 otherwise (the cut-off was chosen following Shelton & Grundy, 2000).[7] We focused on adult children's proximity since historically in the U.K. they have provided the majority of informal care in later life, with much lower proportions of older people receiving regular help from other relatives, friends, or neighbors (Evandrou et al., 2020).

Along with information on non-cohabiting children, we considered a proxy of restrictions on movements due to the "stay-at-home" policy to tackle the spread of the virus. We took advantage of a human mobility data set, the Google Covid-19 Mobility Report (GCMR) (Google LLC, 2021) that

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[6] STATA software provides the statistic $z = S$ to test the hypothesis H_0: $\rho_{ik} = 0$. If the error terms are independent, the maximum simulated likelihood estimation is equivalent to the separate maximum likelihood probit estimation.

[7] We gathered this information from wave #9 in the "Family Networks" module (that was not included in the most recent waves #10 and the COVID-19 Survey) by assuming that proximity with children remained broadly constant over time.

reports changes in the mobility of Google Maps users across different categories (e.g., supermarkets, pharmacies, workplaces, residential areas) with respect to the first two months of 2020 (before the Covid-19 outbreak). This data set is public and available in a variety of countries. Hence, we included both a measure of adult children proximity and the variation in mobility obtained by Google in our model, as well as an interaction term between them. These variables were assumed to be exogenous for the disruption of informal care.

We built a Google mobility index by combing different Google mobility categories into a single variable. We matched two data sources: Understanding Society and the GCMR. Understanding Society considers 12 regions based on the Nomenclature of Territorial Units for Statistics (NUTS-1) Subdivision including namely Wales, Scotland, and Northern Ireland plus nine regions in England (North East, North West, Yorkshire and The Humber, East Midlands, West Midlands, East, London, South East, and South West). We also used data on total population in each region for the years 2015–2019 from the ONS (Office for National Statistics, 2020a).

The GCMR provides daily mobility data for six location categories: residential, workplace, supermarket and pharmacy (grocery), transit, retail, and parks (Google LLC, 2021). Data are reported as percentage variations in the number of visits or time spent in each category with respect to a pre-Covid-19 baseline period defined from January 3 to February 6, 2020. This reference period is decided by Google and thus cannot be modified. To protect users' privacy, absolute mobility values are not available.

Mobility data are available for each GCMR category for 108 sub-national regions (the GCMR's variable is called sub_region_1), from February 15 (the first available date in the data set) to August 14, 2020. We aggregate the GCMR data by week (we focus on March 23–29, 2020 for consistency with Understanding Society's questions on informal and formal care receipt and change in the care provision) and region (taking the weighted average across all counties belonging to a given region, with weights equal to their population sizes).

For each region analysed in our paper, we then extracted the most significant information from the different GCMR categories by merging them into a combined "Google mobility index" (see Basellini *et al*., 2021). In other words, we worked with two dimensions (categories and regions) simultaneously. We performed a principal component analysis (PCA) of the mobility data and extract the first PA component for region, which is identified using as criteria the component with the largest proportion of explained variance. Accordingly, we built a Google mobility index (*Gmobility*) retaining most of the information regarding mobility during the focal week. In constructing the index, we considered five location categories instead of six dimensions; specifically, we did not include the residential category in the PCA because it has too many missing values.

Table 1 shows the other independent variables in the three equations model grouped into listed categories.

[Table 1]

We considered the following categories: demographics, socioeconomic variables, and health conditions before the COVID-19 outbreak. Among demographics, we included the respondent's gender (1: male; 0: female), age, rural living (1: rural area; 0: urban area), ethnicity (1: white British; 0: other), area-level context captured with regional fixed effects (i.e., Wales, Scotland, Northern Ireland, and English region) and type of household categorized into single-household living vs. living with a partner. We also included an indicator of social capital and two COVID-related variables: one belongs to the NHS Shielding category and the other represents cancelled hospital treatment due to COVID-19.

Among the socioeconomic variables, we included an indicator of respondents' living standards that may influence the probability of psychological distress, the probability of accessing formal and informal care, and the respondents' level of education. Specifically, concerning the living standards, we included an indicator of respondents' subjective views of their financial situation as measured by the question "*How well would you say you yourself are managing financially these days?*" Responses were coded with a five-point Likert scale with the following dimensions: (1) living comfortably; (2) doing alright; (3) just getting by; (4) finding it quite difficult; and (5) finding it very difficult. Thus, the score ranged between 1 and 5 with a higher score indicating a worse financial situation. Concerning the level of education, three levels were considered: (1) lower education (no qualification or basic qualification; i.e., level 1–2 in the U.K. education system); (2) medium education (level 3 in the U.K. education system or equivalent qualification); and (3) higher education (i.e., level of education 4–7 in the U.K. education system).[8]

To account for the respondents' "needs" unrelated to the pandemic itself and the associated lockdown, we also included information on their health status before the outbreak (U.K.HLS wave #10). The health-related variables concern an indicator of general health, the self-assessed health (SAH), and the presence of a pre-existing mental condition. The SAH is supported by literature that shows the strong predictive relationship between people's self-rating of their health and mortality or morbidity (Idler & Benyamini, 1997; Kennedy *et al*., 1998). Moreover, the self-assessed health correlates strongly with more complex health indices, such as functional ability or indicators derived

[8] ISCED levels and the U.K. education system are related in the following way: ISCED 1 corresponds to Level 1 and 2 of the U.K. system; ISCED 2 is Level 3; ISCED 3 corresponds to Level 4 in the U.K., while ISCED levels 5,6,7, and 8 (higher education) are equivalent to U.K. levels 5,6, and 7 (Eurydice 2020/2021).

from health service use (Unden & Elofosson, 2006). The following standard self-assessed health status question was asked: '*Would you say that in general your health is: 1) excellent, 2) very good, 3) good, 4) fair, 5) poor.*" Since the answers cannot simply be scored (for example as 1, 2, 3, 4, 5) because the true scale will not be equidistant between categories (O'Donnell *et al*., 2008) according to previous literature (see, for instance, Contoyannis & Jones, 2004; Balia & Jones, 2008; Di Novi, 2010; Di Novi, 2013), we dichotomized the multiple-category responses and construct a binary indicator with value 1 if individuals reported that their health was fair or poor, and zero otherwise (i.e., excellent, very good, or good). Pre-existing mental condition was identified using the GHQ dummy indicator at U.K.HLS wave #10.

Concerning the indicator of social capital, we included a binary variable among the controls that takes value 1 if respondents donated money to a charity organization the year before the COVID-19 outbreak. Donating money to charity organizations is an indicator of social capital that we expect might influence informal care reception in particular (and its disruption); moreover, it is also generally accepted as an altruistic act that may positively influence individuals' psychological health via experiencing well-being from helping (Dunn *et al*., 2008).

Among the regressors, we included a dummy variable that indicates whether respondents belong to the NHS Shielding category. In March 2020 the U.K. government introduced a Shielded Patient List (SPL)— i.e., a record of clinically vulnerable patients thought to be at higher risk of severe COVID-19 complications and COVID-19-related death.[9] Those belonging to the SPL were sent a notification by the NHS or the Chief Medical Officer to encourage them to stay in their homes and stay away from the rest of the population for 12 weeks. In our study, the NHS Shielding category (Yes/No) is ascertained from the COVID-19 Survey on the basis of a self-reported answer to the following question: "*Have you received a letter, text or email from the NHS or Chief Medical Officer saying that you have been identified as someone at risk of severe illness if you catch coronavirus, because you have an underlying disease or health condition*?" We expected that belonging to the NHS shielding category might have directly affected informal and formal care reception as well as older individuals' mental health. Indeed, the elderly, especially those with cognitive decline and long-term conditions, need emotional support through informal networks and health professionals. As such, the lockdown might have created isolation and disruption of care along with a new set of challenges that could also affect other pre-existing health concerns, including mental health consequences (even though strict isolation was necessary to protect the elderly against the risks of

[9] The NHS Shielding (see above query re capitalization) category included organ transplants patients, cancer patients, those who suffer from severe respiratory disease, those who receive some immunosuppressive treatments, and pregnant women with serious heart disease.

the coronavirus). About 10% of our sample was notified as belonging to the NHS Shielding category as individuals extremely vulnerable to COVID-19.

Finally, we also included a binary variable (*treatment cancelled*) that identified the elderly scheduled for hospital treatment at, but received a notification that it was cancelled or postponed. Indeed, because of COVID-19, healthcare systems in the U.K. and all over the world were suddenly under great pressure and had to reorganize quickly to face the emergency. All efforts and resources were devoted straightaway to address the spread of the contagion and treatments were delayed. Thus, delay of routine medical care during the COVID-19 pandemic may have had consequences for the health and functioning of older adults especially those who suffer from long-term conditions that caused additional anxiety and frustration and increased their need for formal and informal care.

The multivariate probit was performed using the STATA 15 software and the use of simulated maximum likelihood estimation (see Cappellari & Jenkins, 2003).

3. Results and Discussion

Table 2 shows a simple descriptive analysis that presents sample means and standard deviations for the variables used in the model (48% male; mean age: 72 years). Note the prevalence of psychological distress based on the GHQ-12 caseness scoring, which increased from 13.7% at the time of wave #10 to 26.4% at the peak in April 2020. About 4% of respondents reported that they experienced informal care disruption and approximately 3% reported formal care disruption. Approximately 21% of the respondents reported fair or poor health before the beginning of COVID-19 outbreak.

[Table 2]

Table 3 presents the results of the multivariate regression model. Columns 1 and 2 report the estimated coefficients for the disruption in informal care and formal care respectively, and Column 3 reports those with psychological distress.

[Table 3]

Starting with Column 1, the probability of informal care disruption decreases with age and for males. It is not significantly affected by the COVID-19 high risk indicator (NHS Shielding category) pre-existing mental health conditions, but instead increases with pre-existing worse self-reported general health conditions.

Table 2, Column 2 shows that formal care disruption is significantly and positively associated with variables that are indicators of a higher risk of adverse health outcomes if one contracts COVID-19. That is, the probability of formal care disruption increases with age and worse pre-existing self-reported health and mental health conditions according to the COVID-19 high-risk indicator used in our study (i.e., being clinically extremely vulnerable to the COVID-19 - NHS Shielding category). In general, these results confirm that older adults with pre-existing health conditions and for whom the consequences of catching the disease may be more serious faced the greatest social restrictions and stringent advice to stay at home. These adults were also more likely to experience a reduction of care, particularly in terms of community services. In such cases, formal care disruption was justified by the aim of protecting them from contracting COVID-19.

As expected, during the COVID-19 pandemic, the likelihood of informal care disruption was higher when adult children did not live close to their parents. Due to movement restrictions and lockdowns, older adults remained isolated in their homes with limited contact with others including those with non-cohabiting adult children, which is considered a critical factor in contributing to the spread of COVID-19 (Arpino *et al.*, 2021; Bayer & Kuhn 2020). The Google mobility index is positively and significantly associated with informal care disruption, which suggests that mobility limitations, as reflected by a decrease of movements, increases the likelihood of informal care disruption. The interaction term between geographic proximity between aging parents and their children and the Google mobility-index variables is significant as well: Living close to adult children in times of lockdown is more important for the elderly, as they are then more likely to receive needed care.

Finally, the indicator of social capital, as expected, appears to have a negative influence on informal care disruption, given the association between social capital and the greater relationships within a community (Makridis & Wu, 2021).

In terms of socioeconomic status, a perceived lower financial stability is associated with disruption in both informal and formal care; moreover, according to our results, a higher level of education positively influences informal care disruption only. Arguably, a higher level of education raises awareness of the virus and may be positively associated with engagement in all types of preventive behaviors—including complying with stay-at-home rules. This implies a higher probability of in-person contact disruption and consequently the informal care provision particularly among the oldest population that is more vulnerable to COVID-19 infections (Li *et al.*, 2020).

According to our results, informal care disruption does not affect formal care disruption, and the two are not simultaneously determined.

In reference to the structural equation (Column 3 in Table 3), our results show that formal and informal care disruption significantly increases the probability of psychological distress. The disruption of routine community care provided by family members, friends, and paid care or social service workers imposes a great psychological burden on older people. Although prompted by the safety of the elderly, reduced home visits and disruption of regular care compromises their psychological well-being through isolation and unmet needs (Allen *et al*., 2014).

Together with the disruption of formal and informal care, the COVID-19 pandemic has also led to a dramatic change in the delivery of routine healthcare in the U.K. The NHS has adopted measures to preserve resources to manage the pandemic and minimize the risk of infection, such as suspending and/or postponing healthcare services for non-COVID-19-related conditions. Cancellations of such care were reported by 21.1% of our sample (see Table 2). Respondents with treatment suspension or postponement reported a higher probability of psychological distress. Indeed, cancellation of care might increase the risk to older people suffering from physical health conditions (they are more likely to suffer from multiple chronic diseases and therefore require regular access to healthcare services) and also brings anxiety to the elderly who perceive themselves as frail (Schuster *et al*., 2021).

Concerning the other variables included in the structural equation, our findings show that being male was associated with a lower probability of psychological distress during the COVID-19 outbreak. According to our results, while perceived lower financial stability increases the probability of suffering from psychological distress, as expected, a higher level of education seems to positively affect the probability of suffering from mental health conditions. A large part of the existing literature that has analyzed the relationship between individuals' mental health and education supports the protective role of education (see, among others, Feinstein, 2002; Chevalier & Feinstein; 2007; Crespo *et al*., 2014; Di Novi *et al*., 2021). Nevertheless, our results are in line with the most recent literature (Niedzwiedz *et al*., 2021; Daly *et al*., 2020; Pierce *et al*., 2020; Belo *et al*., 2020) that concerns mental health conditions following the COVID-19 outbreak. According to these contributions (that actually concerned mainly younger adults), groups most adversely affected in terms of psychological distress included women, younger adults, people from minorities groups, and those with a higher education level. The hypothesis is that the more educated groups were more likely to shift to remote work during the pandemic and, for some, this work was combined with homeschooling and resulted in an increased psychological burden (Niedzwiedz *et al*., 2021; Daly *et al*., 2020; Pierce *et al*., 2020). Concerning older individuals, further research is needed to shed light on this finding. Arguably, a higher level of education in this setting may proxy for an increasing awareness for older adults that they are at higher risk for severe morbidity and mortality from COVID-19, a circumstance that may also bring anxiety and readjustments in day-to-day life and are likely be stressful for this population (see Belo *et al*., 2020).

Consistent with the previous literature and our expectations, respondents' altruistic attitude, proxied by our study by the charitable donations, contributes positively to older adults' psychological wellbeing (Choi & Kim, 2011).

Finally, there exists a positive correlation between pre-existing health conditions, psychological distress (as measured by the SAH and GHQ-12 in 2019, respectively), and worse mental health.

Since the variables "treatment cancelled" and "NHS Shielding category" may be endogenous (because of a potential reverse causality problem with the dependent variables), we re-ran a sensitivity analysis of the model in which we eliminated these two control variables from the set of controls. This construction did not significantly affect the results: The coefficients of the multiviariate probit remain fairly unchanged (see Table 3 Columns 4, 5 and 6). The other sensitivity checks are included in the Appendix.

As previously discussed (see subsection 2.3), we constructed a simultaneous equation model for three binary variables. The multivariate probit estimation allowed us to test for unobserved heterogeneity that may characterize the relationship between informal and formal care disruption and individuals' psychological distress. The unobserved heterogeneity is captured by the correlation between the error terms from the single equation models. Tables 4 and 5 show the correlation coefficients for the full recursive model. The null hypothesis of exogeneity is rejected in only one case. According to our results, there exists a negative statistically significant correlation between the disturbance of the formal care disruption equation and the structural equation for individuals' psychological distress—i.e., unobservable variables that increase the likelihood of depression and decrease the probability of disruption in the formal care provision. Arguably, the inability to access social support services due to COVID contributes to a worsening anxiety and depressive symptoms especially among the elderly affected by pre-existing mental health conditions. As such, it increases their demand of formal care support that in turn decreases the likelihood of formal care disruption.

4. Conclusions

The crisis due to the COVID-19 pandemic is affecting almost every aspect of our society. With no medicines or vaccines available during the first wave of the pandemic, governments have relied upon non-pharmaceutical interventions (NPIs) such as lockdown policies. Although social distancing has reduced the rate at which infected individuals infect others, it has come at the cost of both an economic crisis as well foregone benefits of physical social contacts that have profoundly reshaped long-term care (LTC) patterns. The COVID-19 pandemic has implied a certain level for formal and informal caregiving disruption as caregivers consider the possibility of transmitting the virus to the elderly. Social distancing has been necessary to protect older adults against the risk of severe COVID-19 and COVID-19-related death; however, such isolation may have created a new set of challenges affecting other pre-existing health concerns. It is well known that older people with unmet needs (as a potential consequence of informal and formal care disruption) have to cope with greater challenges and vulnerabilities that are also correlated with poor mental health and anxiety in many instances (Komisar *et al.,* 2005; Momtaz *et al*., 2012; He *et al*., 2015).

In this paper, we investigated how informal and formal care disruption due to the COVID-19 outbreak have affected older people's mental health. For the purposes of our analysis, we relied on individual level data from the U.K. Household Longitudinal Study (U.K.HLS)—Understanding Society.

We modeled the association between the disruption of formal and informal care received by the elderly and their mental health during the first wave of the COVID-19 pandemic by using a recursive simultaneous equation model for binary variables. According to our results, the disruption of formal and informal care due to the COVID-19 emergency—and the aim of protecting the most vulnerable part of the population—has significantly affected older individuals' psychological distress.

With the U.K. addressing additional waves of COVID-19, and as a lesson for future pandemics, the potential impact of the disruption of long-term care on older individuals' mental health should be considered. Indeed, the potential benefits of mandatory lockdown in curbing the virus spread needs to be weighted carefully against the potential psychological health costs. Successful use of isolation as a public health measure requires a realistic reduction in the negative effects associated with it, especially among more vulnerable groups.

Our findings highlight the need for further investigation of the COVID-19 impact on vulnerable older people. A better understanding of the dynamics that effect caregiving disruptions on the elderly's mental health during the outbreak is essential to inform policy in the current situation in which the net benefit of curbing lockdown measures is yet unclear.

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TABLES

Table 1: Variables Name and Definition

Variables name	***Definition***	***COVID-19 Survey wave/ U.K.HLS - Understanding Society wave***
Dependent variables		
Mental Health Conditions/ Psychological Distress 2020 (GHQ>=3)	1 if GHQ-12 items score is greater or equal than 3 reflecting deteriorations in mental health, 0 otherwise.	COVID-19 Survey wave #1
Formal Care Disruption	1 if respondent did not receive formal care or received reduced formal care with respect to period before COVID-19 outbreak, 0 otherwise.	COVID-19 Survey wave #1
Informal Care Disruption	1 if respondent experienced a decreased in the provision of care in the four weeks before the interview, with respect to the period before the outbreak of COVID-19, 0 otherwise.	COVID-19 Survey wave #1
Independent variables		
Age	continuous variable	COVID-19 Survey wave #1
Male	1 if male, 0 female	COVID-19 Survey wave #1
White British	1 if White British, 0 otherwise	
Rural	1 if lives in rural area, 0 urban area	U.K.HLS - Understanding Society wave #10
England	1 if lives in England, 0 otherwise	U.K.HLS - Understanding Society wave #10
Wales	1 if lives Wales, 0 otherwise	U.K.HLS - Understanding Society wave #10
Scotland	1 if lives in Scotland, 0 otherwise	U.K.HLS - Understanding Society wave #10
Northern Ireland	1 if lives in Northern Ireland, 0 otherwise	U.K.HLS - Understanding Society wave #10
Living with partner	1 if lives with partner, 0 if alone	COVID-19 Survey wave #1
Lower education	1 if completed level of education is null or 1-2 of U.K. education system, 0 otherwise	U.K.HLS - Understanding Society wave #10
Medium education and other qualification	1 if completed level 3 of U.K. education system or other qualification, 0 otherwise	U.K.HLS - Understanding Society wave #10
Higher education	1 if completed level of education is 4-7 of U.K. education system, 0 otherwise	U.K.HLS - Understanding Society wave #10
Subjective view of financial situation	five-point Likert scale with the following dimensions: living comfortably; 2) doing alright; 3) just about getting by; 4) finding it quite difficult; 5) finding it very difficult.	U.K.HLS - Understanding Society wave #10
NHS shielding category	1 if NHS told him/her that he/she is at severe risk of COVID-19 infection, 0 otherwise	COVID-19 Survey wave #1

Treatment cancelled/ postponed/ modified	1 if treatment has been cancelled, postponed, modified, 0 otherwise	COVID-19 Survey wave #1
Charitable donations	1 if donates money to charity, 0 otherwise	U.K.HLS - Understanding Society wave #10
Proximity with non-cohabitating children	if lives within 30 minutes journey time of their children, 0 otherwise	U.K.HLS - Understanding Society wave #9
Gmobility index	Google mobility index obtained from the principal component analysis.	Google mobility data
Pre-existing Poor Health Conditions (SAH)	1 if SAH is fair or poor, 0 otherwise	U.K.HLS - Understanding Society wave #10
Pre-existing Mental Health Conditions/ Psychological Distress 2019 (GHQ>=3)	1 if GHQ-12 items score measured in 2019 is greater or equal than 3 reflecting deteriorations in mental health, 0 otherwise.	U.K.HLS - Understanding Society wave #10

Table 2: Descriptive Statistics

	Mean	SD
Age	72.186	5.446
Male	0.481	0.500
Formal Care Disruption	0.027	0.161
Informal Care Disruption	0.041	0.198
Mental Health Conditions/Psychological Distress (GHQ >= 3)	0.264	0.441
Pre-existing Mental Health Conditions/Psychological Distress 2019 (GHQ >= 3)	0.137	0.344
White British	0.935	0.247
Rural	0.334	0.472
England	0.819	0.385
Wales	0.059	0.235
Scotland	0.089	0.285
Northern Ireland	0.033	0.177
Living with partner	0.746	0.435
Lower education	0.275	0.368
Medium education and other qualification	0.277	0.447
Higher education	0.448	0.497
Subjective view of financial situation	1.605	0.727
Treatment cancelled/ postponed/ modified	0.211	0.408
Charitable donations	0.825	0.380
Pre-existing Poor Health Conditions (SAH)	0.213	0.409
Proximity with non-cohabiting children	0.460	0.498
Gmobility Index	-5.54e-09	1.673
NHS shielding category	0.104	0.305
Observations	3,721	

Table 3: Coefficients from the Recursive Multivariate Probit Estimation

	With treatment cancelled/ postponed/ modified and NHS shielding category			Without treatment cancelled/ postponed/ modified and NHS shielding category		
	Informal Care Disruption (1)	Formal Care Disruption (2)	Mental Health Conditions/Psychological Distress (GHQ>=3) (3)	Informal Care Disruption (4)	Formal Care Disruption (5)	Mental Health Conditions/Psychological Distress (GHQ>=3) (6)
Age	-0.020***	0.029***	-0.006	-0.020***	0.029***	-0.006
	(0.008)	(0.008)	(0.004)	(0.008)	(0.008)	(0.004)
Male	-0.242***	0.125	-0.359***	-0.240***	0.155	-0.356***
	(0.082)	(0.097)	(0.049)	(0.082)	(0.099)	(0.049)
White British	0.001	0.065	0.009	-0.000	0.054	0.006
	(0.150)	(0.190)	(0.095)	(0.151)	(0.190)	(0.095)
Rural	0.006	-0.043	-0.029	0.004	-0.058	-0.031
	(0.083)	(0.098)	(0.050)	(0.083)	(0.096)	(0.050)
Wales	-0.389*	0.025	-0.252**	-0.388*	-0.002	-0.255**
	(0.211)	(0.192)	(0.107)	(0.212)	(0.191)	(0.106)
Scotland	0.049	0.040	-0.040	0.047	0.007	-0.046
	(0.128)	(0.149)	(0.081)	(0.128)	(0.149)	(0.081)
Northern Ireland	0.100	0.065	-0.180	0.102	0.080	-0.175
	(0.223)	(0.248)	(0.129)	(0.223)	(0.248)	(0.129)
Living with partner	0.032	-0.059	-0.198***	0.032	-0.075	-0.198***
	(0.091)	(0.103)	(0.054)	(0.091)	(0.103)	(0.054)
Medium education and other qualification	0.231**	0.100	-0.045	0.233**	0.118	-0.038
	(0.105)	(0.113)	(0.063)	(0.105)	(0.113)	(0.063)
Higher Education	0.215**	-0.079	0.155***	0.216**	-0.076	0.161***
	(0.102)	(0.114)	(0.058)	(0.102)	(0.112)	(0.058)
Subjective view of financial situation	0.107**	0.102	0.198***	0.107**	0.109*	0.198***

	(0.052)	(0.063)	(0.033)	(0.052)	(0.064)	(0.033)
Treatment cancelled/postponed/modified	0.017	0.231**	0.145**			
	(0.093)	(0.100)	(0.058)			
Pre-existing Poor Health Conditions (SAH)	0.166*	0.479***	0.140**	0.179*	0.580***	0.176***
	(0.095)	(0.110)	(0.062)	(0.094)	(0.103)	(0.060)
NHS shielding category	0.043	0.273**	0.028			
	(0.125)	(0.122)	(0.079)			
Charitable donations	-0.198**	-0.164	0.138**	-0.196**	-0.145	0.144**
	(0.096)	(0.113)	(0.063)	(0.096)	(0.112)	(0.062)
Proximity with non-cohabiting children	-0.158**			-0.155*		
	(0.080)			(0.080)		
Gmobility index	0.057*			0.057*		
	(0.033)			(0.033)		
Proximity_Gmobility index	-0.098**			-0.098**		
	(0.045)			(0.045)		
Formal Care Disruption			0.624***			0.637***
			(0.181)			(0.182)
Informal Care Disruption		0.401	0.319**		0.405	0.314**
		(0.268)	(0.162)		(0.268)	(0.162)
Pre-existing Mental Health Conditions/ Psychological Distress 2019 (GHQ >= 3)	0.095	0.329***	0.759***	0.096	0.340***	0.770***
	(0.108)	(0.115)	(0.066)	(0.107)	(0.114)	(0.065)
Constant	-0.410	-4.552***	-0.579			
	(0.601)	(0.656)	(0.356)			
N	3,721			3,721		

Standard errors in parentheses

* p-value 0.1, ** p-value 0.05, *** p-value 0.01

Table 4: Correlation Coefficients from the Recursive Multivariate Probit Estimation (model with NHS shielding category and treatment cancelled)

	Informal Care Disruption	Formal Care Disruption	Mental Health Conditions/Psychological Distress (GHQ >= 3)
Informal Care Disruption	1	-0.094 (0.081)	-0.018 (0.054)
Formal Care Disruption		1	-0.096* (0.055)
Mental Health Conditions/Psychological Distress (GHQ >= 3)			1

Standard errors in parentheses
* p-value 0.1

Table 5: Correlation Coefficients from the Recursive Multivariate Probit Estimation (model without NHS shielding category and treatment cancelled)

	Informal Care Disruption	Formal Care Disruption	Mental Health Conditions/Psychological Distress (GHQ >= 3)
Informal Care Disruption	1	-0.094 (0.081)	-0.016 (0.054)
Formal Care Disruption		1	-0.092* (0.055)
Mental Health Conditions/Psychological Distress (GHQ >= 3)			1

Standard errors in parentheses
* p-value 0.1

APPENDIX

Sensitivity Analysis.

In our main analysis, elderly's psychological distress is measured by the 12-items Generalised Health Questionnaire (GHQ-12) and respondents scoring 3 or more out of a possible total of 12 are considered at risk of anxiety and/or depression. First, we re-run the model setting the GHQ-12 threshold at 4, to identify higher intensities of mental health problems and how they are related to formal and informal care disruption (see Jones, 2021).

Secondly, we re-run the model by considering as dependent variables binary indicators for each of the 12 items that comprise the GHQ-12 questionnaire.

A1. Different Threshold for the Generalised Health Questionnaire (GHQ-12)

As stated before, we rely on the same specification of the main model, with one reduced form (informal care disruption) and two structural equations (formal care and mental health), while we move the threshold identifying mental health conditions at 4 symptoms. Results confirm those of the main analysis for informal and formal care disruption. According to our results (columns 1 and 2 of Table A1), elderly with pre-existing health conditions are more affected by social restriction, thus being more likely to experience a reduction of care. Furthermore, concerning provision of informal care, elderly's proximity to adult children decreases the likelihood of care disruption and this is especially important in periods of movement restrictions. Finally, social capital decreases informal care disruption, while a perceived lower financial stability is associated with disruption in both forms of care.

With reference to the structural equation for psychological distress (column 3 in Table A1), results show that formal care disruption significantly raises the likelihood of experiencing psychological distress among elderly with higher intensities of mental health problems, while informal care disruption is no longer statistically significant. Thus, our findings seem to suggest that, among the group of elderly people with more critical psychological conditions, the disruption of routine care provided by paid care workers or social services, due to lockdown policies, represents the main cause of worsening of psychological distress.

Table A1: Coefficients from the Recursive Multivariate Probit Estimation.

	Informal Care Disruption (1)	Formal Care Disruption (2)	Mental Health Conditions/Psychological Distress (GHQ>=4 (3)
Age	-0.020***	0.029***	-0.004
	(0.008)	(0.008)	(0.005)
Male	-0.244***	0.116	-0.378***
	(0.082)	(0.097)	(0.053)
White British	0.000	0.062	-0.051
	(0.151)	(0.190)	(0.099)
Rural	0.006	-0.044	0.050
	(0.083)	(0.098)	(0.054)
Wales	-0.385*	0.026	-0.181
	(0.211)	(0.193)	(0.115)
Scotland	0.048	0.033	-0.057
	(0.128)	(0.151)	(0.088)
Northern Ireland	0.096	0.060	-0.085
	(0.224)	(0.249)	(0.138)
Living with partner	0.032	-0.052	-0.134**
	(0.091)	(0.103)	(0.059)
Medium education and other qualification	0.230**	0.095	-0.077
	(0.105)	(0.113)	(0.069)
Higher Education	0.216**	-0.075	0.182***
	(0.102)	(0.113)	(0.063)
Subjective view of financial situation	0.108**	0.103	0.233***
	(0.052)	(0.064)	(0.035)
Pre-existing Poor Health Conditions (SAH)	0.168*	0.475***	0.183***
	(0.095)	(0.111)	(0.066)
Pre-existing Mental Health Conditions/ Psychological Distress 2019 (GHQ >= 4)	0.094	0.386***	0.834***
NHS shielding category	0.045	0.267**	0.093
	(0.125)	(0.122)	(0.082)
Charitable donations	-0.196**	-0.159	0.133**
	(0.096)	(0.113)	(0.068)
Proximity with non-cohabiting children	-0.159**		
	(0.080)		
Gmobility	0.058*		
	(0.033)		
Proximity_Gmobility	-0.098**		
	(0.045)		
Treatment cancelled/postponed/modified	0.019	0.233**	0.091

	(0.093)	(0.100)	(0.062)
Formal Care Disruption			0.641***
			(0.187)
Informal Care Disruption			0.229
			(0.177)
Constant	-0.411	-4.560***	-1.107***
	(0.601)	(0.660)	(0.387)
N	3721		

2 A. **The Different Dimensions of the GHQ-12**

As second sensitivity analysis, we define a different outcome variable. We take binary indicators for each of the 12 questions that comprise the GHQ-12 questionnaire and re-run the model again (see Jones, 2021). Performing this evaluation allows us to verify if the model is well identified and to further investigate the relation between each of the GHQ dimensions and formal and informal care disruption, identifying which are more related to one or the other dimension of care disruption.

The twelve dimensions of GHQ-12 are concentration, loss of sleep, playing a useful role, ability to make decisions, coping under strain, overcoming difficulties, enjoying activities, facing up problems, feeling depressed or unhappy, feeling worthless and general happiness. As explained in paragraph 2.2, responses are answered on a four-category scale: “not at all”, “no more than usual”, “rather more than usual”, “much more than usual”. In order to create the binary indicator, for each dimension, we attribute the value 1 to the two categories indicating the most depressed states and 0 to the remaining two categories, reflecting better mental health (see Jones, 2021). We run again the multivariate probit model, substituting one at a time each binary indicator as outcome variable.

First of all, this analysis confirms that the model is well identified. In all regressions, with regards to the reduced form, social capital and proximity to adult children are statistically significant: the likelihood of informal care disruption is lower when adult children live closer to their parents, especially during the implementation of movement restrictions and lockdowns.

Secondly, formal care disruption is statistically significant with positive sign in eleven out of twelve regressions, suggesting a positive, consistent relation between reduction or interruption of formal provision and worsening of the different dimensions of mental health. This evidence is not found only in the case of the item “Believe worthless”. On the other hand, informal care disruption is positively associated with the item “Feeling unhappy or depressed” (p-value 5% level) and negatively related to “Believe worthless” (p-value 10%). In other words, as we expected, elderly who suffer disruption of informal care and social distancing are more exposed to depression. According to our results, these two dimensions of psychological distress are the most affected by informal care disruption and are the items that drive the impact of informal care disruption on the aggregate GHQ-12 score.

Table A2: Coefficients of Informal and Formal Care Disruption from the structural regressions of the 12 items of the GHQ-12

	Concentration	Loss of sleep	Playing a useful role	Capable of making decisions
Informal Care Disruption	0.124	0.165	0.218	-0.161
	(0.177)	(0.188)	(0.170)	(0.218)
Formal Care Disruption	0.887***	0.504**	0.348*	0.880***
	(0.195)	(0.200)	(0.183)	(0.232)
N	3721	3721	3721	3721

	Constantly under strain	Problem overcoming difficulties	Enjoy day to day activities	Ability to face problems
Informal Care Disruption	0.243	0.160	0.250	0.046
	(0.183)	(0.226)	(0.159)	(0.251)
Formal Care Disruption	0.438**	0.692***	0.284*	0.590***
	0.200	0.222	(0.168)	(0.219)
N	3721	3721	3721	3721

	Unhappy or depressed	Losing confidence	Believe worthless	General happiness
Informal Care Disruption	0.348**	-0.067	-0.496*	-0.025
	(0.171)	(0.259)	(0.286)	(0.180)
Formal Care Disruption	0.402**	0.681***	0.246	0.429**
	(0.189)	(0.222)	(0.271)	(0.197)
N	3721	3721	3721	3721