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Informal care, older people, and COVID-19: Evidence from the UK[☆,☆☆]

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ABSTRACT

The negative health effects and mortality caused by the COVID-19 pandemic disproportionately fell upon older and disabled people. Protecting these vulnerable groups has been a key policy priority throughout the pandemic and related vaccination campaigns. Using data from the latest survey of the UK Household Longitudinal Study on COVID-19 we found that people who receive informal care have higher probability of being infected when compared to those not receiving informal care. Further, we found that care recipients who are in the lowest income groups have a higher probability of catching the virus when compared to those in the highest income groups. We also estimated the likelihood of being infected for informal carers versus those who did not provide any care during the pandemic and found no significant differences between these two groups. Our empirical findings suggest that the standard measures introduced with the aim of protecting vulnerable groups, such as closing care homes or prioritising the vaccination of their staff, were not sufficient to avoid the spread of the virus amongst disabled and older people. Informal carers play an important role in the social care sector. As such, protecting vulnerable people by investing in the informal care sector should be a priority for future health policy.

1. Introduction

England was placed into their first national lockdown from late March until June 2020 to mitigate the spread of the COVID-19 virus and minimise intensive care utilization. Initially, the government required many businesses to close and told people, especially those vulnerable due to age or illness, to stay at home to minimize their contacts with others (Public Health England, 2020; CabinetOffice, 2020). These restrictions were relaxed in May 2020 when people were permitted to

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leave their homes for outdoor recreation. Further relaxations of these restrictions on 1st June replaced the rules about leaving home with a requirement to be at home overnight, and individuals were permitted to meet outside in groups of up to six people. Furthermore, during the first wave of the pandemic, day care centres closed to avoid the spread of the virus and protect their staff from contracting COVID-19, considerably reducing the supply of formal care. A large survey which looked specifically at infections in care homes across England estimated that over half of these care homes had at least one confirmed case of COVID-19 amongst their staff and residents (ONS, 2020).

As a result of these initial restrictions there was a substitution effect that led to an increase in the amount of informal care provided (Giebel et al., 2021).[1] This rise in informal care is particularly interesting because it produced a higher number of inter-generational contacts across households, contacts that were strongly discouraged by the government and experts, and which were likely to increases the risk of COVID-19 contagion. Further, reduced government support resulted in a larger burden for the main groups of informal caregivers (Maccora et al., 2020) and led to many inexperienced people being called upon to provide care for relatives and acquaintances (Chan et al., 2020a). This created significant pressure for the carers which could have impacted on their quality of life and mental health, and in turn negatively affected the mental health status of the dependents (Schmitz and Westphal, 2015; Chan et al., 2020b; Whitley et al., 2020).

Despite the increasing and pressing demand for social care during the pandemic, informal caregivers were not included as a priority group in the December 2020 COVID-19 vaccination programme,[2] even though their interactions with vulnerable care recipients could be an important driver in the spread of the virus.

In this paper we study the association between informal care and the risk of contracting COVID-19. Using the new COVID-19 survey carried out by the UK Household Longitudinal Study (UKHLS) during the months of April 2020 (wave 1), November 2020 (wave 6) and March 2021 (wave 8)[3] we are able to estimate the different probabilities of catching COVID-19 for the elderly and disabled populations who received care from someone outside their household and for those who did not receive any informal care. Using linear probability models with different specifications, we test the likelihood of having COVID-19 symptoms, taking a COVID-19 test, and testing positive for COVID-19 for these two groups. Amongst these outcome measures, the latter should give the most accurate measure of the likelihood of being infected.

We found that people who received care from a relative or friend who lives outside the household had a positive and significant probability of showing symptoms of COVID-19 and of testing positive compared to those who did not receive informal care. It is plausible that caregivers who provide personal care to family members outside their own household are at higher risk of getting infected by the virus themselves, as they regularly travel to and meet with care recipients, accompany them to healthcare facilities, and also often do shopping for them.

When exploring heterogeneity amongst the people who receive care, we observe that people in poorer households had a higher probability of catching the virus relative to those in the richest households. These results indicate that greater attention should be paid to older and disadvantaged households who receive informal care.

In addition, we also examine whether informal caregivers have higher/lower probability of catching the virus relative to individuals who do not provide care. Our hypothesis is that in order to protect their vulnerable relatives, caregivers take less risks, by for example reducing their social interactions. These behaviours should lead to lower infection rates for caregivers. Results show that there are no statistical differences in the probabilities of testing positive for COVID-19 or having symptoms compatible with COVID-19 between people who provide care and those who do not provide any care. The fact that caregivers do not seem to adjust their behaviour to protect the people they care for is an important finding. Possible explanations may be that most informal caregivers live far away from their care recipients, work, and/or have to undertake other family arrangements and responsibilities. These factors may explain at least in part why we do not find differences in COVID-19-related outcomes between the two groups.

Most importantly, the results for the samples of care recipients and caregivers also hold when taking into account unobserved heterogeneity using individual specific and group specific effects, matching adjustment on observables, sub-samples and lagged models. Overall, our analysis suggests that informal caregivers should be given serious attention when policy interventions are proposed in health and social care settings to protect vulnerable groups from COVID-19.

The remainder of the paper is structured as follows. Section 2 presents the data, Section 3 is devoted to the methods adopted, Section 4 discusses the main empirical results, and Section 5 concludes.

2. Data

In this paper we use data collected by the Household Longitudinal Study (UKHLS) during the COVID-19 period. The survey collects panel data from 40,000 households in the UK. The data are nationally representative, with individuals interviewed annually since 2009 to collect micro-data both at the individual and household level for different subject areas: namely health, socio-economic status and social life. The COVID-19 survey started in April 2020 with a total of eight waves until March 2021 (last wave available). Participants from previous samples of the UKHLS were asked to complete a short web-survey. The objective of this short survey was to understand the impact of the pandemic and track changes as the

[1] An informal caregiver is a person who provides assistance for a person in need of care, mostly non-professional and unpaid.

[2] https://www.gov.uk/government/publications/priority-groups-for-coronavirus-covid-19-vaccination-advice-from-the-jcvi-30-december-2020/annex-a-covid-19-vaccine-and-health-inequalities-considerations-for-prioritisation-and-implementation

[3] These are the waves in which information on informal care is available.

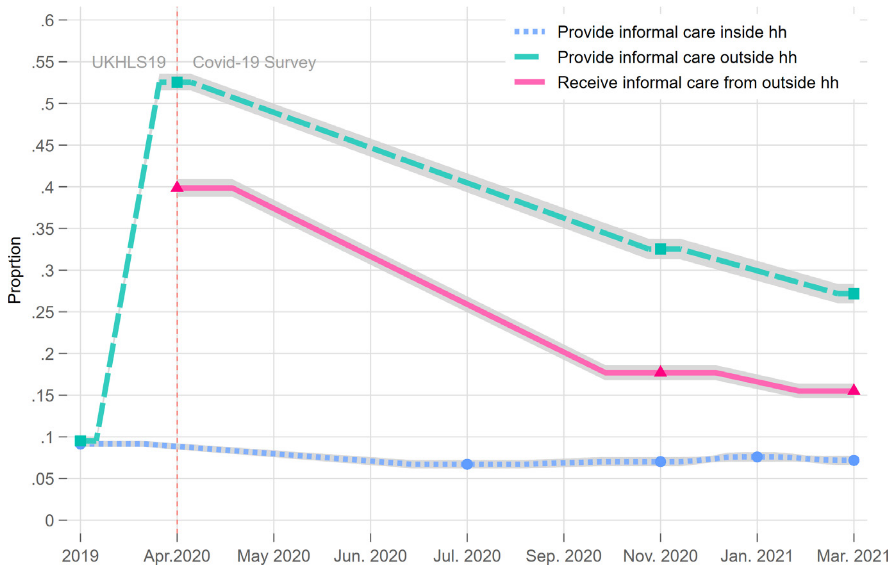

Fig. 1. Proportion of caregivers and care recipients. *Notes:* UKHLS 2019–21, weighted data. The information for those who received care in 2019 is not available in the UKHLS.

coronavirus situation developed.[4] We use waves 1 (April 2020), 6 (November 2020), and 8 (March 2021) of the COVID-19 survey, pooling the data that report information relating to informal social care provided by people from outside the household. This information is missed in the other waves conducted during 2020 and 2021. However, to study the probability of contracting COVID-19 in a more dynamic way, in the robustness checks we used a lag structure, merging participants additional information from other waves that do not contain the informal care measures.

To study the risk of infection for the elderly we selected individuals aged 50 years old and above (nearly 63% of the total sample, 20,420) using the three waves specified above. Our key variable measures whether or not individuals receive care from outside the household in the four weeks prior to the interview, and if this care is provided by family members or other people. Most of the interviews in the waves in which care was measured were conducted at the end of the relevant month. We focus on care provided by someone outside the household because the percentage of people who provide care inside the household is quite small and does not change over time (see Fig. 1). Instead, the percentage of people who provide care and the percentage who receive care from outside the household increased after the pandemic began, suggesting a substitution effect between formal and informal care.[5]

The main outcome variable is the probability of being infected with COVID-19 conditioned on receiving care. We use several measures of COVID-19 infection for which data are available in the UKHLS. We focus on the following outcomes: (i) had symptoms related to COVID-19; (ii) tested positive for COVID-19 (conditioned on being tested) since the last interview; and (iii) tested for COVID-19.[6] Table 1 reports the sample size for each of these outcome variables, for those who receive care and those who provide care. We observe that respondents who receive care are more likely to report having COVID-19 symptoms, testing for COVID-19, and testing positive than those who do not receive care.

To test if informal care is a vector of transmission of COVID-19, we have also performed the same analysis comparing the risk of being infected for the group that provided informal care against the group that did not provide care. For that analysis we included people from 16 to 60 years old, excluding respondents who received care. In this sample we have 14,524 observations.

In the Appendix, Table A.2 shows the descriptive statistics of the variables included in our analyses for those who receive and those who do not receive care. Our analysis also includes economic and socio-demographic controls: gender, age, age-squared, level of education, marital status, living with other people, being long-term disabled, having pre-existing health conditions, areas of residence and ethnicity. People receiving care are usually slightly older than those who do not receive any care. However, the groups are comparable across the other socio-demographic characteristics considered in this study. Table A.3 in the Appendix shows the characteristics of these people for the three waves. Here, we can observe that the groups remain quite similar over time although the sample size slightly decreases due to attrition (see Table A.5).

[4] The survey was conducted online, except for people without connection to internet, in that case the interview was conducted on the telephone.

[5] Unfortunately, the UKHLS COVID-19 survey does not collect information on the provision of formal care during the pandemic.

[6] Although “test for COVID-19” is not a clear outcome of the risk of being infected, for old people who received care, this could be a signal that they may have been in contact with infected people, or have had COVID-19 symptoms.

Table 1
Summary statistics - outcome variables.

	[1] Care recipients								
	Yes				*No*				
Outcomes	mean	min	max	Observations	mean	min	max	Observations	Total observations
Has had COVID-19 symptoms	0.08	0	1	4948	0.05	0	1	15,471	20,419
Tested for COVID-19	0.08	0	1	4949	0.12	0	1	15,471	20,420
Tested positive for COVID-19	0.14	0	1	413	0.05	0	1	1791	2204
	[2] Caregivers								
	Yes				*No*				
Outcomes	mean	min	max	Observations	mean	min	max	Observations	Total observations
Has had COVID-19 symptoms	0.11	0	1	5959	0.09	0	1	8561	14,520
Tested for COVID-19	0.10	0	1	5958	0.14	0	1	8566	14,524
Tested positive for COVID-19	0.09	0	1	492	0.12	0	1	1174	1666

Notes: UKHLS COVID-19 Survey 2020–21; weighted data.

Table 2
Panel Fixed Effects results on the risk of contagious for care recipients by low (1) and high (2) income groups.

	Low income group					
	(1) Had Symp		(2) Tested		(3) Tested pos	
	Coef	Std err	Coef	Std err	Coef	Std err
Receive care						
Yes	0.030*	(0.017)	0.028	(0.025)	0.242***	(0.074)
N	3645		3645		472	
R2	0.019		0.094		0.541	
	High income group					
	(1) Had Symp		(2) Tested		(3) Tested pos	
	Coef	Std err	Coef	Std err	Coef	Std err
Receive care						
Yes	0.054***	(0.017)	0.088***	(0.025)	0.006	(0.073)
N	3853		3853		495	
R2	0.073		0.119		0.205	

Notes: Standard errors in parentheses; clustered at household id level; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
The control variables are the ones listed in Table A.2. UKHLS COVID-19 survey 2020–21; weighted data.

Table A.2 in the Appendix reports the characteristics of informal caregivers versus non-caregivers. Nearly 40% of the sample provides informal care. The typical informal caregiver is aged in their 40s, female, and married. However, the rest of the demographic characteristics are similar to the non-caregivers. The distribution of this sample across the three waves (see Table A.4 in the Appendix), indicates no major differences over time, although attrition is slightly higher for this sample (Table A.5).

The dataset also allows us to explore whether during the COVID-19 period there was a shift in the form of care provided to older people: in particular whether it comes from family members or others. During the pandemic the UK government advised older people to stay at home (Cabinet Office, 2020). Furthermore, as the virus spread among home-care staff (Morciano et al., 2021), many families decided to stop their relatives' home-care services and provide care themselves at home.[7] There was a significant decline in admissions to care homes, which fell by more than a quarter among publicly funded clients and by two-thirds among self-funders (King's Fund, 2020). These facts are in part reflected in Figs. A.5 and A.6 of the Appendix, respectively.

Fig. A.5 displays the proportions of respondents who received care from adult children, parents/grandparents, siblings, spouse/partners, friends, neighbours or someone else. Most of the care during the pandemic is provided by adult sons and daughters and this seems to have increased over time (0.39 in Apr. 2020; 0.43 in Nov. 2020 and 0.46 in Mar. 2021). Notably, there is a high proportion of people reporting that they received help from informal carers outside their family such as a friend or neighbour. However, this form of help decreased between November 2020 and March 2021. This might suggest that during the lockdown many families were struggling to provide care to relatives living outside their households and friends or neighbours took over this responsibility. When the lockdown measures were relaxed this non-family help decreased as

[7] It has been also found that mortality rates due to COVID-19 were also high in many EU countries (see for example Alacevich et al., 2021; Comas-Herrera et al., 2020)

family members were more able to provide informal care. Similar patterns can be observed if we look at those who are providing care during the pandemic (Fig. A.6).

3. Methods

The main specification adopted is a panel fixed effect model which should account for constant unobserved heterogeneity at the individual level. This model exploits the variation in receiving care within individuals (i.e., individuals act as their own control by comparing differences over time). More precisely, we estimate the following models to measure the likelihood of being infected with COVID-19 during the first year of the pandemic (i.e., April 2020, November 2020, and March 2021):

$$Infect_{i,t}^{FE} = \alpha_i + \beta Care_{i,t} + \gamma \mathbf{X_{i,t}} + \lambda_t + \xi_{i,t} \tag{1}$$

Where $Care_{it}$ represents the key variable, and is equal to 1 if the individual i receives care and zero otherwise. $X_{i,t}$ is a set of time-variant control variables (age, marital status, living with others, retired (only for care receivers), having a disability, and pre-existing health conditions), α_i accounts for the regional fixed effects, λ_t controls for wave fixed effects, and $\xi_{i,t}$ refers to time-varying random shocks which we assume to be independently distributed.

For the purpose of informing policy, comparing care recipients and non-recipients might also be useful. This, however, cannot be achieved with the fixed effects specification. Estimating the relationship between being infected and receiving care is quite challenging due to the fact that care recipients or caregivers might differ from those who do not receive or provide any care in other ways. Unfortunately, we do not have survey data rich enough to instrument informal care use and receipt, so as a complementary strategy we have followed Schmitz and Westphal (2015), who used a Propensity Score Matching (PSM) approach to identify the effect of providing care on carers' mental health over time. They first match treatment and control units on the basis of some observable characteristics and then evaluate differences between the two groups via regression. The idea behind this is to reduce differences in the probability to receive the treatment and then through regression adjustment also account for differences in the outcome. Following the potential outcome framework, we can define the different treatment/control status as:

$$\begin{aligned} \widehat{ATT} &= \tfrac{1}{N^{D=1}} \textstyle\sum_{i|T=1} \left[Y_i - \hat{Y}_i^0\right] \quad \text{with} \quad \hat{Y}_i^0 = \textstyle\sum_{j|D=0} w_{ij} Y_j \\ \widehat{ATC} &= \tfrac{1}{N^{D}=0} \textstyle\sum_{i|T=0} \left[\hat{Y}_i^1 - Y_i\right] \text{ with } \hat{Y}_i^1 = \textstyle\sum_{j|D=1} w_{ij} Y_j \\ \widehat{ATE} &= \tfrac{N^{D=1}}{N} \cdot \widehat{ATT} + \tfrac{N^{D=0}}{N} \cdot \widehat{ATC} \end{aligned} \tag{2}$$

where ATE is the average treatment effect; ATT is the a.t.e. on the treated and ATC is the a.t.e. on the untreated; D is binary treatment indicator (0/1); Y represents the observed outcome; Y^1 the potential outcome with treatment and Y^0 p.o. without treatment, and matching weights w_{ij} for groups i and j.

In the case of PSM, to estimate ATE or ATT we expect that treatment assignment is independent of the units' characteristics, i.e., $\left(Y^0, Y^1\right) \perp D|X$, once we prune the sample on the basis of the PS $\left(Y^0, Y^1\right) \perp D|\pi(X)$, where $\pi(X)$ is the treatment probability conditional on X (i.e., the "propensity score") which means that we want to compare $\hat{\pi}(X_i) with \hat{\pi}\left(X_j\right)$ (Rosenbaum and Rubin, 1983). However, King and Nielsen (2019) have recently argued that PSM might increase the imbalance between control and treatment groups as well as model dependence due the difficulty in determining the exact moment when pruning should be stopped. Therefore, they propose to use multivariate distance or exact coarsened matching which is less sensible to this issue, assuring a better comparison between groups. We also employ this approach in addition to the PSM. The matching in this case is based on the Mahalanobis metric which is a measure of the distance between two units in the multivariate space of X:

$$MD\left(X_i, X_j\right) = \sqrt{\left(X_i - X_j\right)' \Sigma^{-1} \left(X_i - X_j\right)} \tag{3}$$

In both matching methods we allow for replacement, i.e., more controls for each treated unit. For estimating the propensity scores, in the first equation we include a set of time-invariant variables: gender, education, ethnicity, area of residence. In addition to these socio-demographic variables, we also include marital status, living with others, retired (only for care receivers), having a disability, and pre-existing health conditions in the period before the pandemic (extracted from the 2019 wave and merged to each individual in our panel dataset). Then, in the second equation we control again for the same socio-demographic variables and the remaining time-variant characteristics originally used in the individual fixed effects strategy. One of the advantages of this approach is that it has a double-robust property, that the estimates of the effects will be consistent if either the treatment model or the outcome model – but not both – are mis-specified.

Subsequently, we estimate the probability of being infected for people who provide care (i.e., the caregivers sample) using the same models described above. While the outcomes and control variables are the same as those described above, the main exposure variable is a dummy that takes value 1 if the individual provides care and zero otherwise.

It is important to stress that while in the individual fixed effect model we look at the within individual variation in the informal carer activities, with these two matching strategies we compare informal carers/care recipients and non-carers/non care recipients who have at least very similar observable characteristics (between groups comparison). The individual fixed effects model and the matching strategies, therefore, can be seen as complementary approaches since they exploit two different sources of variation. We also think that matching strategy is superior to, for example, a pure between- or random-effect model since matching effectively reduces imbalance in the control-treatment observable characteristics. Both methods employed in this study, however, can be affected by unobserved heterogeneity and, thus, results should be still interpreted with caution.

To evaluate if the results are robust, we also perform several robustness and sensitivity checks which we describe below. First, we estimate the Eqs. (1) and (2) removing the people who are more at risk of being infected in the sample of care recipients. The UKHLS has defined a variable that identifies the people at highest risk of being infected.[8] Second, we remove the age bands restriction for the group of individuals who provide care to check that this age selection was not influencing our estimates. In this way, we also include the group of caregivers above the age of 60 (circa 26% of the people aged 61–97 provide some kind of informal care outside the household). Moreover, to check that our results are robust to the nonlinearity of the outcome, we also report a Probit estimation of the Eq. (1) for both samples. To tackle bias from potential reverse causality between being infected and receiving informal care, we also estimate a linear probability model using the lag of the care received in the previous waves $\beta Care_{i_{wave6}}$. We use the wave of November 2020 to estimate the risk infection between January and March 2021. For this analysis, we focus on the last two waves of the survey and merge respondents' retrospective information. That is, we add the information on caring activity of November 2020 (wave 6), as a dummy variable having value 1 if they received care and 0 otherwise, to each individual who participated in January (wave 7) and March (wave 8). In this way we are also able to evaluate the effect of caring on the contagion risk in a time span of two to three months. Since the receiving-care variable does not vary within individuals (only measured at November 2020) and we wish to compare the groups who received care against those who did not receive care, we adopt a random effects specification (i.e., a comparison of care receivers and non receivers). However, given the data structure, we also condition on the fact that the people had not been infected in the previous waves of the care activity, attaching the information on contagion risk to each respondent (tested positive between waves 1 and 6) and included in the set of covariates in $\xi_{i,t}$. Our hypothesis is that receiving care before November 2020 should be less correlated to the chance that the person has been infected in January or March, potentially eliminating this source of bias. The equation of this model is the following:

$$Infect^{RE}_{i,wave8-7} = \alpha_i + \beta Care_{i,wave6} + \gamma \mathbf{X_{i,t}} + \lambda_t + \xi_{i,t} \tag{4}$$

Finally, we explore the heterogeneity across household income groups. It is well known that less affluent people were more badly affected more by the pandemic (Cash and Patel, 2020). However the relationship between the risk of been infected and income is not clear. For example, people who live in poor families may be less able to self-isolate, might not have the possibility of working from home, or have to deal with more family responsibilities inside/outside their household, increasing their risk of contagion. To explore this heterogeneity we re-estimate Eq. 1, splitting the sample by household income into five quintiles. We present the findings for the first quintile (lowest income group) and fifth quintile (highest income group). Importantly, in all analyses we use the individual weights provided in the UKHLS COVID-19 survey to account for the sampling design.

4. Results

In this section we start off by exploring potential changes in the provision of informal care before (2019) and during the COVID-19 pandemic (Apr. 2020–Mar. 2021). Fig. 1 shows the proportion of respondents who said that they provide some kind of informal care outside their household (green line) and those that receive informal care from someone living outside their household (pink line) within each month-year. Both groups of respondents (caregivers and care recipients) show very similar trends over time. The provision of informal care to someone living outside the household was extremely high in the first months of the pandemic and then slowly decreased, although still remained high over the whole observed period. For example, if we look at the provision of informal care to someone living inside the household for the same period of time (blue line), we see that this was constant over time. In other words, in 2019 both informal care inside and outside the household were very similar (around 0.10) but during the pandemic informal care outside the household consistently increased (0.52 in April 2020 and 0.28 in March 2021). These changes in the provision of informal care outside the household could be explained by the lockdown measures, the mobility restrictions for older people, and that many families withdrew their relatives from the care-homes.

Were there any differences in the probability of catching COVID-19 for care recipients and caregivers? Table 1 shows the unconditional average differences between care recipients and non-recipients (upper panel [1]) and also between caregivers and non-caregivers (lower panel [2]) for the three outcomes of interest: (i) has had COVID-19 symptoms; (ii) tested for COVID-19, and (iii) tested positive for COVID-19. In the case of the care recipient sample [1], we observe that those who received some kind of help during the pandemic were more likely to exhibit COVID-19 symptoms (0.08 vs 0.05) and to test positive to the virus (0.14 vs 0.05) although they tested a bit less (0.08 vs 0.12). The caregivers sample [2] also exhibits some interesting patterns, although these differences seem to be smaller. Relative to non-caregivers, caregivers reported more symptoms (0.11 vs 0.09), tested less for COVID-19 (0.10 vs 0.14), and were slightly less likely to test positive for the virus (0.09 vs 0.12).

We now turn to the main conditional analyses. Fig. 2 shows the main estimates for the fixed effects (FE), the Propensity Score Matching (PSM), and the Mahalanobis distance matching approaches. Overall, receiving care has a positive effect on

[8] For more information see the following link: https://www.understandingsociety.ac.uk/documentation/covid-19/dataset-documentation/variable/clinvuln_dv

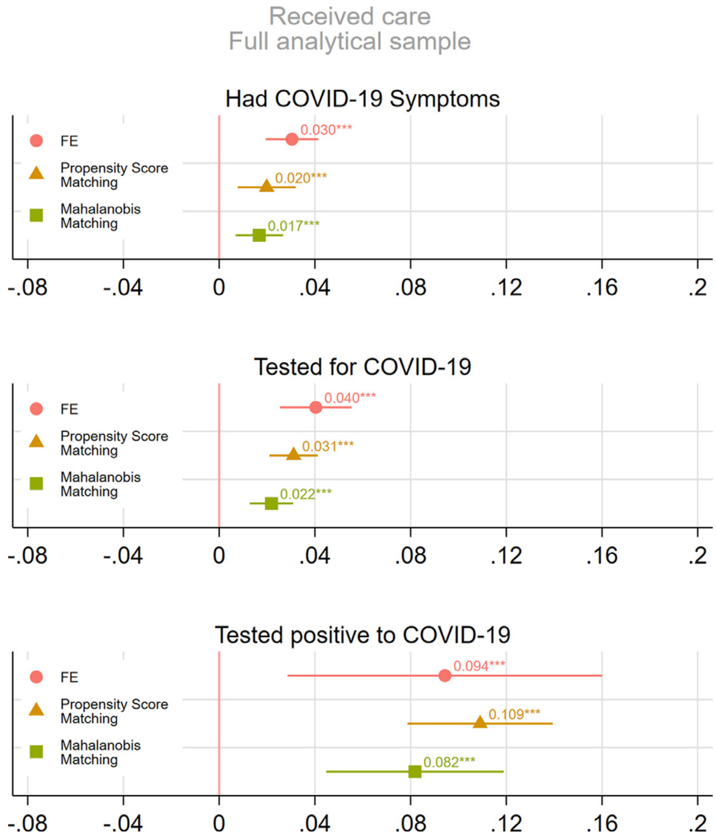

Fig. 2. Main results panel data analysis - Care recipients sample. *Notes:* UKHLS COVID-19 Survey 2020–21, weighted data. Sample size FE: a) N = 20,419 obs; b) N = 20,420 obs; c) N = 2204 obs. Sample size PSM: a) N treatment = 3689 (not used = 261) obs, N control = 13,023 (not used = 3446) obs; b) N treatment = 3690 (not used = 261) obs, N control = 13,024 (not used = 3445) obs; c) N treatment = 382 (not used = 91) obs, N control = 1262 (not used = 469) obs. Sample size MD: N treated = 3950 (not used = 153) obs, N Control = 13,274 (not used 3042) obs; N treatment = 3952 (not used 153) obs, N control = 13,274 (not used 3041) obs; N treatment = 398 (not used 71) obs, N control= 1316 (not used 419) obs. FE = heteroskedasticity robust standard errors; PSM and MD = bootstrapped standard errors (1000 reps).The control variables are the ones listed in Table A.2.

the probability of having had COVID-19 symptoms, conducting a test, and testing positive to COVID-19. Also, the coefficients among the three models are similar in magnitude, indicating that the results are stable across the different specifications. More specifically, looking at the FE estimates, we observe that people who received care are around 3 percentage points (p.p.) more likely to report symptoms compatible with COVID-19, they also test more often (4 p.p., FE estimate), and were more likely to test positive for COVID-19 (8 p.p., FE estimate) than those who have not received any care. Considering that the overall probability of testing positive for COVID-19 in the care recipients sample is around 14%, the last estimate represents a quite substantive effect (see Table 1).

Similarly, Fig. 3 displays the estimates of the probability of having COVID-19 symptoms, testing, and testing positive for the sample of people who provide care. The aim of this analysis is to understand if people who provide care have a higher or lower probability of being infected. The three models present similar coefficients, which are close to zero and not statistically significant. Namely, we find a 1 p.p. lower probability for had COVID-19 symptoms, a 1 p.p decrease in the probability of testing, and a 1p.p increase for testing positive for COVID-19 in the FE models. None of these estimates are statistically significant at conventional levels. This basically means that those who provide care and those who do not provide care appear to have the same risk of being infected once we adjust for individual characteristics. In fact, the small initial differences in the baseline probabilities of being infected for this sample (see Table 1) almost disappeared when accounting for other identifiable differences in the samples.

To ease the interpretation of our coefficients, we estimated our individual FE models assuming linearity. However, this could be problematic in cases in which the probabilities are extreme since these models can produce results beyond the 0–1 interval, biasing the estimates of interest. Therefore as a robustness check, we also report the results of a Probit estimation in the Tables A.6 and A.7 of the Appendix. In these additional analyses we do not observe any changes in the results for those who receive care or for those who provide care.

Moreover, we evaluated the quality of our matching estimators in Fig. A.9 and A.10. In both Figures, the left side panel shows a density function for the distribution of the propensity scores before and after matching for the untreated (non care

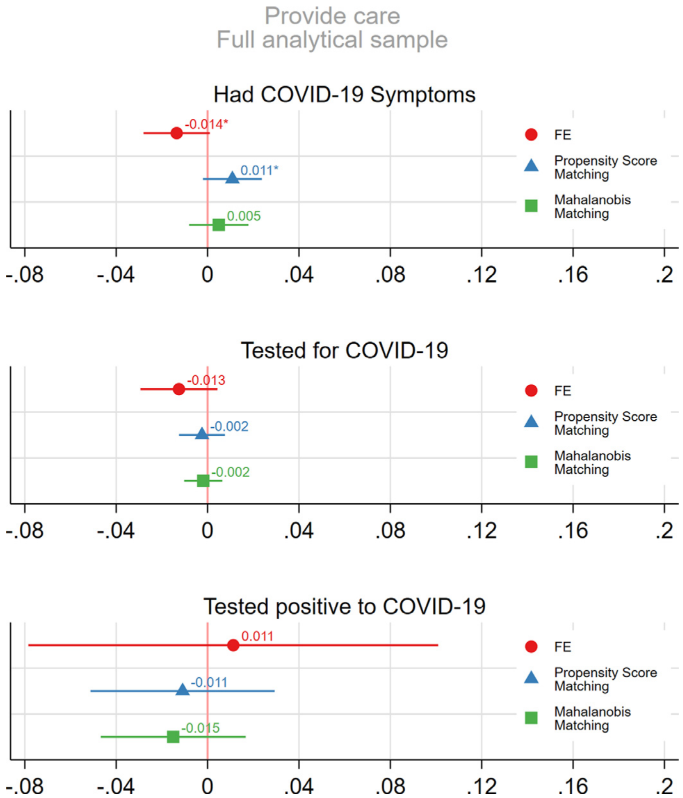

Fig. 3. Main results panel data analysis - Caregivers sample. *Notes:* UKHLS COVID-19 Survey 2020–21, weighted data. Sample size FE: a) N = 14,520 obs; b) N = 14,524 obs; c) N = 1666 obs. Sample size PSM: a) N treatment = 5326 (not used = 364) obs, N control = 7920 (not used = 910) obs; b) N treatment = 5421 (not used = 368) obs, N control = 7923 (not used = 912) obs; c) N treatment = 351 (not used = 134), N control = 781 (not used = 400) obs. Sample size MD: N treated = 5422 (not used = 268) obs, N Control=7930 (not used 900) obs; N treatment = 5421 (not used 268) obs, N control = 7933 (not used 902) obs; N treatment = 365 (not used 120) obs, N control = 783 (not used 398) obs. FE = heteroskedasticity robust standard errors; PSM and MD = bootstrapped standard errors (1000 reps) The control variables are the ones listed in Table A.2.

recipients/non caregiver) and treated observations (care recipients/caregivers). In both figures we can see that PSM managed to balance the sample in a satisfactory way. Moreover, the right side panel of both Figs. A.9 and A.10 show instead the standardized mean difference and the variance ratio for the Mahalanobis Distance Matching. Standardized mean differences relatively close to 0 and variance ratios close to 1 indicate that after matching, our untreated and treated groups are very similar across the observable characteristics included in the model. Overall, both matching strategies seem to balance the sample very well.

As mentioned in the methods section, to ensure that our analysis is not affected by possible reverse causality due to the expectation that old people who are infected with COVID-19 may need more care, we performed further robustness checks using lagged models. That is, we estimate the risk of COVID-19 infections during January 2021 and March 2021 inclusive using a lagged variable for care in the month of November 2020. This variable should not be correlated with the probability of infection in the next period, and, thus, we expect that it would not be correlated with the likelihood of needing care as a consequence of suffering from COVID-19. Additionally, in a more dynamic way, and as a further test, we also control for testing positive in the months before receiving care.This should further reduce any potential bias that could arise from the fact that infected people might need some help. Results for those who receive care are reported in Fig. 4. In these analyses, we observe that the coefficients are still significant and positive for all outcomes, and remain similar to those presented in the main specifications of Fig. 2.

Moreover, the UKHLS survey includes a variable that measures the risk of infection based on medical records. This variable was derived by the UKHLS using the NHS two-level list of health conditions for classifying patients at risk of COVID-19. We use this to estimate a model for people who receive care, excluding those at higher risk of infection (N = 1634, circa 8% of sample) to test if the results we observe remain after we have eliminated the people at highest risk of being infected. These further results are presented in appendix Fig. A.7 and remain similar to those from the main specification.

We also test what happens to the probability of being infected for those who provide care if we eliminate the age bands – results are reported in Fig. A.8 and these do not change. That is, we still observe null effects similar to those reported in Fig. 3.

Finally, as an additional exercise, we explore socio-economic heterogeneity amongst those who receive care. In particular, we re-estimate Eq. (1), splitting the sample by household income into five quintiles, and present the findings for the first

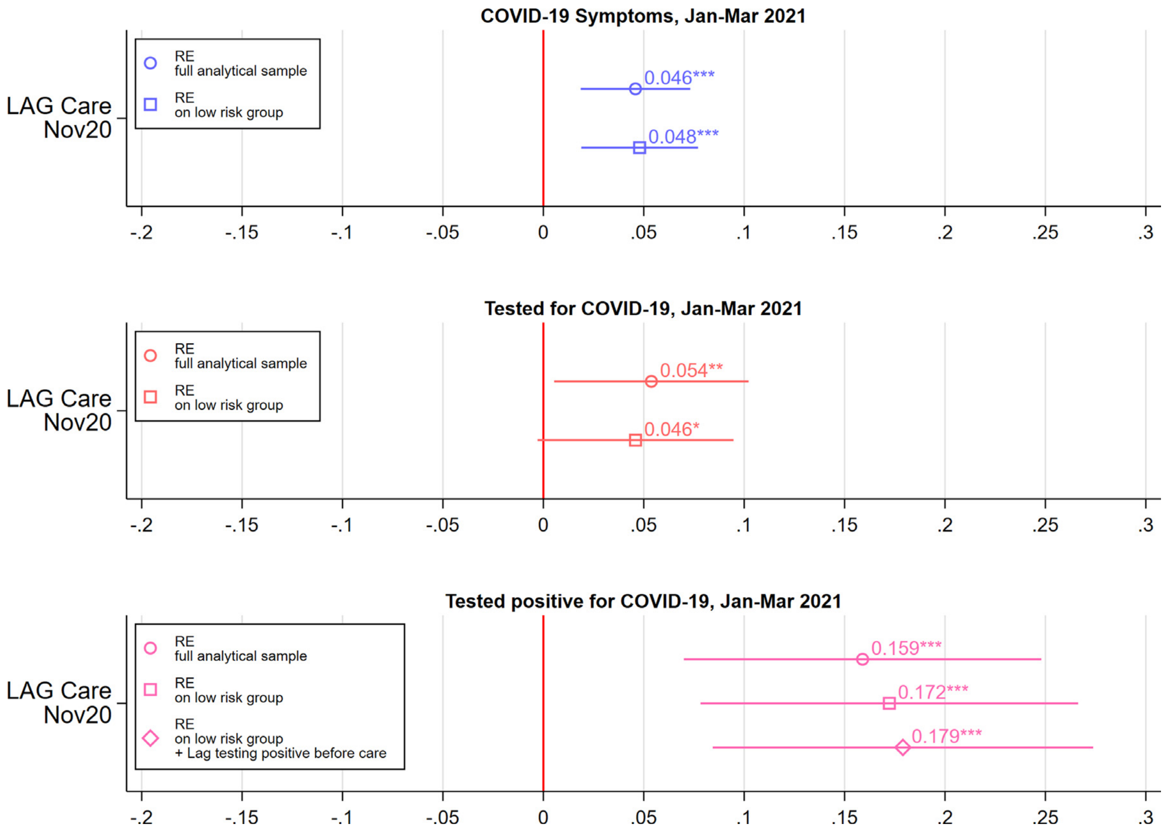

Fig. 4. Care receivers sample with lags. *Notes:* UKHLS COVID-19 Survey 2020–21, weighted data. Sample size: Lag models COVID-19 symptoms: Full analytical sample = 19,007 obs; Low risk sample = 17,498; Tested for COVID-19: Full analytical sample = 19,007 obs; Low risk sample = 17,498; Tested positive for COVID-19: Full analytical sample = 3240 obs; Low risk sample = 2776 obs; Low risk sample + lag testing positive before care = 2776 obs. Heteroskedasticity robust standard errors. The control variables are the ones listed in Table A.2.

quintile (lowest income group) and fifth quintile (highest income group) in Table 2. Results from these estimations indicate that people in the lowest income group have higher probability of getting COVID-19 than people in the highest income group (i.e., 24 p.p. against 1 p.p. for testing positive for COVID-19). This agrees with the extensive literature which has found that low-income groups suffered more severe disease and higher mortality during the COVID-19 pandemic (Williamson et al., 2020; Kontopantelis et al., 2022).

Although our inequality analyses are purely descriptive, these provide further support to the hypothesis that disadvantaged groups were more affected by the pandemic. For people of low socio-economic status, who tend to exhibit more pre-existing conditions, their exposure to COVID-19 has exacerbated their risks of economic hardship and increased health inequalities amongst groups (Daras et al., 2020; Brewer and Gardiner, 2020; Nicodemo et al., 2020). Identifying the underlying inequalities and policy challenges are, therefore, crucial for understanding how the COVID-19 shock has the potential to directly exacerbate some of these pre-existing inequalities (Blundell et al., 2020).

5. Conclusions

In this paper we have explored the association between the supply of informal care and the risk of being infected with COVID-19 during the pandemic. We have exploited rich new survey data collected by the UK Household Longitudinal Study during the first year of the COVID-19 pandemic and run different regression models to estimate the probability of being infected for people who received care from someone living outside their household versus those who did not receive any informal care, and also for caregivers.

Our results suggest that older people who received care had a higher risk of being infected when compared to those who did not receive any informal care from outside the household. Further, we observed that people in the lowest income quintile have a higher probability of being infected with COVID-19 relative to those in the highest income quintile. Moreover, we estimated the probability of being infected for those who provide care to others compared to those who did not provide any care during the pandemic and we do not find any significant difference between these carers and non-carers. One potential hypothesis that emerges from this result is that informal careers might have not adjusted their behaviour to protect the care recipients. Future studies, therefore, should aim to gather data on carers' practices and behaviours in order to better understand the potential mechanisms behind these results.

Importantly, these results are robust to different empirical strategies, sub-sample analysis, and the utilization of a lag structure for care and infections. Overall, the findings of this study provide evidence for policy on the important subject of informal care-giving and are also relevant at an international level for countries with a higher incidence of informal care such as Southern European countries.

In particular, these results inform policy-makers and stakeholders on the importance of testing and offering the possibility of vaccinating those informal carers who, compared to professional carers, might have a higher risk of infecting the elderly due to lack of experience when it comes to infection management and avoidance. In a context where societies are aging and the formal care sector is under serious budget pressure, protecting vulnerable people by investing in the informal care sector could be key in reducing mortality and the strain placed on the primary and secondary health care sectors.

Finally, it is important to bear in mind that the COVID-19 pandemic hit areas of England unevenly, increasing regional health and economic divides. This is well documented by Munford et al. (2021). It is very likely that some socio-economic factors at the regional level have become more important in determining such inequalities. This is likely to be particularly true in the context of England, where there are large socioeconomic and institutional differences between the South East/London area and the rest of the country. Subsequent analysis would benefit from the use of more disaggregated data (e.g. at a census ward level) and the accompanying use of spatial multilevel techniques for disentangling inequalities at a regional level.

Declaration of Competing Interest

None.

Data Availability

Data are available from UK Data service.

Appendix A

Table A.1 .

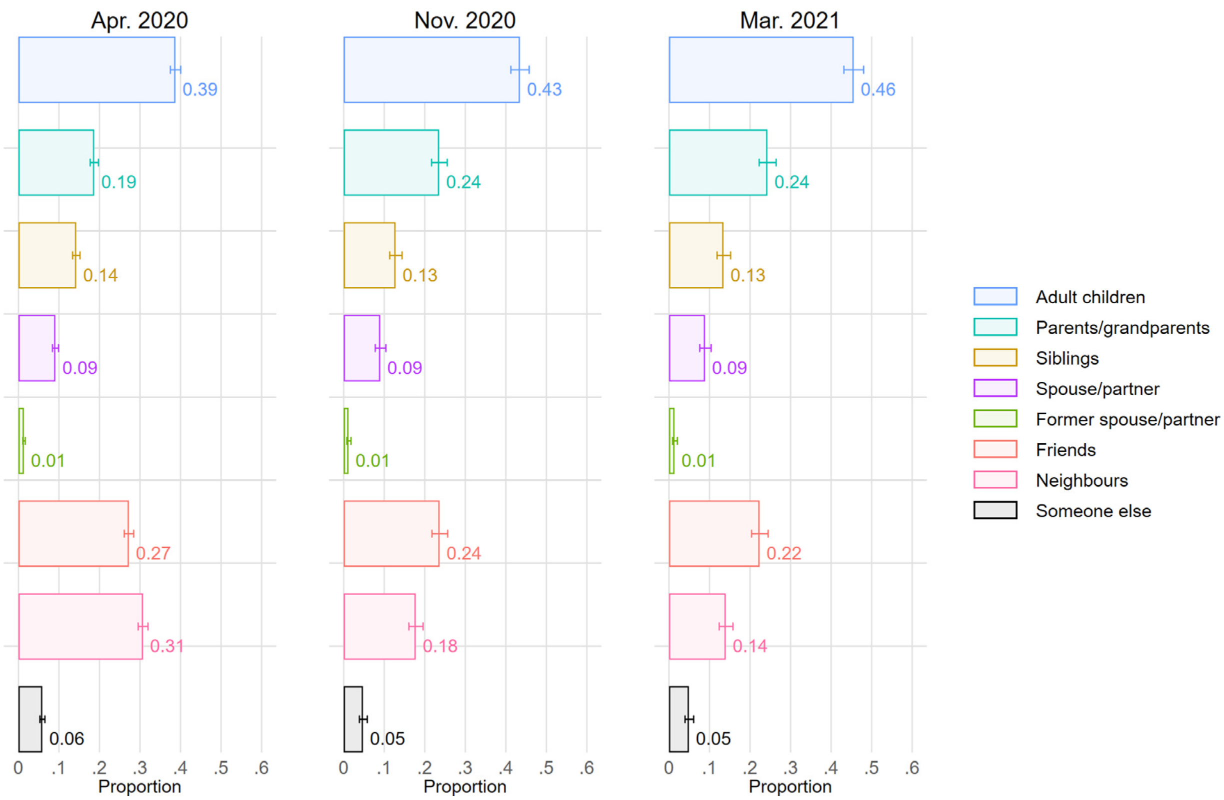

Fig. A1. From whom is receiving help/care outside the household. *Notes:* UKHLS COVID-19 Survey 2020–21, weighted data.

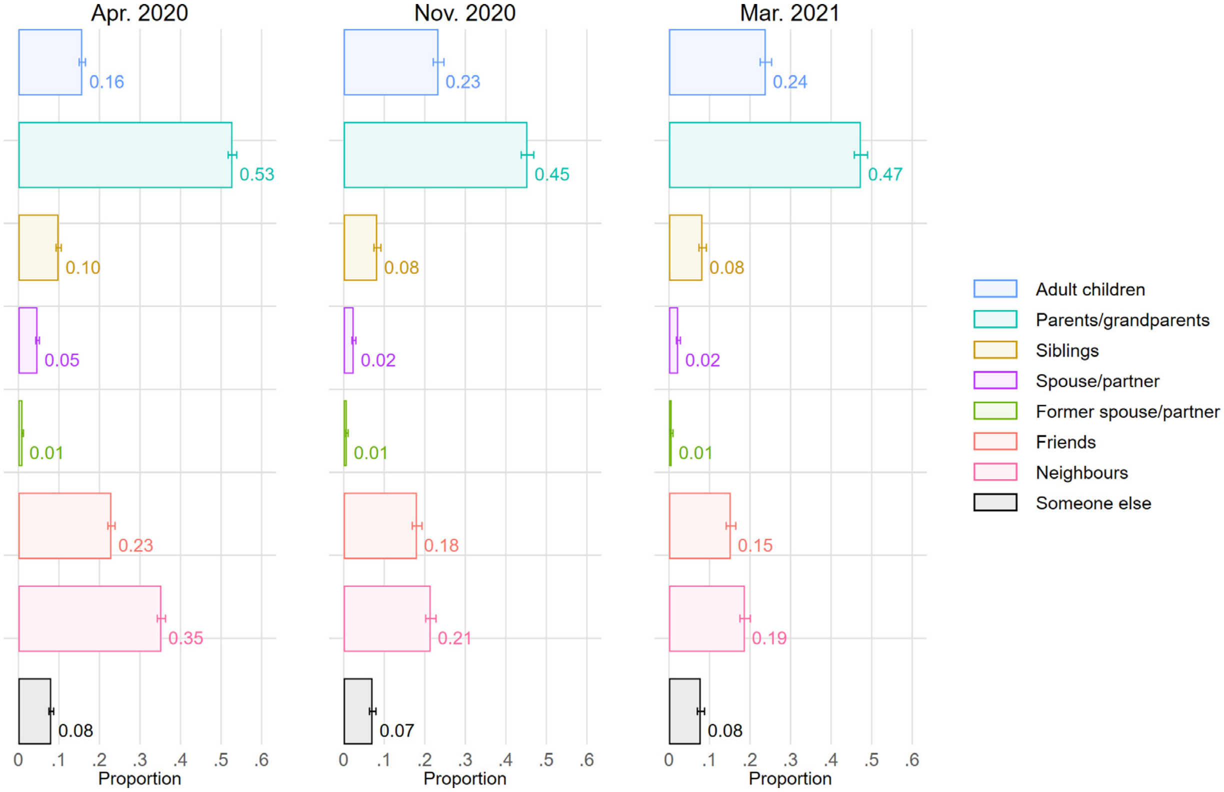

Fig. A2. To whom is providing help/care outside the household. *Notes:* UKHLS COVID-19 Survey 2020–21, weighted data.

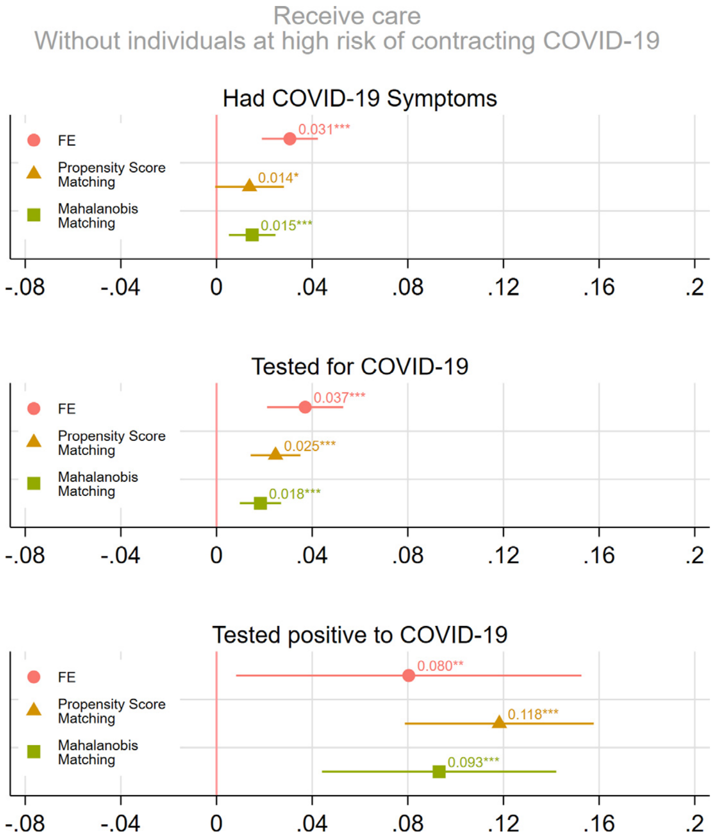

Fig. A3. Care recipients sample without the group at higher risk of contagious. *Notes:* UKHLS COVID-19 Survey 2020–21, weighted data.Sample size FE: a) *N* = 18,785; b) *N* = 18,786; c) *N* = 2,028 Sample size PSM: a) *N* treatment = 3646 (not used = 246), *N* control = 12,671 (not used = 2222); b) *N* treatment = 3647 (not used = 246), *N* control = 12,671 (not used = 2222); c) *N* treatment = 382 (not used = 91), *N* control = 1262 (not used = 469) Sample size MD: *N* treated = 3950 (not used = 153), *N* Control=13,274 (not used 3042); *N* treatment = 3952 (not used 153), *N* control = 13,274 (not used 3041); *N* treatment = 358 (not used 67), *N* control=1205 (not used 398). The control variables are the ones listed in Table A.2.

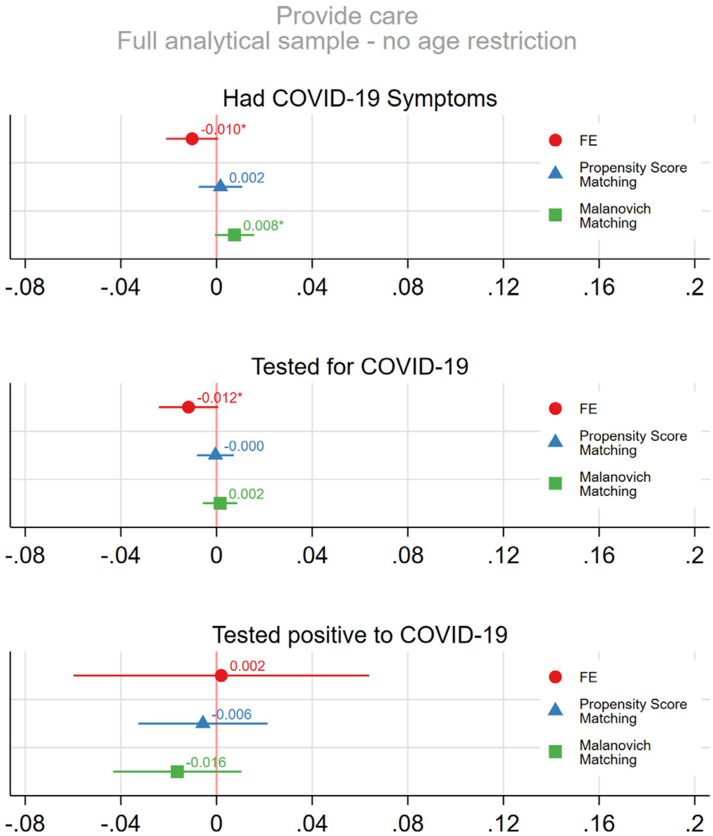

Fig. A4. Caregivers sample, without age restriction. *Notes:* UKHLS COVID-19 Survey 2020–21, weighted data.Sample size FE: a) N = 31,368 ; b) N = 31,372; c) N = 3167 Sample size PSM: a) N treatment = 11,330 (not used = 438), N control = 18,903 (not used = 635); b) N treatment = 11,391 (not used = 439), N control = 18,877 (not used = 664); c) N treatment = 815 (not used = 155), N control = 2021 (not used = 176) Sample size MD: N treated = 11,492 (not used = 338), N Control=17,553 (not used 1985); N treatment = 11,493 (not used 338), N control = 17,554 (not used 1987); N treatment = 855 (not used 115), N control = 1631 (not used 566). The control variables are the ones listed in Table A.2.

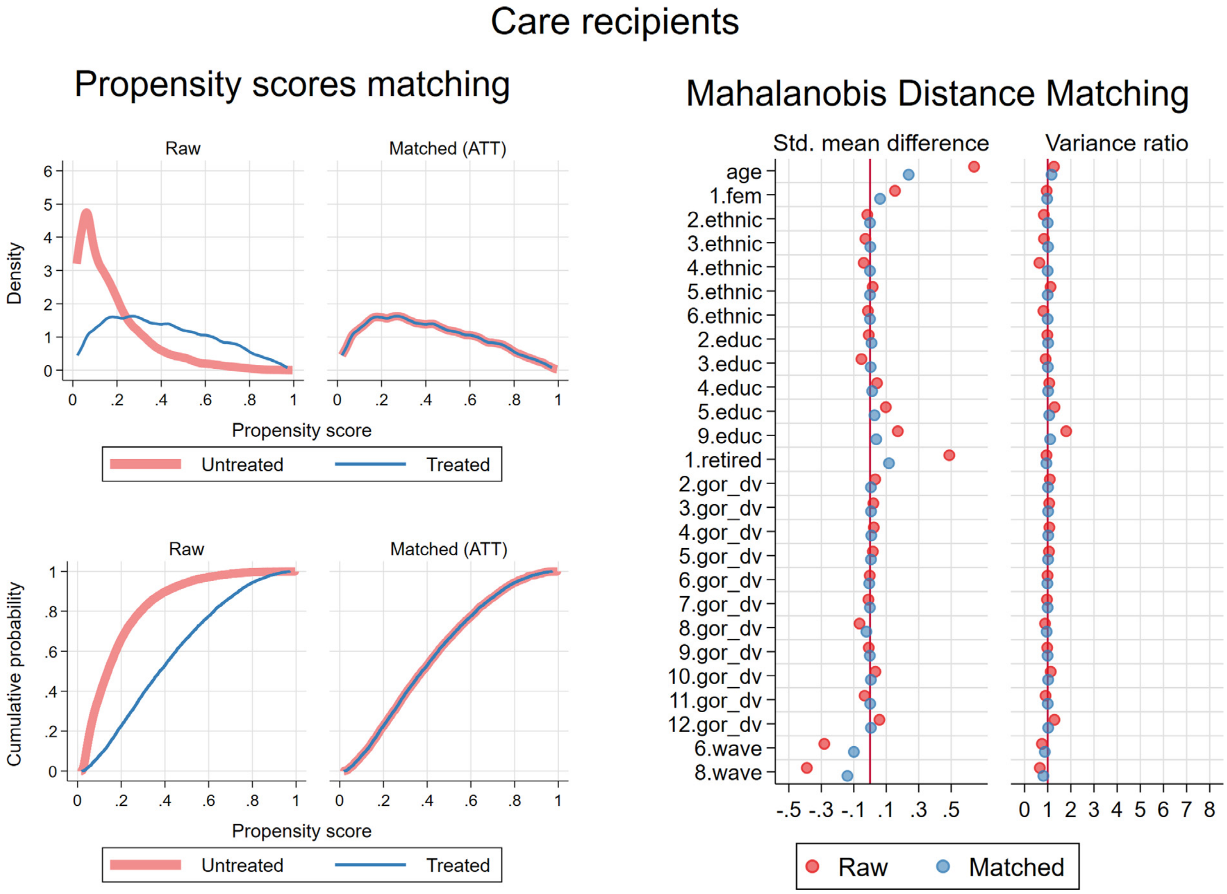

Fig. A5. Care recipient sample - Matching diagnosis. *Notes:* UKHLS COVID-19 Survey 2020–21, weighted data.

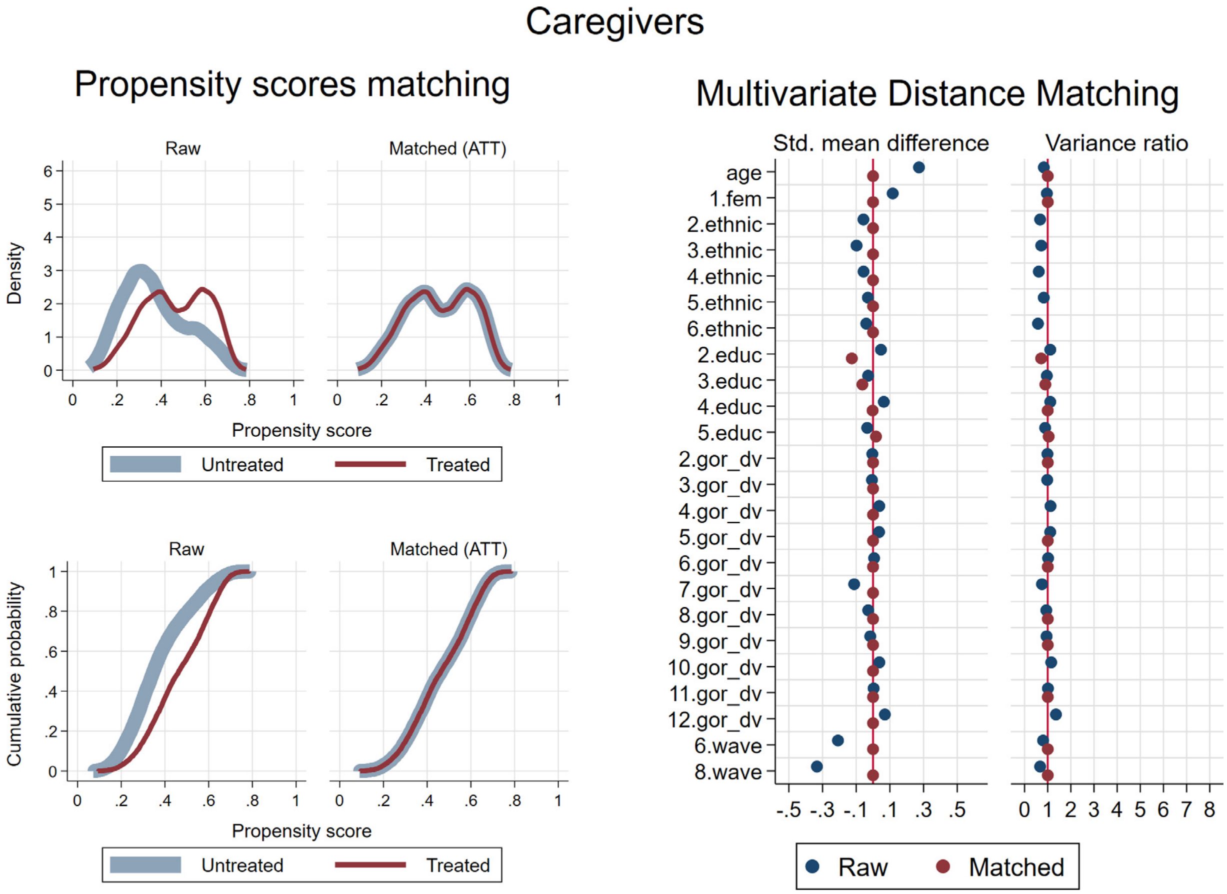

Fig. A6. Caregivers sample - Matching diagnosis. *Notes:* UKHLS COVID-19 Survey 2020–21, weighted data.

Table A.1
Summary statistics on care recipients sample.

	Care recipients					
	Yes			*No*		
	mean	min	max	mean	min	max
Age	69.46	50	97	63.20	50	95
Woman	0.59	0	1	0.49	0	1
Ethnicity						
White	0.96	0	1	0.95	0	1
Mixed	0.00	0	1	0.01	0	1
South Asian	0.01	0	1	0.02	0	1
Chinese & other Asian	0.00	0	1	0.01	0	1
Blacks	0.02	0	1	0.02	0	1
Arabs and other ethnic	0.00	0	1	0.00	0	1
GOR						
North-East	0.03	0	1	0.04	0	1
North-West	0.11	0	1	0.10	0	1
Yorkshire and The Humber	0.09	0	1	0.08	0	1
East Midlands	0.07	0	1	0.09	0	1
West Midlands	0.08	0	1	0.08	0	1
East of England	0.11	0	1	0.11	0	1
London	0.11	0	1	0.09	0	1
South-East	0.15	0	1	0.14	0	1
South-West	0.10	0	1	0.11	0	1
Wales	0.04	0	1	0.04	0	1
Scotland	0.08	0	1	0.08	0	1
Northern Ireland	0.02	0	1	0.02	0	1
Highest educational attainment						
Degree	0.21	0	1	0.27	0	1
Other higher degree	0.14	0	1	0.13	0	1
A-level etc	0.15	0	1	0.17	0	1
GCSE etc	0.22	0	1	0.21	0	1
Other qualification	0.15	0	1	0.13	0	1
No qualification	0.13	0	1	0.07	0	1
Marital status						
Single	0.09	0	1	0.09	0	1
Married/Cohabiting	0.59	0	1	0.76	0	1
Separated/divorced	0.15	0	1	0.09	0	1
Widowed	0.16	0	1	0.06	0	1
Lives with others	0.64	0	1	0.85	0	1
Retired	0.64	0	1	0.39	0	1
Long-term disable	0.07	0	1	0.03	0	1
Has previous health conditions	0.63	0	1	0.43	0	1
Total household net income	2694.8	0	27,835	3735.2	0	50,404
Wave						
Apr. 2020	0.61	0	1	0.33	0	1
Nov. 2020	0.20	0	1	0.33	0	1
March 2021	0.19	0	1	0.33	0	1
Observations	**4949**			**15,471**		

Notes: UKHLS COVID-19 Survey 2020–21; weighted data

Table A.2
Summary statistics on caregivers sample.

	Caregivers					
	Yes			No		
	mean	min	max	mean	min	max
Age	43.50	17	60	39.05	17	60
Woman	0.54	0	1	0.47	0	1
White	0.92	0	1	0.87	0	1
Ethnicity						
Mixed	0.02	0	1	0.03	0	1
South Asian	0.04	0	1	0.05	0	1
Chinese & other Asian	0.01	0	1	0.02	0	1
Blacks	0.02	0	1	0.02	0	1
Arabs and other ethnic	0.00	0	1	0.01	0	1
GOR						
North-East	0.05	0	1	0.04	0	1
North-West	0.12	0	1	0.11	0	1
Yorkshire and The Humber	0.09	0	1	0.09	0	1
East Midlands	0.08	0	1	0.08	0	1
West Midlands	0.10	0	1	0.10	0	1
East of England	0.09	0	1	0.09	0	1
London	0.10	0	1	0.12	0	1
South-East	0.13	0	1	0.14	0	1
South-West	0.08	0	1	0.09	0	1
Wales	0.05	0	1	0.04	0	1
Scotland	0.08	0	1	0.07	0	1
Northern Ireland	0.03	0	1	0.02	0	1
Highest educational attainment						
Degree	0.31	0	1	0.31	0	1
Other higher degree	0.12	0	1	0.11	0	1
A-level etc	0.24	0	1	0.28	0	1
GCSE etc	0.22	0	1	0.21	0	1
Other qualification	0.08	0	1	0.06	0	1
No qualification	0.03	0	1	0.04	0	1
Marital status						
Single	0.30	0	1	0.40	0	1
Married/Cohabiting	0.63	0	1	0.54	0	1
Separated/divorced	0.07	0	1	0.05	0	1
Widowed	0.01	0	1	0.01	0	1
Lives with others	0.87	0	1	0.90	0	1
Long-term disable	0.05	0	1	0.05	0	1
Has previous health conditions	0.33	0	1	0.31	0	1
Total household net income	3746.7	0	62,580	3836.8	0	50,404
Wave						
Apr. 2020	0.57	0	1	0.33	0	1
Nov. 2020	0.24	0	1	0.33	0	1
March 2021	0.19	0	1	0.33	0	1
Observations	**5958**			**8566**		

Notes: UKHLS COVID-19 Survey 2020–21; weighted data

Table A.3
Summary statistics on care recipients by waves.

	Apr. 2020			Nov. 2020			Mar. 2021		
	mean	min	max	mean	min	max	mean	min	max
Receiving care from outside the household	0.40	0	1	0.18	0	1	0.17	0	1
Age	64.83	50	96	64.73	50	97	65.01	50	97
Woman	0.52	0	1	0.52	0	1	0.52	0	1
Ethnicity									
White	0.95	0	1	0.95	0	1	0.95	0	1
Mixed	0.01	0	1	0.01	0	1	0.01	0	1
South Asian	0.02	0	1	0.01	0	1	0.02	0	1
Chinese & other Asian	0.01	0	1	0.01	0	1	0.01	0	1
Blacks	0.02	0	1	0.02	0	1	0.01	0	1
Arabs and other ethnic	0.00	0	1	0.00	0	1	0.00	0	1
GOR									
North East	0.04	0	1	0.04	0	1	0.04	0	1
North West	0.10	0	1	0.10	0	1	0.10	0	1
Yorkshire and The Humber	0.09	0	1	0.08	0	1	0.09	0	1
East Midlands	0.08	0	1	0.08	0	1	0.09	0	1
West Midlands	0.08	0	1	0.08	0	1	0.08	0	1
East of England	0.11	0	1	0.11	0	1	0.11	0	1
London	0.11	0	1	0.09	0	1	0.09	0	1
South East	0.14	0	1	0.15	0	1	0.15	0	1
South West	0.11	0	1	0.11	0	1	0.11	0	1
Wales	0.04	0	1	0.05	0	1	0.04	0	1
Scotland	0.08	0	1	0.08	0	1	0.08	0	1
Northern Ireland	0.02	0	1	0.03	0	1	0.03	0	1
Highest educational attainment									
Degree	0.25	0	1	0.26	0	1	0.25	0	1
Other higher degree	0.13	0	1	0.13	0	1	0.14	0	1
A-level etc	0.16	0	1	0.17	0	1	0.17	0	1
GCSE etc	0.21	0	1	0.22	0	1	0.21	0	1
Other qualification	0.14	0	1	0.13	0	1	0.15	0	1
No qualification	0.09	0	1	0.08	0	1	0.08	0	1
Marital status									
Single	0.09	0	1	0.09	0	1	0.09	0	1
Married/Cohabiting	0.71	0	1	0.72	0	1	0.73	0	1
Separated/divorced	0.11	0	1	0.11	0	1	0.11	0	1
Widowed	0.08	0	1	0.08	0	1	0.08	0	1
Leaving with others	0.79	0	1	0.79	0	1	0.80	0	1
Long-term disable	0.04	0	1	0.04	0	1	0.04	0	1
Has previous health conditions	0.49	0	1	0.48	0	1	0.47	0	1
total household net income	3427.46	0	50,404	3457.55	0	28,172	3502.45	0	50,404
Observations	**7822**			**6473**			**6125**		

Notes: UKHLS COVID-19 Survey 2020–21; weighted data

Table A.4
Summary statistics caregivers sample by waves.

	Apr. 2020			Nov. 2020			Mar. 2021		
	mean	min	max	mean	min	max	mean	min	max
Caring for others outside the household	0.52	0	1	0.33	0	1	0.28	0	1
Age	40.47	17	60	40.68	17	60	40.72	18	60
Woman	0.50	0	1	0.50	0	1	0.49	0	1
Ethnicity									
White	0.89	0	1	0.88	0	1	0.90	0	1
Mixed	0.02	0	1	0.03	0	1	0.02	0	1
South Asian	0.04	0	1	0.05	0	1	0.04	0	1
Chinese & other Asian	0.01	0	1	0.02	0	1	0.02	0	1
Blacks	0.03	0	1	0.02	0	1	0.02	0	1
Arabs and other ethnic	0.01	0	1	0.01	0	1	0.01	0	1
GOR									
North-East	0.04	0	1	0.05	0	1	0.05	0	1
North-West	0.11	0	1	0.11	0	1	0.10	0	1
Yorkshire and The Humber	0.09	0	1	0.08	0	1	0.09	0	1
East Midlands	0.08	0	1	0.08	0	1	0.09	0	1
West Midlands	0.09	0	1	0.10	0	1	0.10	0	1
East of England	0.09	0	1	0.09	0	1	0.09	0	1
London	0.12	0	1	0.11	0	1	0.11	0	1
South-East	0.14	0	1	0.14	0	1	0.14	0	1
South-West	0.08	0	1	0.09	0	1	0.09	0	1
Wales	0.04	0	1	0.05	0	1	0.04	0	1
Scotland	0.08	0	1	0.08	0	1	0.07	0	1
Northern Ireland	0.02	0	1	0.03	0	1	0.03	0	1
Highest educational attainment									
Degree	0.30	0	1	0.31	0	1	0.31	0	1
Other higher degree	0.11	0	1	0.12	0	1	0.12	0	1
A-level etc	0.26	0	1	0.27	0	1	0.26	0	1
GCSE etc	0.22	0	1	0.21	0	1	0.21	0	1
Other qualification	0.07	0	1	0.07	0	1	0.06	0	1
No qualification	0.04	0	1	0.03	0	1	0.04	0	1
Marital status									
Single	0.36	0	1	0.36	0	1	0.37	0	1
Married/Cohabiting	0.57	0	1	0.57	0	1	0.57	0	1
Separated/divorced	0.06	0	1	0.06	0	1	0.05	0	1
Widowed	0.01	0	1	0.01	0	1	0.01	0	1
Lives with others	0.88	0	1	0.89	0	1	0.89	0	1
Long-term disable	0.06	0	1	0.05	0	1	0.05	0	1
Has previous health conditions	0.31	0	1	0.32	0	1	0.33	0	1
Total household net income	3794.72	0	50,404	3792.31	0	62,580	3828.55	0	50,404
Observations	**6691**			**4081**			**3752**		

Notes: UKHLS COVID-19 Survey 2020–21; weighted data

Table A.5
Attrition - Percentage of those who remain in the survey, Apr. 2020-Mar. 2021.

Sample	Period		
	Apr. 2020 (wave 1)	Nov. 2020 (wave 6)	Mar. 2021 (wave 8)
Sample +50 (Care receivers)	100	82.7	78.3
Sample 16–60 (Caregivers)	100	60.9	56.1

Table A.6
Care recipients sample, Probit models with Average Marginal Effects (AME).

Pooled Probit	(1) Had Symp		(2) Tested		(3) Tested pos	
	AME	Std err.	AME	Std err.	AME	Std err.
Receive care						
Yes	0.029***	(0.008)	0.035***	(0.009)	0.143***	(0.027)
Sociodemographic controls	*Yes*		*Yes*		*Yes*	
GOR fixed effects	*Yes*		*Yes*		*Yes*	
Wave fixed effects	*Yes*		*Yes*		*Yes*	
N	20,419		20,420		2204	
Pseudo R^2	0.08		0.16		0.17	
Panel Probit PA	(1) Had Symp		(2) Tested		(3) Tested pos	
	AME	Std err.	AME	Std err.	AME	Std err.
Receive care						
Yes	0.027***	(0.005)	0.052***	(0.007)	0.108***	(0.018)
Sociodemographic controls	*Yes*		*Yes*		*Yes*	
GOR fixed effects	*Yes*		*Yes*		*Yes*	
Wave fixed effects	*Yes*		*Yes*		*Yes*	
N	20,419		20,420		2204	

Notes: UKHLS COVID-19 Survey 2020–21; weighted data; panel Probit population averages (PA) do not provide pseudo R2. The control variables are the ones listed in Table A.2.

Table A.7
Caregivers sample, Probit models with Average Marginal Effects (AME).

Pooled Probit	(1) Had Symp		(2) Tested		(3) Tested pos	
	AME	Std err.	AME	Std err.	AME	Std err.
Provide care						
Yes	0.009	(0.009)	0.008	(0.009)	−0.037*	(0.023)
Sociodemographic controls	*Yes*		*Yes*		*Yes*	
GOR fixed effects	*Yes*		*Yes*		*Yes*	
Wave fixed effects	*Yes*		*Yes*		*Yes*	
N	14,520		14,524		1666	
Pseudo R^2	0.04		0.19		0.07	
Panel Probit PA	(1) Had Symp		(2) Tested		(3) Tested pos	
	AME	Std err.	AME	Std err.	AME	Std err.
Provide care						
Yes	0.007	(0.005)	−0.001	(0.005)	−0.010	(0.014)
Sociodemographic controls	*Yes*		*Yes*		*Yes*	
GOR fixed effects	*Yes*		*Yes*		*Yes*	
Wave fixed effects	*Yes*		*Yes*		*Yes*	
N	14,520		14,524		1666	

Notes: UKHLS COVID-19 Survey 2020–21; weighted data; panel Probit population averages (PA) do not provide pseudo R^2. The control variables are the ones listed in Table A.2.

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