

# The Intensive Margin of Altruism: Impact of **Covid-19 on Charitable Giving in England and Wales**

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## The Intensive Margin of Altruism: Impact of Covid-19 on Charitable Giving in England and Wales

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#### Abstract

This paper studies the impact of the Covid-19 pandemic on private donations using data on charities' annual returns filed to the Charity Commission for England and Wales. By exploiting variation in mortality rates across narrow geographic units (local authorities), I show that donations to health charities operating in more severely hit areas have increased significantly more than those to health charities in areas hit more mildly, and that this effect is quantitatively large. In addition, when comparing the post-pandemic increase in donations to health charities vis-a-vis to non-health charities within a triple-difference setup, the analysis reveals that the growth differential between them turns out to be greater in areas that suffered worse fatality rates. The evidence in the paper suggests that the relative severity of adverse events is a crucial dimension guiding the allocation of charitable giving.

Keywords: Charitable giving, Nonprofit organisations, Covid-19.

JEL Classifications: D64, L30, L31.

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#### **1** Introduction

Understanding what motivates people to give and which causes they choose to contribute to are central questions in the literature on charitable giving.<sup>1</sup> One key factor driving donation decisions is awareness of need. Several studies have indeed provided evidence that altruistic behaviors positively respond to the awareness of adverse shocks that are in high need of support. In these studies, awareness spikes typically arise as a result of purposeful informational/fundraising campaigns [Scharf, Smith and Ottoni-Wilhelm (2022); Meon and Verwimp (2022)], in the aftermath of short-lived and geographically localized calamities [Deryugina and Marx (2021), Schwirplies (2023)], or following individual experiences of suffering [Smith, Kehoe and Cremer (1995); Olsen and Eidem (2003); Black et al. (2021)].<sup>2</sup>

One major recent adverse event witnessed worldwide has been the Covid-19 pandemic. The pandemic has hit virtually all countries and regions on the planet. Furthermore, its salience and coverage on the media worldwide has been pervasive to a historically unprecedented level, including very precise updates on the geographic evolution and distribution of new infections and deaths. The continuos flow of information has beyond doubt impacted on the levels of awareness about severity of the pandemic in different geographic areas. It has also led to swift and large philanthropic responses.<sup>3</sup>

This paper studies the impact of the severity of the Covid-19 pandemic on the level of private donations to health charities in England and Wales. The analysis relies on data on total private donations to individual charities sourced from the annual returns filed to the Charity Commission. It combines this dataset with data on Covid-19 death rates during the years 2020 and 2021 at the level of local authorities in England and Wales.<sup>4</sup> Importantly for the purposes of this study, the UK (and England in particular) has been hit particularly hard by the virus relative to other countries, while it has also experienced wide heterogeneity in mortality rates across narrower geographic areas. I exploit this geographic variability in local death rates to study whether the severity of the Covid-19 pandemic

<sup>&</sup>lt;sup>1</sup>See, e.g., Andreoni (2006), Vesterlund (2006, 2016), List (2011), Bekkers and Wiepkin (2011), Andreoni and Payne (2013), and Ottoni-Wilhelm, Vesterlund and Xie (2017), for general overviews of different theoretical explanations for charitable giving, and for evidence based on experimental and observational data.

<sup>&</sup>lt;sup>2</sup>See also Bauer et al. (2016) for a meta-analysis documenting that people who have been exposed to war violence exhibit later on stronger altruistic and pro-social behaviour, arguably owing to stronger awareness of the endured suffering.

<sup>&</sup>lt;sup>3</sup>For example, for the case of the US, the Center for Disaster Philanthropy (2021) reported that the total philanthropic

funding related to the Covid-19 during the first half of 2020 has dwarfed any funding for other recent disasters.

<sup>&</sup>lt;sup>4</sup>Local authorities are the narrowest geographic units at which this information is available from official UK sources.

has led to differential responses in private donations to health charities serving different areas in the aftermath of the pandemic.

I determine the location of charities based on their main address within England and Wales. Charities may, however, operate well beyond the exact location where they are headquartered. Crucially, the Charity Commission database includes also information on the geographic level of operation of the registered charities. This information allows to distinguish between charities that only operate at the local level, and those that operate beyond or outside that level (for example, at the regional level, country level, or international level).

The analysis shows that health charities headquartered in areas (local authorities) that have suffered higher Covid-19 mortality rates and operate *exclusively* at the local level have experienced a greater increase in total private donations when comparing their levels in year 2022 against those in 2015-19.<sup>5</sup> This qualitative result is robust to controlling for several potential confounding factors, such as fundraising effort and differences in regional time trends. In addition, the heterogeneities in the evolution of private donations are quantitatively large. Health charities located in areas experiencing mortality rates above the median have seen a growth in donations of approximately 28% when comparing the levels in year 2022 versus those in the pre-pandemic years. On the other hand, for health charities located in areas whose death rates were below the median no significant differences are observed in terms of the pre- versus post-pandemic level of donations.

Importantly, the above-mentioned differential responses by private donations are *only* present in the subsample of charities that operate exclusively at the local authority level. Instead, when comparing the evolution donations to health charities that operate beyond/outside the local authority level, I find no significant correlation between their post-pandemic response and the mortality rates in the areas where they are headquartered. This suggests that donors have only adjusted their giving choices in the aftermath of the pandemic for charities that actually cater to more severely affected areas, and it is consistent with the notion that altruistic behaviors are guided by (relative) need of support. Relatedly, one additional interesting null result in the paper is that no heterogenous responses are observed either in the case of other sources of charities' income that are unrelated to donors' choices. In particular, the post-pandemic growth of total income by charities excluding their income from private donations

<sup>&</sup>lt;sup>5</sup>The regression analysis in the main text excludes years 2020 and 2021 from the samples, as those two years are the period when the sheer impact of the Covid pandemic has been suffered. In addition, economic activity during those two years has been impaired by the series of lockdowns that had been implemented to contain the spread of the virus.

displays no correlation with the local severity of the pandemic.

One possible interpretation of the previous results is that they reflect the guiding impact of an adverse health shock on donors' altruistic behavior towards different health charities. However, the heterogeneous post-pandemic response of donations may also be influenced or biased by other contemporaneous confounding factors. The Covid-19 pandemic has led to a major health tragedy, but it also meant a massive negative economic shock. It could arguably be the case that variations in the evolution of donations across charities in different areas may reflect heterogeneities in household income dynamics as the pandemic receded during year 2022. Alternatively, it is likely that the series of lockdowns pushed some of the most inefficient charities out of the market, and this adjustment on the extensive margin could have been stronger in more severely affected areas.<sup>6</sup> To address these concerns, I further expand the previous analysis (based only on health charities) to the entire set of charities registered in England and Wales, and compare the evolution donations to health charities visa-vis that of non-health charities. More precisely, I carry out a triple-difference analysis, and show that the gap in the post-pandemic evolution of donations gifted to health charities relative to those given to non-health charities has been substantial only in areas which have experienced relatively large mortality rates.

The response of charitable giving to a deadly adverse event using administrative data is also studied in Deryugina and Marx (2021). There are some important complementary differences between the two papers. Deryugina and Marx (2021) rely on tornadoes hitting different areas in the US over time, and focus on individual donors with data sourced from their tax returns. This allows them to compare charitable giving by individuals located near areas affected by the tornadoes against those by individuals farther from those areas. Tornadoes are, however, short-lived, sporadic and very localized adverse events, hence the source of variation exploited is mostly the result of isolated spikes of awareness at different moments in time and geographic locations. By contrast, the Covid-19 pandemic offers a unique event in terms of geographic simultaneity and ubiquity, such that it allows focusing on the intensive margin response of charitable giving by exploiting variation in the severity of the same catastrophe across different regions. In addition, by exploiting a pre-post response to an event which was *primarily* a health calamity, this paper can make use of a triple-difference approach that enables it to control for other simultaneous unobservable factors that could impact on charitable

<sup>&</sup>lt;sup>6</sup>The Center for Disaster Philanthropy (2021) reported that the U.S. nonprofit sector lost more than 900,000 jobs during 2020.

giving and correlate with local Covid-19 mortality rates.

The results in this paper link the severity of a major health catastrophe and the ensuing charitable response by private donors. As such, it offers observational evidence that is broadly in line with previous experimental evidence on the salience of the Covid-19 pandemic and its impact on pro-social behavior. For example, Adena and Harke (2022) showed that experiment participants whose attention has been primed by referring to the Covid-19 pandemic have increased their giving relatively more, and especially in the cases of participants from areas more severely affected by it. Similar evidence is found by Fridman et al. (2022) based on a dictator game and by Grimalda et al. (2021) relying on an online experiment with participants from the US and Italy.

The rest of the paper is organized as follows. The next section introduces the two main sources of data used in the analysis. Section 3 studies the differential evolution of private donations across health charities located in geographic areas with different levels of Covid-19 mortality rates. Section 4 proceeds to carry out a triple-difference analysis including both health and non-health charities. Section 5 concludes. Additional details on the data and robustness checks can be found in the Appendices

#### 2 Data

#### 2.1 Donations to Charities and Definition of 'Health Charities'

The main data source used in the paper is the annual returns submitted to the Charity Commission for England and Wales. All charities registered in England and Wales are required to file an annual return to the Charity Commission reporting their income and spending during the year. The annual report is divided in a number of separate sections. Depending on their total annual income, charities are required to fill in some or all the sections, which vary in terms of the level of detail of historical information. For example, while all registered charities must report back their total income and expenditure over their financial year, larger charities must do so with a finer degree of disaggregate total income between six separate source categories; namely: donations, legacies, income from charitable activities, investment income, income from other trading activities, and other income.<sup>7</sup> In addition,

<sup>&</sup>lt;sup>7</sup>Income from donations exclude income from government grants received by the charity, which are included in the category 'income from charitable activities', defined as 'income received as fees or grants specifically for goods and

those charities must also specify how much of their total expenditure was due to fundraising activities. Given that the purpose of the paper is to study evolution of donations before and after the Covid-19 pandemic, the analysis will thus focus only on charities surpassing the £500,000 income threshold.<sup>8</sup>

The panel of charities used in the paper covers the years 2015-2022. I restrict the analysis to charities which always received positive donations every time they appeared in the sample. This trims off about 20% of the available observations. Restricting the analysis to charities that always exhibit positive donations allows focusing on those for which donations represent an important source of regular income. One peculiarity of the charity sector in England and Wales is that some of the charities may opt for some flexibility in terms of the length of their fiscal year. In particular, a charitable incorporated organization may choose its financial year to run for a length of time between six months to eighteen months, and it can adjust the fiscal year (within those boundaries) every three years. Although the vast majority of charities in the dataset do follow the rule that the fiscal year must equal twelve months, a smaller fraction have chosen at some point a different length, and/or also have changed the length at some point in their history. To avoid comparing fiscal years with different lengths, all observations originating from charities whose fiscal year differs at some point during 2015-22 from twelve months have been excluded – this amounted to dropping an additional 6% of the remaining observations.

The Charity Commission's registry includes as well a database with a classification of 'what' each charity does across seventeen different areas of charitable activities. (The full list of areas of activity is provided in Table A.1 in Appendix A.) Charities may select one of more areas of activity within the classification (see Table A.2 in Appendix A). The registry also includes a brief description of the charitable activities written by the charity itself. The key question in this paper is whether the Covid-19 pandemic has predominantly impacted charitable giving to charities whose main mission is in health-related issues. This requires identifying/classifying the main area of activity of each charity. Throughout the analysis I classify a charity as a 'health charity' if one of the following two (non-overlapping) conditions is verified: i) the charity has selected 'The Advancement of Health or Saving of Lives' as their *only* area of activity; ii) the charity has selected its activity to be in more than one

services supplied by the charity to meet the needs of its beneficiaries'.

<sup>&</sup>lt;sup>8</sup>The distribution of gross income across charities is highly skewed to the right, with median gross yearly income approximately equal to  $\pounds$ 50,000 and mean gross yearly income slightly above  $\pounds$ 800,000. The share of charities with mean gross yearly income greater than  $\pounds$ 500,000 is 12.5% of those registered in the Charity Commission.

area, one of which is 'The Advancement of Health or Saving of Lives', and it has also made explicit reference to health activities its own description of what it does or in its own charity name.<sup>9</sup> Charities that do not comply with either of the above two conditions are classified as 'non-health charities'.

Finally, I also rely on the Charity Commission's registry for geographically locating charities based on their main address. The geographic unit of analysis throughout the paper will be the local authorities. England and Wales comprise 329 local authorities.<sup>10</sup> The Charity Commission's registry includes as well information on whether the charity operates exclusively at the local authority level, or at geographic levels beyond/outside the local authority level (such as UK regional, UK national, or international level). With the exception of the "placebo" test carried out in Table 2 (*Panel A*), all the regression analysis in the paper has been performed on the subset of charities that operate exclusively at the local authority level.

#### 2.2 Covid-19 Deaths

I rely on the Office for National Statistics (ONS) for data on Covid-19 deaths at the local authority level. This is the narrowest geographic unit at which Covid-19 death rates have been officially counted by the ONS. A death is deemed to be a 'Covid-19 death' when Covid-19 is mentioned in the deceased's death certificate. I compute the total number of Covid-19 deaths by local authority during years 2020 and 2021. Next, I compute the share deaths during those two years over the total population of the local authority. Focusing on the death rates during 2020 and 2021 to measure the severity of the Covid-19 pandemic seems the appropriate choice, since those two years comprise the period of the sheer impact of the pandemic in England and Wales. In addition, it was during 2020-21 that those regions went through a series of lockdown policies (varying in terms of restrictive intensity), all

<sup>&</sup>lt;sup>9</sup>More precisely, whenever a charity selects 'The Advancement of Health or Saving of Lives' as one of its areas of activities (alongside one or more other areas of activity), I classify the charity as a 'health charity' when in its own description of what it does or in its own charity name (at least) one of the following words is mentioned at least once: health, disease, illness, sickness, medicine, medical, pathology, hospital, therapeutic, immunology, vaccination. The reference to any of these words is irrespective of the use of lower case or capital letters, or whether it is in its singular or plural form. See Table A.3 in Appendix A for some examples of the classification in the cases of charities selecting multiple areas of activity.

<sup>&</sup>lt;sup>10</sup>The financial district in London, known as the 'City of London Corporation' was excluded from the sample, as this is a small geographic area in the centre of London with barely above 7,000 permanent residents, and to which approximately half million people commute daily. (The median population amongst the local authorities is 136,000 people.)

aimed at containing the spread of the virus.<sup>11</sup> The share of deaths for which Covid-19 is mentioned in the death certificate remained of relative importance during 2022 (especially in the first few months of that year). Nevertheless, by 2022 economic life in England and Wales had returned to almost complete normalcy. By then, lockdown measures had all been lifted, and the Covid-19 pandemic was in general considered vanishing as vaccine campaigns reached the vast majority of the population and milder virus variants like the Omicron became the prevalent ones.

The Covid-19 pandemic has been an unprecedented event in terms of number of fatalities and its ubiquity worldwide. The UK has been no exception. In fact, the UK (and especially England) ranked comparatively high in terms of death rates across the globe. Despite fatalities being extensively widespread in England and Wales, its geographic distribution exhibited substantive variability.



Figure 1. Histogram of Covid-19 Death Rates

Notes: The figure plots the distribution of Covid-19 death rates as percentage of total population for the 329 local authorities in England and Wales. The median and mean values are 0.285% and 0.284%, respectively. The maximum and minimum values are 0.517% and 0.097%, respectively. Data source: Office for National Statistics.

<sup>&</sup>lt;sup>11</sup>The main three lockdown measures (imposed starting on 26-03-2020, 05-11-2020 and 06-01-2021) were all introduced at the national level, with essentially no variation across different areas in England and Wales.

Figure 1 presents a histogram with the death rates as a percentage of the total population across the 329 local authorities in England and Wales. This histogram displays a relatively symmetric distribution of death rates. The median death rate across local authorities is 0.285% (and almost identical to the mean 0.284%). The values of the death rates across local authorities range from its lowest 0.097% in South Hams (located in Devon county) to its highest 0.517% in Tendring (located in Essex county).<sup>12</sup> The degree of geographic variation in death rates is also attested by comparing the top decile of the distribution (exhibiting death rates above 0.378%) against its bottom decile (exhibiting death rates below 0.19%). The empirical analysis will exploit this geographic variation in death rates, and study the differential evolution of donations to health charities in areas more severely hit by the pandemic vs. those located in areas hit more mildly.<sup>13</sup>

#### **3** Empirical Analysis I: Health Charities Sample

#### 3.1 Difference-in-Difference Analysis on Donors Behavior

As a first step, I conduct an event study analysis focused on charities classified as 'health charities' that operate exclusively at the local authority level. I split local authorities into two subsets depending on whether their Covid-19 death rate lies below or above the median death rate across all local authorities in England and Wales. For each subset of local authorities, I regress separately the logarithm of private donations received by each individual charity on a set of year dummies, excluding years 2020 and 2021 from the sample (that is, the two main years of the pandemic). The regressions include charity fixed effects, and hence exploit within-charity variation in donations.

The results of the event study are displayed in Figure 2, where year 2019 has been set as reference year. Confidence level intervals are set at 95% and standard errors are clustered at the county-year level. The dynamic behavior of donations to charities located in local authorities whose death rate is

<sup>&</sup>lt;sup>12</sup>Counties represent a coarser geographic unit. England and Wales comprise 34 counties. The median number of local authorities per county is 7.

<sup>&</sup>lt;sup>13</sup>The empirical analysis will take the severity of the impact of the pandemic at the local level as exogenous. Fetzer (2022) offers an explanation for geographic variations in the spread of the virus in the UK based on the implementation of the so-called 'Eat-Out-to-Help-Out' scheme.



Figure 2. Pre- and Post-Covid-19 Donations to Health Charities: High vs. Low Death Rates Areas

*Notes* : The dependent variable is the logarithm of donations received by the charity during the year. The left-side red lines show the estimates for charities in areas with low death rates (below the median) and the right-side blue lines the estimates of charities in areas with high death rates (above the median). The regressions include charity fixed effects. Standard errors are clustered at the county-year level with 95% confidence intervals displayed.

below the median (resp. above the median) is displayed by the left-side red lines (resp. by the rightside blue lines).

Figure 2 showcases a drastically divergent behavior in terms of donations channelled to health charities in high mortality rate areas relative to those in low mortality rate areas, when comparing before and after the Covid-19 pandemic. Quantitatively the gap is substantial: the point estimates indicate an average increase approximately 24% larger in terms of donations to health charities located in severely hit areas versus those in areas hit more mildly, comparing the levels in year 2022 against those in 2019. Visual inspection of Figure 2 also seems to reassure against the presence of non-parallel

trends during years 2013-19 between the two subsets of health charities under analysis.<sup>14</sup> In light of these results, I will take as valid the assumption of parallel trends, and carry out a difference-indifference regression analysis of the impact of the relative severity of the pandemic on the allocation of donations across geographically dispersed health charities.

The results showcased in Figure 2 seem to arguably rule out the presence of heterogeneous pretrends across geographic areas differently impacted by the Covid-19 pandemic. I study now the relationship between the (post-pandemic) change in donations to health charities and the Covid-19 fatality rate in the local authority where the charities are headquartered, restricting the sample of analysis to health charities that operate *exclusively* at the local authority level. The benchmark regression has the following structure:

$$\ln(D_{i(l)t}) = \alpha \cdot postcovid_t + \beta \cdot (postcovid_t \times high\_deathate_l) + \tau \cdot year_t + \varsigma_{i(l)} + \varepsilon_{i(l)t}.$$
 (1)

The dependent variable in (1) is again the logarithm of the total amount of donations received in year t by health charity i, which is located in local authority l. postcovid<sub>t</sub> is a dummy variable that equals one in year 2022, and equals zero during years 2015-19. I exclude the two main years of the Covid-19 pandemic (years 2020 and 2021) from the sample. In the interaction term, high\_deathrate<sub>l</sub> is a dummy variable which equals one when the Covid-19 death rate in local authority l (computed as the number of Covid-19 deaths recorded in l during years 2020 and 2021 over l's total population in year 2020) is greater than the median death rate across all local authorities in England and Wales, and zero when it is below it. The regression (1) also includes a full set of charity fixed effects,  $\varsigma_{i(l)}$ , and hence it exploits the time variation in donations within charities. Note that since charities in the sample do not change the geographic location where they are registered,  $\varsigma_{i(l)}$  will also implicitly be controlling for fixed effects at the local authority level.<sup>15</sup> I also include in (1) a linear trend term ( $\tau \cdot year_t$ ). Standard errors are clustered at the county-year level. The main coefficient of interest is  $\beta$ , which captures heterogeneities in the post-pandemic evolution of donations to health charities across areas varying in terms of the relative severity of the Covid-19 catastrophe.

The estimation results of (1) are displayed in column (1) of Table 1. The estimated value of  $\beta$  is positive and highly significant, implying that health charities located in areas that suffered higher

<sup>&</sup>lt;sup>14</sup>Private donations actually display a mild positive time trend, but this trend is *not* heterogeneous across local authorities that would eventually experience different levels of Covid-19 death rates. See results of a regression test for the presence of non-parallel trends in Appendix B.3.

<sup>&</sup>lt;sup>15</sup>This fact also entails that (1) does not need to explicitly include  $high\_deathrate_l$  as one of their regressors.

Covid-19 death rates have seen a larger increase in donations received in year 2022 relative to the average level of donations received during years 2015-19. Interestingly, the point estimate for  $\alpha$  is virtually zero. This means that the level of post-pandemic donations to health charities in areas with below-median mortality rates has remained essentially at the same level as it was before the pandemic (after accounting for the linear time trend growth in private donations). On the other hand, donations to health charities in areas experiencing above-media mortality rates have increased approximately 28% comparing the level in year 2022 against its pre-pandemic level.

Columns (2)-(4) in Table 1 proceed to include some additional controls as robustness checks. Column (2) includes year fixed effects to control for any confounding effect generated by time trends or temporary shocks. Naturally, once time fixed effects are included the regression can no longer identify the parameter  $\alpha$ , but it can still identify the main parameter of interest ( $\beta$ ). The estimated value of  $\beta$  remains essentially identical compared to column (1). Another possible confounding factor could be that health charities may have responded to the impact and gravity of the pandemic by increasing their fundraising efforts. To address this issue, in column (3), I include fundraising expenditures by each charity as additional control. As it would be expected if donations do respond to fundraising efforts or campaigns, this variable carries a positive and statistically significant coefficient. The estimated value of  $\beta$  remains, however, almost intact quantitatively and in terms of statistical significance. Column (4) includes county-by-year fixed effects. These fixed effects would control, for example, for the impact of income shocks that heterogeneously affect different (larger) geographic areas. This would also partly control for the fact that some counties comprise essentially large cities (like London, Greater Birmingham, and Greater Manchester) while others comprise mostly rural areas. The estimated value of  $\beta$  remains still positive and statistically significant.

Lastly, as additional robustness check, the regression in column (5) restricts the sample to charities located outside Central London (this removes 13 local authorities from the sample). This sample restriction would mitigate concerns one may have about selection across geographic areas (for example, one may worry that people who live in a large and cosmopolitan city may exhibit a different propensity to respond to an adverse shocks relative to those who live in smaller towns or rural areas).<sup>16</sup> The estimate of  $\beta$  in column (5) remains virtually identical to the one in column (4).

Appendix B.1 presents additional robustness checks with a series of alternative specifications to

<sup>&</sup>lt;sup>16</sup>See also Table B.1.3 in Appendix B.1 as further robustness check, where all large cities with population above 500,000 people were excluded from the sample.

	(1)	(2)	(3)	(4)	(5)
postcovid x high deathrate	0.2761***	0.2760***	0.2821***	0.2194***	0.2205***
1 0	(0.0900)	(0.0901)	(0.0897)	(0.0829)	(0.0835)
postcovid	-0.0037	( · · · · )	(construction)	( · · · · )	(*****)
-	(0.0778)				
year	0.0268**				
	(0.0129)				
fundraising			0.0007*	0.0008**	0.0011**
			(0.0004)	(0.0004)	(0.0005)
observations	3,113	3,113	3,113	3,111	2,928
charities	605	605	605	605	568
R-squared	0.86	0.86	0.86	0.87	0.87
charity FE	Yes	Yes	Yes	Yes	Yes
year FE	No	Yes	Yes	No	No
county-year FE	No	No	No	Yes	Yes
London	Yes	Yes	Yes	Yes	No

Table 1. Donations to Health Charities: heterogeneous responses to the Covid-19 pandemic

*Notes* : Only health charities that operate exclusively at the local authority level are included in the sample. The dep. variable is the logarithm of total donations received by charity *i* in local authority *l* during year *t*. The main years of the pandemic (2020 and 2021) are excluded from the sample. Postcovid equals 1 in year 2022 and 0 in years 2015-19. High deathrate is a dummy variable equal to 1 for local authorities whose Covid-19 death rate (computed using deaths in year 2020 and 2021) was above the median and 0 otherwise. Robust standard errors clustered at the county-year level in parenthesis. \*p<0.1 \*\*p<0.05; \*\*\*p<0.01

the regressions in Table 1. Table B.1.1 runs the same set of regressions but replacing the dummy variable  $high\_deathrate_l$  by a continuous variable  $(deathrate_l)$  which is defined as the total number of Covid-19 deaths during 2020-21 in local authority *l* over *l*'s population. The results are all in line with those in Table 1. Furthermore, the point estimates computed at the 25% and 75% percentile levels of the Covid-19 death rates are similar to those based on the dummy variable in Table 1. Next, Table B.1.2 runs a set of regressions analogous to those in Table 1, but using all years in the sample (i.e., including also 2020 and 2021), and separating the impact in each year by including interaction terms with different dummies for years 2020, 2021, and 2022. Interestingly, the results show a differential impact of the severity of the Covid-19 pandemic on donations to health charities both for years 2021 and 2022, but not yet in year 2020.<sup>17</sup> Lastly, Table B.1.3 re-runs the regressions in columns (1)-(4) in Table 1, but excluding from the used sample all metropolitan agglomerations with population above half million people (i.e., London, Birmingham, Manchester, Liverpool, Leeds, Sheffield, and Cardiff). Despite the large reduction in sample size, all the results remain in line with those in Table 1.

<sup>&</sup>lt;sup>17</sup>In a sense, the results in Table B.1.2 seem to reasonably support the ones in Table 1, as reflecting the notion that donors had already started responding differently by year 2021 when the impact of the pandemic was already well known. Instead, the data on donations for year 2020 include several months before the pandemic had even hit England and Wales, and also that one is the year with the strongest lockdowns impairing economic activity.

#### 3.2 Difference-in-Difference Analysis: Placebo Tests

The results in Table 1 provide robust evidence of heterogeneities in the post-pandemic response of charitable giving directed to geographically distributed health charities. The interpretation of these results put forward by this paper is that they reflect the fact that altruistic behavior is guided by the (relative) harmfulness of adverse events. Thus, in the aftermath of the pandemic, private donors would shift or increase giving towards health charities operating in areas that have been more badly hit by the pandemic. If this interpretation is correct, one should *not* then expect to find such a strong differential response by donations to health charities whose area of operation lies instead *beyond* the local authority where they are headquartered. In addition, if the results displayed in Table 1 are indeed driven by changes in charitable giving behavior awaken by the relative severity of the Covid-19 pandemic, one should *not* expect to observe either analogous heterogeneities when looking at the evolution of sources of charities' income that are *unrelated* to private donors' behavior. Table 2 shows the results of two sets of "placebo" tests that aim at addressing in turn each of the above considerations.

Panel A of Table 2 displays the results of the exact same set of regressions as those in Table 1, but run on the subsample of health charities that operate beyond/outside the local authority level.<sup>18</sup> As it can be readily observed, the point estimate for the parameter  $\beta$  is essentially zero across the board. In other words, there is essentially no differential impact on the level of private donations channelled to health charities located in areas that have been hit more severely by the Covid-19 pandemic when looking at charities that operate across *wider* geographic areas than the local authority level.

The results of the second "placebo" test are shown in Panel B of Table 2. The regressions in Panel B are conducted on the same subsample of health charities as those of Table 1 (that is, those that operate exclusively at the local authority level), but where the dependent variable has been replaced by the logarithm of income stemming from all other sources of charities' income except private donations. These include income from legacies, charitable activities (including fees and grants), investment income, other trading activities, and other sources of income. Unlike the case when using the logarithm of donations as dependent variable, none of the regression in Panel B of Table 2 yields a significant

<sup>&</sup>lt;sup>18</sup>More precisely, the health charities included in the regressions in Table 1 are those that operate exclusively at the local authority level. Instead those included in Table 2, panel A, are those that either operate not only at the local authority level but also beyond it (such as the regional UK level, the national UK level or the international level), or those that do not operate at all at the local authority level but only beyond it.

	(1)	(2)	(3)	(4)	(5)
Panel A. Alternative Sample: Hea	alth charities operating n	on-locally (beyond	the local authority	level)	
postcovid x high deathrate	0.0206	0.0214	0.0203	0.0696	0.0680
	(0.0894)	(0.0885)	(0.0882)	(0.1569)	(0.1594)
postcovid	0.0568				
-	(0.1090)				
year	0.0051				
	(0.0160)				
fundraising			0.0001*	0.0001*	0.0006**
-			(0.0000)	(0.0000)	(0.0003)
observations	3,266	3,266	3,266	3,259	1,934
charities	677	677	677	676	403
R-squared	0.87	0.87	0.87	0.88	0.88
postcovid	0.0267 (0.0495) 0.0426***	(0.0371)	(0.0371)	(0.0020)	(0.0033)
,	(0.0052)				
fundraising	()		0.0008***	0.0008***	0.0007**
5			(0.0002)	(0.0002)	(0.0003)
observations	3,097	3,097	3,097	3,095	2,912
charities	602	602	602	602	565
R-squared	0.89	0.89	0.89	0.89	0.91
charity FE	Yes	Yes	Yes	Yes	Yes
year FE	No	Yes	Yes	No	No
county-year FE	No	No	No	Yes	Yes
London	Voc	Voc	Voc	Voc	No

Table 2. Placebo Tests on Health Charities

*Notes* : Regressions in *Panel A* are based on the subsample of health charities that operate beyond the local authority level (at the regional, national and international level). Regressions in *Panel B* replace the dependent variable used in Table 2 by the log of the total income received by charity *i* in local authority *I* during year *t*, after excluding the income originating from private donations. Oher sources of income include: legacies from wills investment income, income from charitable activities (including fees and grants), income from other trading activities, and other sources of income. Robust standard errors clustered at the county-year level in parenthesis. \*p<0.1 \*\*p<0.05; \*\*\*p<0.01.

estimate for the coefficient associated to the interaction term.<sup>19</sup>

### 4 Empirical Analysis II: Triple Difference Approach

As previously mentioned, the event-study analysis displayed in Figure 2 does not raise major concerns about divergent pre-trends that would correlate with the severity of the Covid-19 pandemic. Nevertheless, interpreting the estimates of  $\beta$  in Table 1 as reflecting the impact of the severity of the

<sup>&</sup>lt;sup>19</sup>Analogous null results are obtained when looking at each alternative source of charities' income as a separate dependent variable – see Table B.1.4 in Appendix B.1.

pandemic on donors' altruistic behavior may be unwarranted if there are other confounding factors influencing the post-pandemic evolution of donations across charities located in different areas. One possibility could be that the results in Table 1 stem from differences in income dynamics as the pandemic receded during year 2022. For example, it could be the case that areas suffering higher death rates may have also had to constrain their spending more strongly during the pandemic receded them to save relatively more, and could in turn mean that as the pandemic receded those areas may end up catching up with their spending (including their spending in charitable donations). An alternative confounding factor could be that the pandemic years may have forced some of the most inefficient charities to leave the market, and this cleansing mechanism may have worked more strongly in worse affected areas.

Drastic changes in donors' altruistic behavior awaken by the gravity of the pandemic should arguably be mainly reflected in variations in charitable giving to health-related causes. On the other hand, other potential confounding effects of the pandemic on donations (as those mentioned in the previous paragraph) should exert a relatively even impact across all charities in a given geographic area, irrespective of their specific social missions. To assess this source of heterogeneity across areas and charities' missions, I now proceed to carry out a triple-difference regression analysis including *all* charities (irrespective of their social mission) operating exclusively at the local authority level present in the dataset. To that end, I introduce now the dummy variable  $health_i$ , which is equal to one when charity *i* is classified as a 'health charity' and zero otherwise, and run the following regression:

$$\ln(D_{i(l)t}) = \alpha \cdot postcovid_t + \beta \cdot (postcovid_t \times high\_deathate_l) + \delta \cdot (postcovid_t \times health_i)$$
$$\gamma \cdot (postcovid_t \times high\_deathate_l \times health_i) + \tau \cdot year_t + \varsigma_{i(l)} + \varepsilon_{i(l)t}.$$
(2)

The main coefficient of interest in (2) is  $\gamma$ . If donors' altruism does indeed respond to the severity of the pandemic, we should then observe a relatively more pronounced increase in donations to health charities compared to non-health ones when looking at areas that suffered high mortality rates. That is, we should observe a positive estimate for  $\gamma$ . The results of (2) are displayed in the first column of Table 3. The estimated value of  $\gamma$  is positive and highly significant, implying that the post-pandemic response in donations to 'health charities' relative to donations to 'non-health charities' tends to favour the former relatively more in those areas that experienced worse Covid-19 death rates. One additional interesting result in Table 3 is that the estimate of the coefficient associated to the interaction term  $postcovid_t \times high\_deathate_l$  is quantitatively small and insignificantly different from zero. This

	(1)	(2)	(3)	(4)	(5)	(6)
postcovid x high deathrate x health	0.2759***	0.2768***	0.2768***	0.2538***	0.2408***	0.2814***
	(0.0844)	(0.0845)	(0.0844)	(0.0837)	(0.0868)	(0.0839)
postcovid x high deathrate	0.0022	0.0019	0.0020	0.0006		
	(0.0369)	(0.0366)	(0.0366)	(0.0463)		
postcovid x health	0.0295	0.0294	0.0291	0.0385	0.0409	0.0009
	(0.0610)	(0.0608)	(0.0606)	(0.0597)	(0.0572)	(0.0549)
postcovid	0.1337***					
	(0.0384)					
year	-0.0077					
	(0.0069)					
fundraising			0.0000213	0.0000213	-0.000002	-0.000005
			(0.00006)	(0.00007)	(0.00007)	(0.00007)
observations	21,922	21,922	21,917	21,917	21,835	19,725
charities	4408	4408	4407	4407	4393	3967
R-squared	0.84	0.84	0.84	0.84	0.86	0.86
charity FE	Yes	Yes	Yes	Yes	Yes	Yes
year FE	No	Yes	Yes	No	No	No
county-year FE	No	No	Yes	Yes	No	No
local authority-year FE	No	No	No	No	Yes	Yes
London	Yes	Yes	Yes	Yes	Yes	No

Table 3. Donations to Charities: triple difference response to the Covid-19 pandemic

*Notes* : The sample used include both health and non-health charities that operate exclusively at the local authority level. The dependent variable is the logarithm of total donations received by charity *i* in local authority *l* during year *t*. The main years of the pandemic (2020 and 2021) are excluded from the sample. Postcovid equals 1 in year 2022, and 0 in years 2015-2019. Health equals 1 if charity *i* is classified as a 'health charity', and 0 if classified as non-health charity'. High deathrate is a dummy variable equal to 1 for local authorities whose Covid-19 death rate (computed using deaths in year 2020 and 2021) was above the median and 0 otherwise. Robust standard errors clustered at the county-year level in parenthesis. \*p<0.1 \*\*p<0.05; \*\*\*p<0.01

means that when considering non-health charities, the evolution of donations received by them after the pandemic bears no relation with the severity of the pandemic in the areas where those charities are located.

Similarly as previously done in Table 1, Columns (2)-(5) in Table 3 add subsequently additional controls in the form of different layers of fixed effects. Columns (2), (3), and (4), follow the same sequence of fixed effects as in Table 1. In addition to those specifications, column (5) includes local authority-by-year fixed effects. Unlike the previous regressions based on equation (1), including such fixed effects becomes feasible in this case (at the cost of failing to identify the coefficient associated with *postcovid*<sub>t</sub> × *high\_deathate*<sub>l</sub>) since equation (2) contains variation of social missions by charities *within* the same local authority. Notice that the introduction of local authority-by-year fixed effects allows the triple-difference regression to control for *any* source of variation that stems from income shocks or differences in income dynamics at the local authority level. Irrespective of the exact specification, all the results in Table 3 carry a very similar point estimate for  $\gamma$ . Lastly, column (6) excludes charities located in Central London from the regression sample; the estimated value of  $\gamma$  remains again essentially intact.

In Appendix B.2, Tables B.2.1, B.2.2 and B.2.3 display the results of robustness checks on Table 3, analogously to those in Tables B.2.1, B.2.2 and B.2.3 for Table 1 in Appendix B.1. In these alternative specifications for the triple-difference regressions all the estimates of the main parameter of interest ( $\gamma$ ) are in line with those presented in Table 3.

Lastly, Table B.2.4 in Appendix B.2 shows the results of two sets of placebo tests analogous to those in Table 2, but adjusted for the case of the triple-difference setup. That is, in Panel A of Table B.2.4, the set of triple-difference regressions are run of the subset of charities (including both health and non-health charities) operating beyond/outside the local authority level. In Panel B of that table the logarithm of private donations is replaced as dependent variable by the logarithm of charities' income originating from other sources (excluding income from private donations).

#### 5 Concluding Remarks

Relying on data sourced from the Charity Commission for England and Wales, the analysis in the paper has revealed that the relative severity of the Covid-19 pandemic has significantly influenced the post-pandemic growth in donations channeled to charities whose main mission is to address health-related issues. Health charities located in areas that suffered higher Covid-19 death rates have experienced a larger increase in private donations in the aftermath of the pandemic. Consistent with the notion that charitable giving is guided by the relative severity of adverse shocks, this differential evolution in post-pandemic private donations is *only* observed for health charities that operate at the local authority level, but it is absent for those that operate across wider geographic areas (that is, beyond the local level). Furthermore, when exploiting a triple-difference approach, the analysis has shown that in the aftermath of the pandemic private donations to health charities have significantly outgrew those to non-health charities in areas that suffered higher Covid-19 fatalities, but that no growth differential between them was observed in areas where death rates have been milder.

One caveat with the analysis in the paper is that while the regressions have systematically uncovered a larger post-pandemic growth in donations to health charities located in areas that experienced higher mortality rates, these results cannot be ascribed to a differential response of donors residing in a specific geographic area. More precisely, the data from the annual returns specify the yearly amount of income from donations received by each charity (in the cases of charities whose total annual income surpassed the £500,000 threshold), but it does not specify the identity or location of the individual donors. As such, the results in this paper cannot be interpreted as being driven by differentials in the *direct* exposure of individual donors to the severity of the pandemic, but only as a response by donors at large to the differential exposure of geographic areas to it.

Given the current data availability (up to the 2022 annual returns), this paper has only managed to study the short-run response of donations after the Covid-19 pandemic started to recede. An interesting question that remains pending is therefore the lengthiness of its impact. In particular, whether the differential effect of the severity of the pandemic on donations to health charities proves to be long-lasting, or if it is the case that donors' behavior will quickly/eventually revert back to its previous trend. This question is left open as follow-up research on this paper, as future annual returns are submitted to the Charity Commission over the next few years.

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#### **Appendix A (not intended for publication)**

Table A.1 lists the seventeen areas of activity among which charities self-report 'what' they do. The table reports the number of charities per activity when considering all charities in the sample ['# Charities (all)'], and also when restricting the sample to charities that operate exclusively at the local authority level ['# Charities (only local)']. Charities may select one or more areas of activity within the classification of the Charity Commission for England and Wales. The total number of charities that appears in each of the rows in Table A.1 may count therefore multiple times the same charity (whenever the charity selects more that one area of activity).

Table A.2 displays some basic summary statistics for some of the key variables used in the empirical analysis. To get a sense of heterogeneities across the subsamples of charities, the table breaks down the sample of charities between 'health' and 'non-health' charities. In addition, for each of those subsets it considers in turn all charities in the subset, and then only those that operate locally. In general, charities that operate exclusively at the local authority level tend to be "smaller" in terms of total income, income received from private donations, and total fundraising expenditure. These differences in size are observed for both 'health' and 'non-health' charities. When comparing the subgroups 'health' vis-a-vis 'non-health' charities, they appear to be quite similar in terms of their total income and their income sourced from donations. Charities dealing with health-related issues tend to spend slightly more in fundraising than those whose main mission is not in health. Importantly, the statistics for the variable 'death rate' are also very similar across the two subgroups, which suggests that the geographic distribution of health and non-health charities may not differ much across the set of local authorities in the dataset. Finally, in terms of 'number of years present in the sample', the differences appear to be very small as well.

For the purposes of the analysis, a charity has been classified as 'health charity' if and only if one of the following two (non-overlapping) conditions is verified: i) the charity has selected 'The Advancement of Health or Saving of Lives' as their *only* area of activity; ii) the charity has selected its activity to be in more than one area, one of which is 'The Advancement of Health or Saving of Lives', and it has also made explicit reference to health activities its own description of what it does or in its own charity name. In particular, a charity that selects multiple areas of activity, including 'The Advancement of Health or Saving of Lives' as one of those, is classified as a 'health charity' when in its own description of what it does or in its own charity name includes (at least) one of the following words at least once: health, disease, illness, sickness, medicine, medical, pathology, hospital, therapeutic, immunology, vaccination. The reference to any of the words above is irrespective of the use of lower case or capital letters, or whether it is in its singular or plural form.

Table A.3 shows the distribution of number of activities selected by charities classified as 'health charities' and those classified as 'non-health charities'. Only the subset of charities that operate exclusively at the local authority level are considered in Table A.3. Approximately 65% of the local charities that have been classified as 'health charities' for the purposes of the analysis have listed more than one area of activity. A similar share of local charities classified as 'non-health charities' have listed more than one area of activity.

Table A.4 displays, as illustration, six examples of charities that have selected 'The Advancement of Health or Saving of Lives' as one of their areas of activity, alongside some other areas of activities. The top three cases are examples of charities that have been classified as 'health charity' based on the its own description of the activities they carry out. The bottom three cases are instead examples of charities classified as 'non-health charity', as their descriptions of what they do make any reference to dealing with health-related issues.

Area of Charitable Activity	# Charities (all)	# Charities (only local)
Accommodation/Housing	1160	688
Amateur Sport	940	607
Animals	366	154
Armed Forces/Emergency Service Efficiency	100	27
Arts/Culture/Heritage/Science	1774	945
Disability	2100	1170
Economic/Community Development/Employment	1786	930
Education/Training	6310	3132
Environment/Conservation/Heritage	1308	670
General Charitable Purposes	3057	1398
Human Rights/Religious or Racial Harmony/Equality or Diversity	526	209
Other Charitable Purposes	932	463
Overseas Aid/Famine Relief	747	123
Recreation	676	483
Religious Activities	2359	1211
The Advancement of Health or Saving of Lives	2864	1341
The Prevention or Relief of Poverty	2706	1140

Table A.1. Areas of Charitable Activity

	Health Charities (all)		Health Chariti	ies (only local)
	mean	median	mean	median
Total Income	5,983,876	1,648,423	3,216,954	1,580,468
Income from Donations	2,006,293	488,461	675,453	275,231
Fundraising Expenditure	781,231	60,368	579,657	48,000
Death Rate	0.262	0.256	0.276	0.281
# Years Present in Sample	7.09	8	7.21	8
	Non-Health (	Charities (all)	Non-Health Chai	rities (only local)
	Non-Health (	Charities (all) median	Non-Health Char mean	r <b>ities (only local)</b> median
Total Income	Non-Health ( mean 6,438,164	Charities (all)           median           1,414,120	Non-Health Chan mean 3,852,696	rities (only local) median 1,280,938
Total Income Income from Donations	Non-Health ( mean 6,438,164 2,121,208	Charities (all) median 1,414,120 399,690	Non-Health Chan mean 3,852,696 725,175	rities (only local) median 1,280,938 192,380
Total Income Income from Donations Fundraising Expenditure	Non-Health ( mean 6,438,164 2,121,208 503,532	<u>median</u> 1,414,120 399,690 18,482	Non-Health Chan mean 3,852,696 725,175 241,663	rities (only local) median 1,280,938 192,380 9,287
Total Income Income from Donations Fundraising Expenditure Death Rate	Non-Health ( mean 6,438,164 2,121,208 503,532 0.253	<u>median</u> 1,414,120 399,690 18,482 0.242	Non-Health Chan mean 3,852,696 725,175 241,663 0.263	rities (only local) median 1,280,938 192,380 9,287 0.264

 Table A.2.
 Summary Statistics

Table A.3. Number of Areas of Activity by Charity

# Areas of Activity	health cl (only l	harities non-healtl local) (only		health charities non-health chariti (only local) (only local)		charities ocal)
	Number	%	Number	%		
1	1,661	36.2	233	34.3		
2	971	21.1	96	14.1		
3	708	15.4	91	13.4		
4	510	11.1	76	11.2		
5	313	6.8	66	9.7		
6	176	3.8	52	7.7		
7	116	2.5	26	3.8		
8	62	1.4	16	2.4		
9	30	0.7	12	1.8		
10	20	0.4	10	1.5		
11	14	0.3	2	0.3		
12	3	0.07	0	0		
13	4	0.09	0	0		
14	6	0.13	0	0		
15	1	0.02	0	0		
Total	4595	100	680	100		

		I and A.4. Examples of	Italul allu Avul-Healul Challues	
Charity Name	# Areas	Areas of Activity	Charitable Activities (own description by charities)	Classification
wrightington, wigan and leigh health services charity	4	<b>The Advancement of Health or Saving of</b> Lives: Education/Training: Disability; General Charitable Purposes	The mission of wrightington, wigan and leigh <b>health</b> service charity is to further improve the quality of patient care, through staff training, purchasing <b>medical</b> equipment and enhancing the patient environment and experience. this is achieved through the generosity of the general public and by fundraising activities, events and appeals.	Health Charity
the francis crick institute limited	ŝ	<b>The Advancement of Health or Saving of</b> Lives: Education/Training. Arts/culture/heritage/science	the francis crick institute is dedicated to understanding the fundamental biology underlying <b>health</b> and <b>disease</b> . our work is helping to understand why <u>disease</u> . develops and to translate discoveries into new ways to prevent, diagnose and treat <b>theseses</b> such as cancer, heart <b>disease</b> , stroke, infections and neurodegenerative <b>diseases</b> .	Health Charity
british society for immunology	7	The Advancement of Health or Saving of Lives: Education/ Training	running innovative events in research, public engagement & education promoting & disseminating research, good practice in <u>immunology</u> . translational <u>medicine</u> and <u>vaccination</u> working with its members to develop the benefits of membership & the relevance of the society providing bursaries & grants enhancing public awareness of <u>immunology</u> working with other societies	Health Charity
CT4N Charitable Trust	ŝ	Disability; <b>The Advancement of Health or</b> <u>Saving of Live</u> s; The Prevention or Relief of Poverty	Provision of localised accessible transport services to local residents and groups $$ who have a specific mobility need not covered by normal public transport.	on-Health Charity
hastings and rother voluntary association for the blind	ŝ	Disability <b>; The Advancement of Health or</b> Saving of Lives; Accommodation/housing	the associations principle acitivities are the residential home (care home) carried out at healey house, full day provision at the john taplin centre, social and rehabilitation acitivites in bexhill, mountfield and at clubs run by the association, N together with the provision of advice, information and support to visually impaired people of all ages living in hastings and rother areas.	on-Health Charity
Become Charity	4	The Prevention or Relief of Poverty; <u>The</u> <u>Advancement of Health or Saving of Lives</u> ; Education/Training, Economic/Community Development/Employment	We work to improve the lives and life chances of young people in care & care leavers. We inform and support them via our publications and learning & skills workshops; we influence policy & practice by ensuring their views and experiences are heard; we provide support materials for foster carers and others responsible for their welfare & education and we develop innovative projects & best practice.	on-Health Charity

#### **Appendix B** (not intended for publication)

#### **B.1: Robustness checks on Section 3**

Table B.1.1 carries out the same set of regressions as those in Table 1, but replacing the dummy variable  $high\_deathrate_l$  (which equals one when the Covid-19 death rate in local authority l lies above the median death rate across all local authorities, and zero otherwise) by the continuous variable  $deathrate_l$  which is defined as the total number of Covid-19 deaths during 2020-21 in local authority l over l's total population. All the results remain in line with those in Table 1, albeit the level of statistical significance becomes slightly lower. In terms of magnitude, the point estimates in column (1) of Table B.1.1 computed at the 25% and 75% percentile levels of the Covid-19 death rates (which are equal to 0.227 and 0.337, respectively) imply that post-pandemic private donations have grown 4.2% for the former and 23.3% for the latter relative their respective levels before the pandemic.

Next, Table B.1.2 expands the definition of "treatment" years to include years 2020, 2021, and 2022, while allowing a heterogeneous impact each year. More precisely, I include three separate interaction terms ( $dummy_2020 \times high_deathrate, dummy_2021 \times high_deathrate$  and  $dummy_2022 \times high_deathrate$ ), where each  $dummy_202x$  is a dummy variable equal to one for observations corresponding to year 200x, and zero otherwise. The results are quantitatively similar and significant for the interaction terms for years 2021 and 2022, but are quite smaller in magnitude and fail to reach significance in year 2020. Notice that observations dated in year 2020 include donations made in several months before the pandemic had even hit the UK, and also the early months of the pandemic when its impact across different areas was yet not well known by the public at large.

Table B.1.3 excludes from the analysis all health charities located in large metropolitan agglomerations (defined as those whose population is greater than half million people). The excluded metropolitan areas are: London, Birmingham, Manchester, Liverpool, Leeds, Sheffield, and Cardiff. The reason for this is that one may worry that the results could be essentially driven by the behavior of donors residing in large cities contributing mostly to charities located there too. The results, however, are still present (and, moreover, remain quite similar to those in Table 1) when the analysis is carried out only on health charities located in smaller cities or rural areas, and that operate exclusively at the local authority level.

	(1)	(2)	(3)	(4)	(5)
postcovid x deathrate	1.7369**	1.7293**	1.7672**	1.4074*	1.4686*
	(0.7706)	(0.7678)	(0.7727)	(0.7513)	(0.7718)
postcovid	-0.3526	, ,			, c
	(0.2200)				
year	0.0270**				
-	(0.0129)				
fundraising			0.0007*	0.0008**	0.0011**
			(0.0004)	(0.0004)	(0.0005)
observations	3,113	3,113	3,113	3,111	2,928
charities	605	605	605	605	568
R-squared	0.86	0.86	0.86	0.87	0.87
charity FE	Yes	Yes	Yes	Yes	Yes
year FE	No	Yes	Yes	No	No
county-year FE	No	No	No	Yes	Yes
London	Yes	Yes	Yes	Yes	No

Table B.1.1.	Donations to	Health	Charities:	Continuous	variable	specification
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*Notes*: The regressions in this table follow the same structure are those in Table 1, except for continuous variable *deathrate* that replaces the dummy variable *high deathrate*. *Deathrate* is defined as total Covid-19 deaths during years 2020 and 2021 in local authority *l* divided by *l*'s total population. Robust standard errors clustered at county-year level in parenthesis. \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

	(1)	(2)	(3)	(4)
dummy_2020 x high deathrate	0.0828	0.0868	0.1157	0.1099
	(0.0713)	(0.0710)	(0.0797)	(0.0815)
dummy_2021 x high deathrate	0.2966***	0.2987***	0.2629***	0.2602***
	(0.0910)	(0.0909)	(0.0966)	(0.0977)
dummy_2022 x high deathrate	0.2704***	0.2754***	0.2130***	0.2124***
	(0.0769)	(0.0767)	(0.0680)	(0.0686)
fundraising		0.0006**	0.0007**	0.0009**
		(0.0003)	(0.0003)	(0.0004)
observations	4,355	4,355	4,354	4,094
charities	690	690	690	649
R-squared	0.85	0.85	0.86	0.86
charity FE	Yes	Yes	Yes	Yes
year FE	Yes	Yes	No	No
county-year FE	No	No	Yes	Yes
London	Yes	Yes	Yes	No

Table D.1.2. Donations to nearth charmers interaction remission years 2020, 2021 and 2022	Table B.1.2.	Donations to	Health	Charities:	Interaction	Terms fo	or years	2020,	2021	and 2022
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*Notes* : The regressions include three separate interaction terms between year dummies (dummy\_2020, dummy\_2021, dummy\_2022) and the high\_deathrate dummy variable as defined in the main text, where dummy\_202X is equal to 1 for observations in year 202X and zero otherwise. The sample used include all years 2015-22. Robust std. errors clustered at local county-year in parenthesis. \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

	(1)	(2)	(3)	(4)
postcovid x high deathrate	0.2957***	0.2962***	0.3023***	0.2215**
	(0.0902)	(0.0899)	(0.0896)	(0.0885)
postcovid	0.0587			
-	(0.0929)			
year	0.0059			
	(0.0149)			
fundraising			0.0010***	0.0012***
C C			(0.0004)	(0.0004)
observations	2,490	2,490	2,490	2,487
charities	481	481	481	481
R-squared	0.87	0.87	0.87	0.88
charity FE	Yes	Yes	Yes	Yes
year FE	Yes	Yes	No	No
county-year FE	No	No	Yes	Yes

	Table B.1.3.	Donations to	Health	Charities:	Excludes	Charities in	Large Citi	ies
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*Notes*: Only health charities that operate exclusively at the local authority level are included in the regressions. The regression samples exclude all metropolitan agglomerations with population over 500,000 people (i.e., London, Birmingham, Manchester, Liverpool, Leeds, Sheffield, and Cardiff) All the other variables are defined as in Table 1. Robust std. errors clustered at the county-year level in parenthesis. \*p<0.1 \*\*p<0.05; \*\*\*p<0.01.

	(1)	(2)	(3)	(4)	(5)
	legacies	investments	char act	trading	others
postcovid x high deathrate	0.040 (0.121)	-0.101 (0.141)	-0.130 (0.089)	-0.104 (0.094)	-0.327 (0.335)
observations	1,567	2,794	2,565	2,066	1,048
charities	316	555	508	431	272
R-squared	0.79	0.89	0.89	0.91	0.62
charity FE	Yes	Yes	Yes	Yes	Yes
vear FE	Yes	Yes	Yes	Yes	Yes

Table B.1.4. Impact on other sources of income of health charities

*Notes*: Only health charities that operate exclusively at the local authority level are included in the sample. The dependent variable is  $\log(X_{til})$ , where where X is income from legacies in column (1), investment income in (2), charitable activities income in (3), other sources of trading income in (4), and other sources of income in (5). Robust standard errors clustered at the county-year level in parenthesis. \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Lastly, Table B.1.4, expands on the results shown in Panel B of Table 2, by carrying out a set of regressions following the specification in column (2), but replacing the dependent variable in each of the columns by one specific source of charities' income (other than income from private donations). The dependent variable in column (1) is income from legacies as the result of a deceased person's will, in (2) it is the income from investments (including rents), in (3) it is the income received as fees and grants (including government grants), in (4) is the income received from other sources of trading activities, and in (5) income from other exceptional sources of income. None of the regressions in Table B.1.4 yields a significant estimate for the coefficient associated to the interaction term.

#### **B.2:** Robustness checks on Section 4

Table B.2.1 carries out the same set of regressions as those in Table 3, but replacing the dummy variable  $high\_deathrate_l$  by the continuous variable  $deathrate_l$  (defined as the total number of Covid-19 deaths during 2020-21 in local authority l over l's total population). Table B.2.2 expands the definition of "treatment" years to include also years 2020 and 2021 (in addition to year 2022). More precisely, these regressions include a full set of interaction terms with separate dummies for years 2020, 2021, and 2022. The results for the interaction terms with year 2021 and year 2022 are in general very similar. On the other hand, the main results do not seem to be yet present in year 2020. Table B.1.3 excludes from the analysis all large metropolitan agglomerations, defined as those whose population is greater than half million (London, Birmingham, Manchester, Liverpool, Leeds, Sheffield, and Cardiff). Lastly, in Table B.1.4, I carry out a set of "placebo" tests analogous to those presented in Table 2, but in this case applied to the triple-difference context. That is, *Panel A* shows the results of the triple-difference regressions on the subset of charities that operate beyond/outside the local authority level, while *Panel B* replaces the dependent variable by the logarithm of total charities' income excluding private donations. As it may be readily observed, none of the results in Table B.1.4

	(1)	(2)	(3)	(4)	(5)	(6)
postcovid x deathrate x health	1.8217**	1.8214**	1.8215**	1.6060**	1.6942*	2.0255**
	(0.7989)	(0.7971)	(0.7958)	(0.7741)	(0.9003)	(0.9293)
postcovid x deathrate	-0.0771	-0.0788	-0.0776	-0.1268	( )	, j
	(0.3094)	(0.3066)	(0.3060)	(0.3876)		
postcovid x health	-0.3408	-0.3404	-0.3406	-0.2827	-0.3103	-0.4216*
	(0.2225)	(0.2217)	(0.2213)	(0.2137)	(0.2382)	(0.2491)
postcovid	0.1546*					
	(0.0861)					
year	-0.0076					
	(0.0069)					
fundraising			0.00002	0.00002	-0.000002	-0.00001
-			(0.00065)	(0.00067)	(0.00007)	(0.00007)
observations	21,922	21,922	21,917	21,917	21,835	19,725
charities	4408	4408	4407	4407	4393	3967
R-squared	0.84	0.84	0.84	0.84	0.86	0.86
charity FE	Yes	Yes	Yes	Yes	Yes	Yes
year FE	No	Yes	Yes	No	No	No
county-year FE	No	No	Yes	Yes	No	No
local authority-year FE	No	No	No	No	Yes	Yes
London	Yes	Yes	Yes	Yes	Yes	No

Table B.2.1. Donations to Charities: triple difference response with continuous variable specification

*Notes*: The regressions in this table follow the same structure are those in Table 3, except for continuous variable *deathrate* that replaces the dummy variable *high deathrate*. *Deathrate* is defined as total Covid-19 deaths during years 2020 and 2021 in local authority *l* divided by *l*'s total population. Robust standard errors clustered at county-year level in parenthesis. \*p<0.1; \*p<0.05; \*\*p<0.01

	(1)	(2)	(3)	(4)	(5)
dummy_2020 x high deathrate	-0.0422	-0.0419	-0.0316		
	(0.0334)	(0.0334)	(0.0465)		
dummy_2021 x high deathrate	0.0132	0.0136	-0.0037		
	(0.0310)	(0.0310)	(0.0386)		
dummy_2022 x high deathrate	-0.0142	-0.0139	-0.0205		
	(0.0358)	(0.0358)	(0.0454)		
dummy_2020 x health	0.0054	0.0053	0.0027	-0.0018	0.0021
	(0.0501)	(0.0500)	(0.0508)	(0.0565)	(0.0637)
dummy_2021 x health	-0.0784	-0.0783	-0.0794	-0.0804	-0.0912
	(0.0509)	(0.0509)	(0.0522)	(0.0579)	(0.0642)
dummy_2022 x health	0.0040	0.0039	0.0109	0.0158	-0.0137
	(0.0582)	(0.0581)	(0.0560)	(0.0548)	(0.0524)
dummy_2020 x high deathrate x health	0.1265*	0.1263*	0.1221*	0.1304	0.1213
	(0.0735)	(0.0734)	(0.0735)	(0.0800)	(0.0845)
dummy_2021 x high deathrate x health	0.2856***	0.2852***	0.2679***	0.2297**	0.2371**
	(0.0960)	(0.0960)	(0.0940)	(0.0964)	(0.0986)
dummy_2022 x high deathrate x health	0.2871***	0.2869***	0.2655***	0.2436***	0.2737***
	(0.0775)	(0.0774)	(0.0767)	(0.0790)	(0.0755)
fundraising		0.00001	0.00001	-0.00002	-0.00002
		(0.0001)	(0.0001)	(0.0001)	(0.0001)
observations	30,607	30,601	30,601	30,503	27,541
charities	5031	5030	5030	5019	4534
R-squared	0.83	0.83	0.83	0.84	0.84
charity FE	Yes	Yes	Yes	Yes	Yes
year FE	Yes	Yes	No	No	No
county-year FE	No	No	Yes	No	No
local authority-year FE	No	No	No	Yes	Yes
London	Yes	Yes	Yes	Yes	No

Table B.2.2. Triple difference response:	Interaction terms for years	2020, 2021 and 2022
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*Notes* : The regressions include a full set of interaction terms between a year dummy (dummy\_202X), the 'high\_deathrate' dummy variable and the dummy variable 'health' as defined in Table 3, where dummy\_202X is equal to 1 for observations in year 202X, and zero otherwise. The sample used include all years 2015-22. Robust std. errors clustered at county-year level in parenthesis. \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

	(1)	(2)	(3)	(4)	(5)
postcovid x high deathrate x health	0.2867***	0.2878***	0.2880***	0.2574***	0.2122**
pooleo na mign dodan do micardi	(0.0920)	(0.0920)	(0.0918)	(0.0930)	(0.0978)
postcovid x high deathrate	0.0099	0.0095	0.0097	0.0034	(0.07.0)
	(0.0425)	(0.0423)	(0.0422)	(0.0452)	
postcovid x health	-0.0011	-0.0015	-0.0021	0.0145	0.0217
	(0.0674)	(0.0670)	(0.0668)	(0.0608)	(0.0559)
postcovid	0.1509***				
	(0.0465)				
year	-0.0128				
	(0.0083)				
fundraising			0.0001	0.0001	0.0001
			(0.00005)	(0.00005)	(0.00004)
observations	16,893	16,893	16,890	16,890	16,808
charities	3379	3379	3379	3379	3365
R-squared	0.84	0.84	0.84	0.84	0.86
charity FE	Yes	Yes	Yes	Yes	Yes
year FE	No	Yes	No	No	No
county-year FE	No	No	Yes	Yes	No
local authority-year FE	No	No	No	No	Yes

	Table B.2.3.	Triple Difference	Analysis: Excludes	Charities in Large Cities
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*Notes* : Only health charities that operate exclusively at the local authority level are included in the regressions. The regression samples exclude all metropolitan agglomerations with population over 500,000 people (i.e., London, Birmingham, Manchester, Liverpool, Leeds, Sheffield, and Cardiff All the other variables are defined as in Table 4. Robust std. errors clustered at the county-year level in parenthesis. \*p<0.1 \*\*p<0.05; \*\*\*p<0.01.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Alternative Sample: Charitie	es operating non-lo	cally (beyond	the local author	rity level)		
postcovid x high deathrate x health	0.0792	0.0790	0.0780	0.0647	0.0569	-0.0217
	(0.0933)	(0.0934)	(0.0928)	(0.0895)	(0.0796)	(0.1076)
postcovid x high deathrate	-0.0586	-0.0585	-0.0585	-0.0020		
	(0.0542)	(0.0541)	(0.0539)	(0.0608)		
postcovid x health	-0.0718	-0.0718	-0.0705	-0.0738	-0.0863	-0.0100
	(0.0632)	(0.0633)	(0.0632)	(0.0635)	(0.0646)	(0.0940)
postcovid	0.1273***	( )	( )	( )	c ,	( )
	(0.0470)					
vear	0.0054					
	(0.0056)					
fundraising			0.00007***	0.00007***	0.00006***	0.00006***
			(0.00002)	(0.00002)	(0.00002)	(0.00002)
observations	19.481	19.481	19.477	19.477	19.157	11.097
charities	3990	3990	3990	3990	3937	2281
R-squared	0.87	0.87	0.87	0.87	0.88	0.89
Panel B. Alternative Dependent Vari	able: Other sources	of income to c	harities (exclud	es private dond	ations)	
postcovid v high deathrate v health	0.0012	0 0009	-0.0005	0.0051	0.0278	-0.0102
posicovia x nigii acadirate x iteartii	(0.0638)	(0.0638)	(0.0640)	(0.0659)	(0.0270)	(0.0780)
nostcovid v high deathrate	0.0116	0.0117	0.0117	0.0331	(0.0754)	(0.0700)
posicovia x nigii acatinate	(0.0359)	(0.0357)	(0.0358)	(0.0331		
nostcovid v health	0.0376	0.0375	0.0397	0.0367	0.0215	0.0609
	(0.0448)	(0.0449)	(0.0357	(0.0470)	(0.0526)	(0.0505)
nostcovid	0.0477**	(0.0440)	(0.0430)	(0.0470)	(0.0520)	(0.0303)
posicovia	-0.0477					
voor	0.0192					
ycai	(0.0302					
fundraising	(0.0037)		-0.0002	-0.0002	-0.0001	-0.0002
Tunuraising			(0.0002)	(0.0002)	(0.0001)	(0.0002
observations	21 705	21 705	21 700	21 700	21 619	19 582
charities	4261	1261	4360	4360	1346	2025
P squared	4301	4301	4300	4300	4340	0 02
K-squareu	0.91	0.91	0.91	0.91	0.92	0.92
	17	v	V	v	v	37
Charity FE	Yes	Yes	Yes	Yes	Yes	Yes
year FE	No	Yes	No	No	No	No
county-year FE	No	No	Yes	Yes	No	No
local authority-year FE	No	No	No	No	Yes	Yes
London	Yes	Yes	Yes	Yes	Yes	No

Table B.2.4. Placebo Tests on Triple-Difference Analysis

*Notes*: *Panel A* is based on the subsample of charities (both health and non-health) that operate beyond/outside the local authority level (at regional national and international level). *Panel B* replaces the dependent variable used in Table 3 by the logarithm of the total income received by charity *i* in local authority *l* during year *t*, after excluding all the income originating from private donations. The other sources of income include: legacies investment income, income from charitable activities (including fees and grants), income from other trading activities, and other sources of income. Robust standard errors clustered at the county-year level in parenthesis. \*p<0.1 \*\*p<0.05; \*\*\*p<0.01.

#### **B.3: Non-Parallel Trend Test**

In this Appendix I show the results of a regression formally testing for the presence of non-parallel trends during the pre-pandemic years. To that end, I use only data on donations from years 2015 to 2019, and run the following regression on the sample of health charities operating exclusively at the local authority level:

$$\ln(D_{i(l)t}) = \tau \cdot year_t + \rho \cdot (year_t \times high\_deathate_l) + \varsigma_{i(l)} + \varepsilon_{i(l)t}.$$
(3)

The dependent variable in (3) is the logarithm of the total amount of donations received in year t by health charity i, which is located in local authority l.  $high\_deathrate_l$  is a dummy variable which equals one when Covid-19 death rate in local authority l is greater than the median death rate across all local authorities in England and Wales, and zero when is below the median death rate. The regression (3) also includes a full set of charity fixed effects,  $\varsigma_{i(l)}$ . Standard errors are clustered at the county-year level.

The estimation results of (3) are presented in the first column of Table B.3. The estimated value of  $\rho$  is not statistically significantly different from zero. The null hypothesis of parallel pre-trends across local authorities that would eventually experience different levels of Covid-19 death rates cannot thus be rejected. As robustness check, in column (2), I replace the linear trend term  $(\tau \cdot year_t)$  by a full set of year fixed effects. The presence of parallel pre-trends cannot be rejected in this case either. Lastly, in column (3), I run a regression that aims at testing for the presence of parallel pre-trends, showing some mild evidence of a linear time trend during the years 2015-2019.

	(1)	(2)	(3)
year	0.0272		0.0244*
-	(0.0180)		(0.0126)
year x high deathrate	-0.0057	-0.0055	. ,
	(0.0275)	(0.0274)	
observations	2,560	2,560	2,560
charities	574	574	574
R-squared	0.88	0.88	0.88
charity FE	Yes	Yes	Yes
year FE	No	Yes	No

Table B.3. Donations to Health Charities: Non-Parallel Pre-Trends Tests

*Notes:* The sample comprises health charities that operate exclusively at the local authority level, and is based on years 2015-19. The dependent variable is the logarithm of total donations received by charity *i* in local authority *l* during year *t*. High deathrate is a dummy variable that equals 1 for local authorities whose Covid-19 death rate (aggregating 2020 and 2021 deaths) was above the median, and 0 otherwise. Robust std. errors clustered at county-year level in parenthesis. \*p<0.1, \*\*p<0.05, \*\*\*p<0.01.