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

Esteban Jaimovich*

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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 geographic units (local authorities), I show that donations to health charities located 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. This differential evolution is, however, not observed in the case of sources of charities' income that are unrelated to donors' giving decisions. 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 higher 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.

*University of Turin (ESOMAS Department). E-mail: esteban.jaimovich@unito.it

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.[1] 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)].[2]

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. This included very precise updates on the geographic evolution and distribution of new infections and deaths. This constant 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.[3]

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 for England and Wales. 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.[4] Importantly for the purposes of this study, the UK (and England in particular) has been hit particularly hard by the virus in relative terms, and also mortality rates across different regions there have shown wide heterogeneity. I exploit the geographic

[1]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.

[2]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.

[3]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.

[4]Local authorities are the narrowest geographic units at which this information is available from official UK sources.

variability in death rates to study whether the severity of the Covid-19 pandemic has led to differential responses in terms of private donations to health charities in the aftermath of the pandemic.

The analysis shows that health charities located in areas (local authorities) that have suffered higher Covid-19 mortality rates have also experienced a significantly greater increase in total private donations when comparing their levels in year 2022 to the average level of donations during 2015-19.[5] This qualitative result is not only robust to controlling for several potential confounding factors (such as fundraising effort by charities and differences in regional time trends), but also it is seemingly quantitatively large. Health charities located in areas experiencing mortality rates above the median have seen a growth in private donations of approximately 19% when comparing the levels in year 2022 versus those in the pre-pandemic years. On the other hand, when carrying out the same comparison for health charities located in areas whose death rates were below the median, the estimates imply a growth in donations of just 3%.

Interestingly, the starkly heterogeneous responses by private donations across health charities is not observed in the case of other sources of income (such as legacies originating from a deceased person's will, investment income, fees/grants, and income arising from trading activities and other exceptional sources of income). In particular, when looking at the post-pandemic growth of sources of income that are unrelated to donors' choices, the regressions find no significant correlation between them and the severity of the pandemic in the area (measured by death rates at the local authority level).

One possible interpretation of the previous results is that they reflect the guiding impact of the severity of the pandemic on donors' altruistic behavior towards different 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 an enormous negative economic shock. It could arguably be the case that variations in the evolution of donations across charities in different areas 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.[6] To address these

[5]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.

[6]The Center for Disaster Philanthropy (2021) reported that the U.S. nonprofit sector lost more than 900,000 jobs during 2020.

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 vis-a-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 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.

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 in some cases differ in terms of the level of detail of historical information. For example, while all registered charities must report their total income and expenditure over their financial year, larger charities must report back that information with a higher degree of disaggregation. In particular, charities whose gross yearly income has been above £500,000 must disaggregate total income between six separate source categories; namely: donations, legacies, income from charitable activities, investment income, other trading activities, and other income.[7] In addition, 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.[8]

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 28% 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. Notwithstanding, in the Appendix, I show that the results are robust to including all observations in which donations are equal to zero, by using the inverse hyperbolic sine (IHS) of donations as dependent variable.[9] One peculiarity of the charity sector in England and Wales is

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

[8] The distribution of gross income across charities is highly skewed to the right, with median gross yearly income approximately equal to £50,000 and mean gross yearly income slightly above £800,000. The share of charities with mean gross yearly income greater than £500,000 is 12.5% of those registered in the Charity Commission.

[9] Relying on the IHS (arcsinh) transformation to approximate the logarithm function, while simultaneously accounting for the presence of zeros in the variable of interest, has been increasingly used in Economics. See the discussion in

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 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.[10] All the charities that do not comply with either of the above two conditions are classified as 'non-health charities'.

Bellemare and Wichman (2020), and for examples of its use in the literature see Pence (2006), Clemens and Tiongson (2017), Jayachandran et al. (2017), McKenzie (2017), and Deryugina and Marx (2021).

[10]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.

Finally, I also rely on the Charity Commission's registry for geographically locating charities, based on their main address and their postcodes. The geographic unit of analysis throughout the paper will be the local authorities. England and Wales comprise 329 local authorities.[11]

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 when the sheer impact of the pandemic was suffered 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 aimed at containing the spread of the virus.[12] 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.

[11]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.)

[12]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.

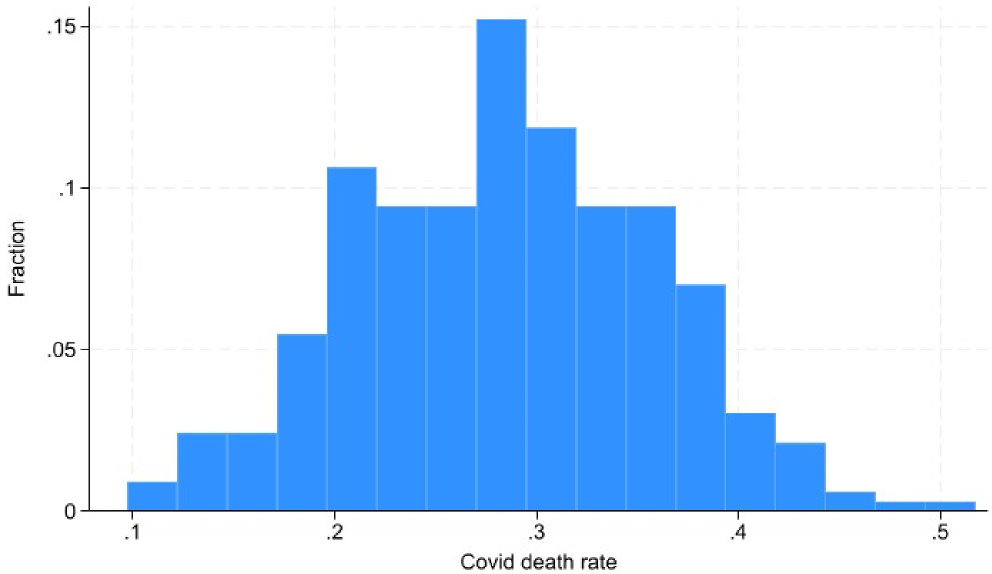

Figure 1. Histogram of Covid-19 Death Rates

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.

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).[13] 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.[14]

[13]Counties represent a coarser geographic unit. England and Wales comprise 34 counties. The median number of local authorities per county is 7.

[14]The empirical analysis will take the severity of the impact of the pandemic at the local level as exogenous. Fetzer

3 Empirical Analysis I: Health Charities Sample

3.1 Difference-in-Difference Analysis on Donors Behavior

As a first step, before conducting the analysis comparing donations in the pre- vs. post-pandemic years across different areas in England and Wales, I test for the presence of non-parallel trends in the evolution of donations during the pre-pandemic years. More specifically, I run the following regression using data from years 2015-19:

$$\ln(D_{i(l)t}) = \tau \cdot Year_t + \rho \cdot (Year_t \times Deathrate_l) + \varsigma_{i(l)} + \varepsilon_{i(l)t}, \tag{1}$$

where the dependent variable in (1) is the natural logarithm of the total amount of donations received in year t by charity i, which is located in local authority l. $Deathrate_l$ is equal to the total number of Covid-19 deaths during 2020-21 in local authority l over the total population of l. 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.[15] Standard errors are clustered at the local authority level.

The estimation results of (1) are presented in the first column of Table 1. The estimated value of ρ 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.

The previous results seem to rule out the presence of heterogeneous pre-trends across geographic areas with varying levels of Covid-19 death rates. In light of this, I proceed next to carry out a difference-in-difference analysis of the response of donations to health charities in areas varying in terms of the severity of the pandemic. In particular, I study now the relationship between the (post-pandemic) change in donations to 'health charities' and the Covid-19 fatality rate in the area where

(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.

[15] This fact also entails that (2) does not need to explicitly include $Deathrate_l$ as one of their regressors.

Table 1. Donations to Health Charities: Non-Parallel Pre-Trends Tests

	(1)	(2)	(3)
year	0.042		0.019*
	(0.045)		(0.011)
year x deathrate	-0.088	-0.087	
	(0.174)	(0.174)	
Observations	5,148	5,148	5,158
charities	1188	1188	1190
R-squared	0.898	0.898	0.898
charity FE	Yes	Yes	Yes
year FE	No	Yes	No

Notes: Only 'health charities' and years 2015-2019 are included in the sample. The dependent variable is ln($D_{i(l)t}$), where $D_{i(l)t}$ equals donations during year t to charity i localed in local authority l. Deathrate is defined as total Covid-19 deaths during 2020 and 2021 in l divided by l's total population. Robust standard errors clustered at local authority level in parenthesis.

the charities are located. The benchmark regression has the following structure:

$$\ln(D_{i(l)t}) = \alpha \cdot Postcovid_t + \beta \cdot (Postcovid_t \times Deathrate_l) + \tau \cdot Year_t + \varsigma_{i(l)} + \varepsilon_{i(l)t}. \qquad (2)$$

The dependent variable in (2) is again the natural logarithm of the total amount of donations received in year t by charity i, which is located in local authority l. $Postcovid_t$ is a dummy variable that equals one in year 2022, while it equals zero during years 2015-19. For the regression analysis, I exclude the two main years of the Covid-19 pandemic (that is, years 2020 and 2021) from the sample. The regression (2) also includes a full set of charity fixed effects, $\varsigma_{i(l)}$. Given the evidence of a mild linear trend in column (3) of Table 1, I include in (2) the term $\tau \cdot Year_t$. Standard errors are clustered at the local authority level. The main coefficient of interest is β, which captures heterogeneities in the post-pandemic evolution of donations to health charities given the Covid-19 mortality rates in the areas where they are located.

The estimation results of (2) are displayed in column (1) of Table 2. The estimated value of β is positive and highly significant. This implies that health charities located in areas that suffered higher death rates have seen a larger increase in donations received in year 2022 relative to the average level of donations during years 2015-19. Notice that since all local authorities in England and Wales have experienced positive death rates during the Covid-19 pandemic, the estimated value of α has no meaningful interpretation in this context. However, the combination of the estimates of α and β at different levels of $Deathrate_l$ reveals large quantitative variations in the post-Covid-19 responses of donations to health charities across areas with different mortality rates. For example, the 75th-percentile death rate across local authorities was equal to 0.337%, and based on the estimates in column (1) the implied increase in post-pandemic donations to health charities in that area would be approximately 18%. On the other hand, considering the local authority in 25th percentile, which had a death rate equal to 0.227%, the implied post-pandemic rise donations to health charities there would be just 3.5%.

Columns (2)-(4) in Table 2 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 α, but it can still identify the main parameter of interest (β). The estimated value of β 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 the inverse hyperbolic sine (IHS) of fundraising expenditures by each charity as additional control.[16] 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 β 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 geographic areas. The 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 β 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). In a sense, one could fear that the exact local authority within Central London where a particular charity is located is much less meaningful than in other areas of England and Wales, being Central London by far the largest commuting centre in the UK. This sample restriction additionally further mitigates concerns one may have about selection across geographic areas (for example, in case one may worry that people who live in cities may exhibit a different propensity to respond to an adverse shocks relative to those who live in rural areas).[17] The results in column (5) remain, however, essentially intact relative to

[16] A large number of charities report spending zero in terms of fundraising. Hence, the IHS is used to approximate the logarithm of fundraising expenditure in the presence of zeros, rather than having to discard all these data points.

[17] As further robustness check, I have run the same regressions as in column (5), but also excluding (in addition to London) the following cities from the sample: Birmingham, Manchester, Liverpool, Leeds, and Cardiff. The main results remain essentially intact, and are available from the author upon request.

Table 2. Donations to Health Charities: heterogeneous responses to the Covid-19 pandemic

	(1)	(2)	(3)	(4)	(5)
postcovid x deathrate	1.283**	1.287**	1.333**	1.900**	1.930**
	(0.601)	(0.602)	(0.599)	(0.858)	(0.893)
postcovid	-0.256				
	(0.163)				
year	0.018*				
	(0.011)				
IHS fundraising			0.019***	0.020***	0.021***
			(0.006)	(0.006)	(0.008)
observations	6,281	6,281	6,281	6,281	4,805
charities	1262	1262	1262	1262	958
R-squared	0.874	0.874	0.875	0.878	0.877
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

Notes: Only 'health charities' are included in the sample. The dependent variable is log($D_{i(l)t}$), where $D_{i(l)t}$ equals donations during year t to charity i localed in local authority l. 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. Deathrate is defined as total Covid-related deaths during years 2020 and 2021 in local authority l divided by l's total population. Robust standard errors clustered at the local authority level in parenthesis. *p<0.1 **p<0.05; ***p<0.01

those in column (4).

Appendix B.1 presents a series of robustness checks. One possible concern with the results in Table 2 is that it restricts the sample to charities receiving positive donations. In Table B.1.1, by using as dependent variable the IHS of donations, I run a series of alternative specifications that include as well those observations where donations are equal to zero. Next, Table B.1.2 runs the same regressions but replacing $Deathrate_l$ by 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, and zero otherwise. In Table B.1.3, I restrict the analysis to the subsample of charities that operate only at the local authority level (hence, removing all charities that operate as well at the national and/or international level). Despite the large reduction in the size of the sample, the results remain qualitatively in line with those in Table 2. Lastly, Table B.1.4 runs a set of regressions analogous to those in Table 2, but using all years in the sample (i.e., including also years 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 are present in interaction terms for years 2021 and 2022, but not yet significantly in year 2020.[18]

[18] In a sense, the results in Table B.1.4 seem to reasonably support the ones in Table 2, as reflecting the notion that donors had already started responding differently by year 2021 when the impact of the pandemic was already well known.

3.2 Difference-in-Difference Analysis on Other Sources of Income

The results in Table 2 provide evidence of strong heterogeneities in the post-pandemic response of charitable giving to health charities depending on whether they are located in areas that suffered higher mortality rates or where the impact of the pandemic has been milder. The interpretation of these results entertained by this paper is that donors' altruistic behavior responds to the harmfulness of adverse events, and hence charitable giving will increase more strongly in areas where it is needed relatively more. If the results in Table 2 do reflect essentially this effect, one should not expect to observe such strong heterogeneities before and after the pandemic when looking at other sources of charities' income which are *unrelated* to donors' behavior.

In Table 3, I show the results of a series of regressions analogous to that one in column (2) of Table 2, but where the dependent variable (natural logarithm of donations) has been replaced by alternative sources of charities' income. In column (1) the dependent variable 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 other exceptional sources of income. Unlike the case when using donations as dependent variable, none of the regression in Table 3 yields a significant estimate for the coefficient associated to the interaction term $Postcovid_t \times Deathrate_l$.[19]

4 Empirical Analysis II: Triple Difference Approach

As previously mentioned, the results in Table 1 do not raise in principle major concerns about divergent pre-trends across local authorities which would eventually experience varying levels of Covid-19 mortality rates. Nevertheless, interpreting the estimates of β in Table 2 as reflecting the impact of the severity of the pandemic on donors' altruistic behavior may be unwarranted in the presence of other confounding factors influencing such heterogeneities. One possibility could be that the results in

Instead, the data on donations for year 2020 include several months before the pandemic had even hit, and also that one is the year with the strongest lockdowns impairing economic activity.

[19] The number of observations (and charities) present in the different columns in Table 3 is always smaller than those in Table 2. This is due to the fact that there are many more zeroes for the dependent variables used in the different specifications used in Table 3. All the qualitative results in Table 3 are, however, robust to replacing the log of each dependent variables by their respective IHS, so as to allow including all the observations with zeros.

Table 3. Health Charities: other sources of income (pre- and post-Covid-19 pandemic)

	(1)	(2)	(3)	(4)
	legacies	*investments*	*charit. Act.*	*other income*
postcovid x deathrate	0.840	-0.902	0.172	-0.016
	(0.855)	(0.764)	(0.548)	(0.872)
Observations	2,851	5,473	4,465	4,419
charities	604	1116	904	941
R-squared	0.792	0.901	0.902	0.827
charity FE	Yes	Yes	Yes	Yes
year FE	Yes	Yes	Yes	Yes

Notes: Only 'health charities' are included in the sample. The dependent variable is $\log(X_{i(l)t})$, where X is legacies in (1), investment income in (2), charitable activities income in (3) and other sources of trading and exceptional sources of income in (4). The main years of the pandemic (2020-21) are excluded from the sample. Postcovid equals 1 in year 2022 and 0 in years 2015-19. Deathrate equals total Covid-related deaths during 2020-21 in local authority l divided by l's total population. Robust std. errors clustered at local authority level in parenthesis. *p<0.1; **p<0.05; ***p<0.01

Table 2 are actually driven by 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 years. This could then have led 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). Another possibility could be that the pandemic years forced some of the most inefficient charities to leave the market, and this cleansing mechanism may have worked more strongly in more severely 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 including all charities present in the dataset (regardless of their area of activity). 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:

$$\ln(D_{i(l)t}) = \alpha \cdot Postcovid_t + \beta \cdot (Postcovid_t \times Deathrate_l) + \delta \cdot (Postcovid_t \times Health_i)$$
$$\gamma \cdot (Postcovid_t \times Deathrate_l \times Health_i) + \tau \cdot Year_t + \varsigma_{i(l)} + \varepsilon_{i(l)t}. \tag{3}$$

The main coefficient of interest in (3) is γ. 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 higher mortality rates. That is, we should observe a positive estimate for γ. The results of (3) are displayed in the first column of Table 4. The estimated value of γ 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 that emerges from Table 4 is the fact that the estimate of the coefficient associated to the interaction term $Postcovid_t \times Deathrate_l$ is negative. This would suggest that (unlike to the case of health charities) in the case of non-health charities the post-pandemic response of donations seems to display a negative association with Covid-19 mortality rates. One possible reason behind this negative relation could simply be post-pandemic negative income effects on donors brought about by the pandemic. However, it could be also the consequence of donors shifting their gifts from non-health to health charities, especially in areas that experienced worse Covid-19 fatalities.

Jointly considered the estimates in column (1) lead to some noteworthy quantitative results. According to those estimates, the post-pandemic growth in donations to health charities located in the 75th-percentile-mortality local authority (with death rate 0.337%) turns out to be approximately 19% greater than that of non-health charities in that local authority. Conversely, when considering the 25th-percentile-mortality local authority (with death rate 0.227%), there turns out to be almost no quantitative difference in the post-pandemic change in donations when comparing health charities against non-health charities located in that area. These quantitative gaps tend to suggest again that donors' choices in terms of charitable giving have been heavily guided by the gravity of the pandemic across geographic areas.

Columns (2)-(5) in Table 4 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 previously done in Table (1). In addition to those specifications, column (5) includes local authority-by-year fixed effects. Unlike the previous regressions based on (2), including such fixed effects is feasible in this case (at the cost of failing to identify the coefficient associated with $Postcovid_t \times Deathrate_l$) since (3) contains variation of social missions by charities within the same local authority. Notice that the incorporation 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 γ. Lastly, column (6) excludes charities located in Central London from the

Table 4. Donations to Charities: triple difference response to the Covid-19 pandemic

	(1)	(2)	(3)	(4)	(5)	(6)
postcovid x deathrate x health	1.739***	1.742***	1.748***	1.686***	1.969***	2.029**
	(0.646)	(0.645)	(0.644)	(0.636)	(0.666)	(0.785)
postcovid x deathrate	-0.452**	-0.453**	-0.439*	-0.342		
	(0.229)	(0.229)	(0.228)	(0.311)		
postcovid x health	-0.401**	-0.402**	-0.405**	-0.393**	-0.472***	-0.491**
	(0.168)	(0.168)	(0.167)	(0.165)	(0.173)	(0.215)
postcovid	0.225***					
	(0.059)					
year	0.002					
	(0.005)					
IHS fundraising			0.008***	0.007***	0.007***	0.006**
			(0.002)	(0.002)	(0.002)	(0.002)
observations	40,464	40,464	40,455	40,455	40,432	30,545
charities	8203	8203	8202	8202	8200	6175
R-squared	0.866	0.867	0.867	0.868	0.874	0.872
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

Notes: The dependent variable is $\ln(D_{i(l)t})$, where $D_{i(l)t}$ is donations received during year t by charity i located in local authority l. The two 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. Deathrate is defined as total Covid deaths during years 2020 and 2021 in local authority l divided by l's the total population. Health is equal to 1 if charity i is classified as a 'health charity' and 0 if it is classified as 'non-health charity'. Robust std. errors clustered at the local authority level in parenthesis. *p<0.1 **p<0.05; ***p<0.01

regression sample; the estimated value of γ remains again essentially intact.

Appendix B.2 presents a series of robustness checks on Table 4, analogously to those in Appendix B.1 for Table 2. In particular, Table B.2.1 allows including the observations where donations are equal to zero by using an IHS transformation of the dependent variable. Table B.2.2 runs the same set of regressions as in Table 4, but substitutes the continuous variable $Deathrate_l$ by the dummy variable $High\_deathrate_l$ (equal to one when the Covid-19 death rate in local authority l lies above the median death rate). Table B.2.3 restricts the analysis to the subsample of charities that operate only at the local authority level. Lastly, Table B.2.4 enlarges the set of years in the sample to include also years 2020 and 2021.

5 Concluding Remarks

The analysis in the paper reveals that the 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. Relying on data sourced from the annual returns submitted to the Charity Commission for England and Wales, the analysis has shown that charities dealing with health issues located in areas that suffered higher Covid-19 death rates have benefitted from a relatively larger increase in private donations after the pandemic receded (in year 2022). This differential behavior across health charities is *only* observed for private donations, while it is absent in the case of other sources of charities' income. Furthermore, when exploiting a triple-difference approach, the analysis shows that post-pandemic donations to health charities have significantly outgrew donations to non-health charities in areas experiencing higher Covid-19 fatalities, but such a gap in the post-pandemic evolution of donations across types of charities is *not* present in areas where death rates have been relatively 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. 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 counts 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. The two subgroups appear very similar in terms of their total income and their income sourced from donations, albeit the dispersion measure is somewhat larger in the case of non-health charities (possibly as a result of comprising a more heterogeneous set of charities). Charities dealing with health-related issues tend to spend 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, considering all charities and also only those charities classified 'health charities' in the paper. About 75% of the charities that have been classified as 'health charities' for the purposes of the analysis have listed more than one area of activity. Charities classified as health charities seem overall to report a wider set of areas of activity than those classified as non-health charities.

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.

Table A.1. Areas of Charitable Activity

Area of Charitable Activity	# Charities
Accommodation/Housing	1143
Amateur Sport	923
Animals	361
Armed Forces/Emergency Service Efficiency	103
Arts/Culture/Heritage/Science	1747
Disability	2070
Economic/Community Development/Employment	1752
Education/Training	6189
Environment/Conservation/Heritage	1284
General Charitable Purposes	2996
Human Rights/Religious or Racial Harmony/Equality or Diversity	514
Other Charitable Purposes	919
Overseas Aid/Famine Relief	737
Recreation	666
Religious Activities	2324
The Advancement of Health or Saving of Lives	2815
The Prevention or Relief of Poverty	2666

Table A.2. Summary Statistics

	Health Charities		
	mean	median	coef. var.
Total Income	5,982,838	1,645,328	3.844
Income from Donations	2,021,314	498,398	7.718
Fundraising Expenditure	784,530	62,029	4.920
Death Rate	0.262	0.260	0.262
# Years Present in Sample	7.09	8	0.239
	Non-Health Charities		
	mean	median	coef. var.
Total Income	6,468,049	1,410,195	4.793
Income from Donations	2,155,994	409,279	8.581
Fundraising Expenditure	506,730	18,950	7.030
Death Rate	0.254	0.242	0.264
# Years Present in Sample	6.95	8	0.265

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

# Areas of	all charities		health charities	
Activity	Number	%	Number	%
1	2977	30.3	367	25.7
2	2144	21.8	241	16.9
3	1642	16.7	208	14.6
4	1167	11.9	165	11.6
5	756	7.7	150	10.5
6	436	4.4	113	7.9
7	309	3.2	71	5.0
8	169	1.7	51	3.6
9	89	0.9	20	1.4
10	66	0.7	25	1.8
11	40	0.4	9	0.6
12	17	0.2	3	0.2
13	10	0.1	3	0.2
14	9	0.1	0	0
15	3	0	1	0.07
16	1	0	0	0
17	1	0.01	1	0.07
Total	**9836**	**100**	**1428**	**100**

Table A.4. Examples of 'Health' and 'Non-Health' Charities

Charity Name	# Areas	Areas of Activity	Charitable Activities (own description by charities)	Classification
wrightington, wigan and leigh health services charity	4	**The Advancement of Health or Saving of Lives**; Education/Training; Disability; General Charitable Purposes	The mission of wrightington, wigan and leigh **health** service charity is to further improve the quality of patient care, through staff training, purchasing **medical** 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	3	**The Advancement of Health or Saving of Lives**; Education/Training; Arts/culture/heritage/science	the francis crick institute is dedicated to understanding the fundamental biology underlying **health** and **disease**. our work is helping to understand why **disease** develops and to translate discoveries into new ways to prevent, diagnose and treat **illnesses** such as cancer, heart **disease**, stroke, infections and neurodegenerative **diseases**.	Health Charity
british society for immunology	2	**The Advancement of Health or Saving of Lives**; Education/ Training	running innovative events in research, public engagement & education promoting & disseminating research, good practice in **immunology**, translational **medicine** and **vaccination** working with its members to develop the benefits of membership & the relevance of the society providing bursaries & grants enhancing public awareness of **immunology** working with other societies	Health Charity
CT4N Charitable Trust	3	Disability; **The Advancement of Health or Saving of Live**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.	Non-Health Charity
hastings and rother voluntary association for the blind	3	Disability; **The Advancement of Health or 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, together with the provision of advice, information and support to visually impaired people of all ages living in hastings and rother areas.	Non-Health Charity
Become Charity	4	The Prevention or Relief of Poverty; **The Advancement of Health or Saving of Lives**; 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.	Non-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 2, but replacing the dependent variable in (2) by $IHS(D_{i(l)t})$, where $IHS(\cdot)$ is the inverse hyperbolic sine transformation. The set of regressions in Table B.1.1 include all observations where $D_{i(l)t} = 0$. All the results displayed on this table are in line with those in the benchmark regressions in Table 2.

Next, Table B.1.2 shows the results of a series of regressions analogous to those in Table 4, but where the variable $Deathrate_l$ in (3) is replaced by 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 in the sample of all local authorities (which is equal to 0.285%), and zero otherwise. All the results are qualitatively in line with those of Table 2. In addition, the interpretation of the results would entail that donations to health charities in local authorities suffering death rates above the median have growth approximately 20% in 2022 relative to their pre-pandemic levels, while donations to health charities in local authorities whose death rates have been below the median have not shown any change in terms of donations when comparing pre- vs. post-pandemic levels.

Table B.1.3 restricts the analysis to the subsample of health charities that operate only at the local authority level. While this reduces substantially the set of charities included in the regressions (to less than half relative to the benchmark sample in Table 2), it ensures that those that remain in the sample are only operating in their local area. Despite the large reduction in the size of the sample, the results remain qualitatively in line with those in Table 2. Interestingly, the point estimates suggest that the heterogeneities in the post-pandemic evolution of donations to health charities are slightly larger when considering only charities operating at the local authority level. This last result would indeed be in line with the notion that donors' altruistic behavior towards different charities is guided by the relative severity of the pandemic in the areas where they operate.

Lastly, in Table B.1.4, I expands the definition of "treatment" years to include years 2020, 2021, and 2022, but allowing a differential impact each year. More precisely, I include three separate interaction terms ($dummy\_2020 \times deathrate$, $dummy\_2021 \times deathrate$ and $dummy\_2022 \times deathrate$), where each $dummy\_202x$ is a dummy variable equal to one for observations corresponding to year $200x$, and zero otherwise. The results in Table B.1.4 are quantitatively similar and significant for the interaction terms for years 2021 and 2022, but seem to be smaller and fail to reach significance yet 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.

Table B.1.1. Donations to Health Charities: Inverse Hyperbolic Sine of Donations (includes zeros)

	(1)	(2)	(3)	(4)	(5)
postcovid x deathrate	2.693**	2.691**	2.748**	3.756**	2.908*
	(1.354)	(1.354)	(1.357)	(1.747)	(1.742)
postcovid	-0.566				
	(0.380)				
year	0.023				
	(0.025)				
IHS fundraising			0.032***	0.034***	0.035***
			(0.012)	(0.012)	(0.013)
observations	8,125	8,125	8,125	8,125	6,172
charities	1621	1621	1621	1621	1224
R-squared	0.811	0.811	0.812	0.816	0.827
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

Notes: The regressions in this table follow the same structure as those in Table 2, except that the dependent variable is the IHS($D_{i(l)t}$) and it includes observations where donations are equal to zero. Robust standard errors clustered at local authority level in parenthesis. *p<0.1; **p<0.05; ***p<0.01

Table B.1.2. Donations to Health Charities: response to the Covid-19 pandemic in high vs. low death rates areas

	(1)	(2)	(3)	(4)	(5)
postcovid x high-deathrate	0.195***	0.196***	0.201***	0.204**	0.204**
	(0.074)	(0.074)	(0.074)	(0.088)	(0.090)
postcovid	0.005				
	(0.064)				
year	0.018				
	(0.011)				
IHS fundraising			0.019***	0.020***	0.021***
			(0.006)	(0.006)	(0.008)
observations	6,281	6,281	6,281	6,281	4,805
charities	1262	1262	1262	1262	958
R-squared	0.874	0.874	0.875	0.878	0.877
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

Notes: The regressions in this table follow the same structure as those in Table 2, except for the dummy variable high-deathrate replacing deathrate. High-deathrate equals 1 when the death rate in local authority l is above median death rate across all local authorities in the sample, and 0 otherwise Robust standard errors clustered at local authority level in parenthesis. *p<0.1; **p<0.05; ***p<0.01

Table B.1.3. Donations to Health Charities: Charities Operating Only at Local Level

	(1)	(2)	(3)	(4)	(5)
postcovid x deathrate	1.921**	1.916**	1.972**	1.658*	1.755*
	(0.824)	(0.824)	(0.822)	(0.993)	(0.998)
postcovid	-0.418*				
	(0.241)				
year	0.029*				
	(0.017)				
IHS fundraising			0.015*	0.013	0.016*
			(0.009)	(0.009)	(0.009)
observations	3,083	3,083	3,083	3,081	2,898
charities	598	598	598	598	561
R-squared	0.859	0.860	0.860	0.868	0.868
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

Notes : The regressions follow the same structure as in Table 2, but restricting the sample to include only those charities that operate only at the local level. Robust standard errors clustered at local authority level in parenthesis. *p<0.1; **p<0.05; ***p<0.01

Table B.1.4. Donations to Health Charities: Interaction Terms for years 2020, 2021 and 2022

	(1)	(2)	(3)	(4)
dummy_2020 x deathrate	0.387	0.437	0.332	0.168
	(0.406)	(0.410)	(0.571)	(0.594)
dummy_2021 x deathrate	2.044***	2.171***	2.243**	2.274**
	(0.558)	(0.562)	(0.889)	(0.941)
dummy_2022 x deathrate	1.294**	1.361**	1.804**	1.855**
	(0.597)	(0.594)	(0.859)	(0.890)
IHS fundraising		0.026***	0.026***	0.027***
		(0.007)	(0.007)	(0.008)
observations	8,817	8,817	8,817	6,735
charities	1442	1442	1442	1094
R-squared	0.864	0.865	0.869	0.866
charity FE	Yes	Yes	Yes	Yes
year FE	Yes	Yes	No	No
county-year FE	No	No	Yes	Yes
London	Yes	Yes	Yes	No

Notes : The regressions include three interaction terms between a year dummy (dummy_202X) and the deathrate 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 authority level in parenthesis. *p<0.1; **p<0.05; ***p<0.01

B.2: Robustness checks on Section 4

Table B.2.1 carries out the same set of regressions as those in Table 4, but replacing the dependent variable in (2) by $IHS(D_{i(l)t})$, where $IHS(\cdot)$ is the inverse hyperbolic sine transformation. The set of regressions in Table B.2.1 include all observations where $D_{i(l)t} = 0$. All the results displayed are in line with those in the benchmark regressions in Table 4, with the only exception is column (6) in Table B.2.1 (controlling for county-year fixed effects and excluding Central London from the sample of charities), in which case the estimate is still positive but fails to reach statistical significance.

Table B.2.2 shows the results of a series of regressions analogous to those in Table 4, but where the variable $Deathrate_l$ in (3) is replaced by 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 in the sample of all local authorities (which is equal to 0.285%), and zero otherwise. All the results for the main coefficient of interest (that is, the triple interaction term) are qualitatively in line with those of Table 4. On the other hand, the estimates associated to the other interaction terms become much smaller in magnitude, and lose statistical significance as well.

Table B.2.3 restricts the analysis to the subsample of charities that operate only at the local authority level. As a result, the set of charities included in the regressions falls substantively (to almost half as in the benchmark sample in Table 4). Nevertheless, despite the large reduction in the size of the sample, the results remain qualitatively in line with those in Table 4. Furthermore, analogously to what it is observed with the results in Table B.1.3 relative to those in Table 2, the quantitative point estimates suggest that the heterogeneities in the post-pandemic evolution of donations across charities are slightly larger when considering only charities operating at the local authority level, which would indeed be consistent with the notion that donors' altruistic behavior towards different charities is guided by the relative severity of the pandemic in different areas.

Lastly, in Table B.2.4 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.2.1. Donations to Charities: Inverse Hyperbolic Sine of Donations (includes zeros)

	(1)	(2)	(3)	(4)	(5)	(6)
postcovid x deathrate x health	3.239**	3.240**	3.226**	3.053**	2.671*	0.256
	(1.511)	(1.511)	(1.512)	(1.513)	(1.524)	(1.521)
postcovid x deathrate	-0.547	-0.548	-0.502	0.649		
	(0.506)	(0.505)	(0.503)	(0.617)		
postcovid x health	-0.800*	-0.800*	-0.800*	-0.766*	-0.691	0.093
	(0.416)	(0.416)	(0.416)	(0.419)	(0.422)	(0.423)
postcovid	0.123					
	(0.143)					
year	0.045***					
	(0.011)					
fundraising			0.018***	0.017***	0.016***	0.016**
			(0.005)	(0.005)	(0.005)	(0.006)
observations	56,607	56,607	56,592	56,592	56,581	42,930
charities	11348	11348	11346	11346	11346	8590
R-squared	0.785	0.785	0.785	0.786	0.793	0.793
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

Notes: The regressions in this table follow the same structure as those in Table 3, except that the dependent variable is the IHS($D_{i(l)t}$) and it includes observations where donations are equal to zero. Robust standard errors clustered at local authority level in parenthesis. *p<0.1; **p<0.05; ***p<0.01

Table B.2.2. Donations to Charities: triple difference response to the Covid-19 pandemic (high vs. low death rates)

	(1)	(2)	(3)	(4)	(5)	(6)
postcovid x high-deathrate x health	0.223***	0.224***	0.224***	0.223***	0.253***	0.248***
	(0.078)	(0.078)	(0.077)	(0.076)	(0.077)	(0.083)
postcovid x high-deathrate	-0.028	-0.028	-0.026	-0.004		
	(0.034)	(0.034)	(0.034)	(0.042)		
postcovid x health	-0.035	-0.035	-0.036	-0.039	-0.055	-0.050
	(0.048)	(0.048)	(0.047)	(0.046)	(0.047)	(0.056)
postcovid	0.119***					
	(0.024)					
year	0.002					
	(0.005)					
fundraising			0.008***	0.007***	0.007***	0.006**
			(0.002)	(0.002)	(0.002)	(0.002)
observations	40,464	40,464	40,455	40,455	40,432	30,545
charities	8203	8203	8202	8202	8200	6175
R-squared	0.866	0.867	0.867	0.868	0.874	0.872
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

Notes: The regressions in this table follow the same structure as those in Table 3, except for the dummy variable high-deathrate replacing deathrate. High-deathrate equals 1 when the death rate in local authority l is above median death rate across all local authorities in the sample, and 0 otherwise Robust standard errors clustered at local authority level in parenthesis. *p<0.1; **p<0.05; ***p<0.01

Table B.2.3. Triple difference response: Charities Operating Only at Local Level

	(1)	(2)	(3)	(4)	(5)	(6)
postcovid x deathrate x health	2.107**	2.108**	2.122**	1.907**	2.104**	2.424**
	(0.920)	(0.919)	(0.919)	(0.922)	(0.992)	(1.008)
postcovid x deathrate	-0.178	-0.180	-0.175	-0.177		
	(0.323)	(0.323)	(0.323)	(0.395)		
postcovid x health	-0.420*	-0.420*	-0.426*	-0.366	-0.419	-0.525*
	(0.249)	(0.248)	(0.248)	(0.248)	(0.263)	(0.267)
postcovid	0.162*					
	(0.090)					
year	-0.004					
	(0.007)					
fundraising			0.005*	0.004	0.003	0.002
			(0.003)	(0.003)	(0.003)	(0.003)
observations	21,465	21,465	21,460	21,460	21,377	19,319
charities	4315	4315	4314	4314	4301	3886
R-squared	0.842	0.843	0.843	0.844	0.858	0.858
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

Notes: The regressions follow the same structure as in Table 4, but restricting the sample to include only those charities that operate only at the local level. Robust standard errors clustered at local authority level in parenthesis. *p<0.1; **p<0.05; ***p<0.01

Table B.2.4. Triple difference response: Interaction terms for years 2020, 2021 and 2022

	(1)	(2)	(3)	(4)	(5)
dummy_2020 x deathrate	-0.314	-0.295	-0.217		
	(0.206)	(0.205)	(0.295)		
dummy_2021 x deathrate	0.206	0.229	0.175		
	(0.254)	(0.254)	(0.338)		
dummy_2022 x deathrate	-0.475**	-0.456**	-0.394		
	(0.226)	(0.225)	(0.307)		
dummy_2020 x health	-0.171	-0.172	-0.162	-0.255**	-0.117
	(0.120)	(0.119)	(0.121)	(0.123)	(0.158)
dummy_2021 x health	-0.486***	-0.493***	-0.478***	-0.511***	-0.500**
	(0.163)	(0.162)	(0.165)	(0.174)	(0.211)
dummy_2022 x health	-0.429***	-0.433***	-0.427***	-0.492***	-0.477**
	(0.164)	(0.164)	(0.161)	(0.168)	(0.212)
dummy_2020 x deathrate x health	0.702	0.701	0.651	1.031**	0.606
	(0.457)	(0.457)	(0.464)	(0.479)	(0.570)
dummy_2021 x deathrate x health	1.839***	1.862***	1.780***	1.872***	1.848**
	(0.614)	(0.614)	(0.622)	(0.666)	(0.764)
dummy_2022 x deathrate x health	1.771***	1.777***	1.744***	1.963***	1.929**
	(0.630)	(0.628)	(0.621)	(0.647)	(0.769)
fundraising		0.009***	0.009***	0.008***	0.007***
		(0.002)	(0.002)	(0.002)	(0.002)
observations	56,608	56,596	56,596	56,573	42,726
charities	9356	9354	9354	9354	7061
R-squared	0.854	0.854	0.856	0.863	0.859
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

Notes : The regressions include a full set of interaction terms between a year dummy (dummy_202X) and the 'deathrate' variable and the dummy variable 'health' 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 authority level in parenthesis. *p<0.1; **p<0.05; ***p<0.01