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Altruism born of suffering? The impact of an adverse health shock on pro-social behaviour☆

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ABSTRACT

'Altruism born of suffering' (ABS) predicts that, following an adverse life event such as a health shock, individuals may become motivated to help others and act pro-socially. However, despite anecdotal support this has not been examined systematically. Using data from the United States Panel Study of Income Dynamics, we find that an adverse health shock does not lead to a general increase in pro-social behaviour; it neither causes people to start giving, nor does it spark an increase in donations across charitable causes. Instead, ABS is akin to a specific shock that affects giving to health charities. We find a significant increase in the probability of giving to health charities, with no change for other charity types. Accompanying this is an increase in amounts given to health charities, which comes at the expense of non-health, non-religious charities. The impact is greatest in the year after the health shock, attenuating thereafter.

1. Introduction

> *"With more and more people affected by cancer every day, I believe we are in a world desperate for healing, and I'm committed to doing whatever I can to help."*
>
> Olivia Newton-John (Olivia Newton-John Cancer Wellness & Research Centre, 2019)

Actress and singer, Olivia Newton-John, most famous for her role in the film Grease, was diagnosed with breast cancer in 1992 and subsequently became an advocate for cancer research and prevention. She donated the proceeds from various album sales to benefit breast cancer research, volunteered to lead fundraising activities and prevention campaigns, and helped to raise funds for public health services. Her pro-social behaviour[1] and generosity following a major health event has been held up as an example of what social psychologists refer to as 'altruism born of suffering' (ABS), which describes how individuals who have suffered may become particularly motivated to help others – not only despite their difficult

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[1] Defined as voluntary contributions to public goods (Gneezy et al., 2011).

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experiences but precisely because of them (Staub, 2003; Staub, 2005; Staub and Vollhardt, 2008; Vollhardt and Staub, 2011). This phenomenon has been reported to encompass a range of pro-social behaviours such as donating blood, helping others and activism; and different types of adverse health events such as stroke and heart attack (Vollhardt and Staub, 2011). However, despite anecdotal support for ABS, the effect of an adverse health shock on pro-social behaviour has not been examined systematically. This paper addresses that gap.

We present new evidence on the effect of adverse health shocks on pro-social behaviour using data from the United States (US) Panel Survey of Income Dynamics (PSID) from 2001 – 2015. We follow previous studies in defining an adverse health shock as an unanticipated change in health through a new diagnosis of a potentially life-threatening condition, namely cancer, heart attack or stroke (Jones et al., 2016; Smith et al., 2001).[2] We focus on charitable giving as the key pro-social behaviour of interest. Charitable giving is widespread in the US, with an estimated 70 per cent of households giving to charity each year, and these donations play an important role in the private provision of public goods.[3] We explore the effect of an adverse health shock on overall giving and on giving to different charity types (separating health, religious and other non-health causes). We look both at the extensive margin (whether or not people give) and the intensive margin (how much people give). We also carefully examine the timing of charitable giving in relation to the health shock to provide insights into the dynamic nature of pro-social behaviour following a health shock. We use the rich set of variables available in the PSID to control for a wide range of mediating influences in our analysis.

Adverse health shocks are associated with poorer health status, reduced income and increased healthcare expenditure, although we find no effect on religiosity. We find that, following an adverse health shock, there is no change in the probability of donating to a charity overall, nor is there any increase in total giving. However, there is a change in the type of charities to which people give. There is a significant increase in the probability of giving to health charities with no change in the probability of donating to religious or other non-health charities. This indicates that existing donors add health charities to their charity portfolio. Effects on amounts given are imprecisely estimated but donors give more to health charities and less to other, non-health charities. The effect on religious giving is positive but insignificant.

We find important dynamic effects. The impact of the adverse health shock is greatest in the year immediately after the health shock – the probability of donating to health charities is 11 percentage points above the baseline rate of around 30%; it attenuates thereafter, but the probability of donating to health charities remains higher – and is 6 percentage points above baseline – more than one year after the health shock.

We find that neither income, health expenditure, religiosity nor health status appears to influence the relationship between the health shock and pro-social behaviour. This implies that the health shock itself appears to be directly influencing charitable giving and that there is limited mediation through the pathways of income, healthcare expenditure, health status and religiosity.

These findings provide important insights into the nature of 'altruism born of suffering'. In our study, an adverse health shock does not lead to a general increase in pro-social behaviour; it neither causes people to start giving, nor does it spark an increase in donations across charitable causes. Instead, altruism born of suffering is akin to a specific shock that affects giving to health charities. There are several possible causes for this: people experiencing an adverse health shock may gain insights into the need for healthcare services, they may experience feelings of reciprocity, they may also have a greater degree of sympathy towards people with similar conditions and want to help a newly-formed ingroup.

We interpret the observed patterns as arising from an increase in the salience of a specific charitable cause, similar to the effect of a charity fundraising appeal examined by Scharf et al. (2017). Their paper investigated the effect of major disaster appeals which were found to cause a lift in total donations and a shift in the share of giving going to different causes, but no overall decline in other charities. In our case, we find no overall lift but only a shift in the level of donations to health charities away from other, non-health charities.

This paper bridges existing literatures in social psychology and economics. There is a substantial economics literature on the consequences of adverse health shocks (e.g. Garcia-Gomez, 2011, Liu, 2016, Lindeboom et al., 2016). We build on this literature and follow existing studies in how we define adverse health shocks; we add to it by studying the impact of health shocks on an outcome that has previously received little attention, i.e. pro-social behaviour. There is a literature outside economics that investigates pro-social behaviour following adverse life events (e.g. Reeves et al., 1999, Gillen, 2005) but, to date, it has been largely qualitative and it remains unclear as to whether the self-reported altruistic intentions in these studies ultimately translates into action; we add to it by providing quantitative evidence on the impact of adverse health shocks and we focus on a widespread pro-social action, namely charitable giving. We also contribute to a large literature on philanthropy that has investigated the effect of different demographic and socio-economic characteristics on charitable giving (summarised in Bekkers and Wiepking, 2011, Wiepking and Bekkers, 2012); we add to this by providing new evidence on a determinant of giving that has not previously been considered. We therefore offer further understanding of the determinants of giving that can inform charity fundraising strategies.

The finding that the effect of adverse health shocks varies between the immediate aftermath and longer-term reinforces the findings from recent studies that it is important to move beyond static analyses to consider the dynamics of charitable

[2] These studies focus on these conditions because they occur suddenly and largely unexpectedly, and are regarded as 'unanticipated' because the exact timing of onset is unknown. So, while risk factors may inform an individual about their health risks, it remains largely uninformative with respect to the timing of the event.

[3] Charitable giving totalled around US$410 billion in 2017, with 70% of giving coming from individuals (Giving USA, 2018).

giving over time (Andreoni and Serra-Garcia, 2018; Scharf et al., 2017; Rooney et al., 2019); by showing an increase in giving to health charities occurs at the expense of giving to non-health charities, we also add to a growing number of papers that provide evidence on substitutability / complementarity between different types of giving (Reinstein, 2011; Harwell et al., 2015; Filiz-Ozbay and Uler, 2018).

The rest of the paper is structured as follows. Section 2 discusses how a health shock might affect giving – and summarises the hypotheses to be investigated. Section 3 outlines the data. Section 4 outlines the methodology. Section 5 presents the main results. Section 6 presents a discussion of the findings, implications, limitations and concludes.

2. Health shocks and donations

In this section we discuss ways in which a health shock might impact on charitable giving – focusing on individuals' total giving, their giving to different charities and their giving over time.

2.1. The impact of a health shock

'Altruism born of suffering' is a concept originating in the social psychology literature as the experiences and psychological processes that, following an adverse life event, might increase pro-social behaviour. These include greater awareness of suffering; increased perspective-taking; empathy and sympathy; perceived similarity and identification with common-fate groups or ingroups; and a greater sense of responsibility to prevent others' suffering (Staub and Vollhardt, 2008; Vollhardt, 2009). Bringing this concept to the economics literature on motivations to give, these changes could lead to an increase in either altruistic giving (i.e. utility from public goods provided) or warm-glow giving (i.e. utility from own contributions). They may trigger altruistic giving by making public services, or health services, more salient or by changing beliefs about the public good benefits from such services. For example, following a diagnosis of a rare cancer, someone may become more aware of the lack of resources and knowledge regarding the cancer relative to what they knew before their diagnosis. The changes may also trigger warm glow giving by increasing the degree of sympathy that people have towards others. In a model of impure altruism with conditional altruism, for example, warm glow is conditional on perceived need, deservingness and reciprocity (Konow, 2010; Fong, 2007). The additional sympathy could be towards other people in general (increasing total giving) or focused on a specific (newly-formed) ingroup who share their health condition with whom they may now feel a deeper connection; individuals' may also be motivated by reciprocity and the desire to give back (Meier, 2006; Konow, 2010; Fong, 2007). This is supported by Bekkers (2008), who found that people are more likely to donate to the Dutch Heart Association (rather than other health charities) when they have higher levels of empathic concern and social responsibility, and when they have experience with cardiovascular diseases.

An increase in pro-social behaviour may not always occur, with a range of inhibiting factors working against 'altruism born of suffering'. Under conditions of ongoing threat, victims may become so absorbed by their own suffering that they are unable to perceive or empathise with the suffering of others (Lim and DeSteno, 2016). Many individuals who have suffered from traumatic experiences may also lack the necessary resources to help. Vollhardt and Staub (2011) note that suffering is often characterised by a loss of material and psychological resources, as well as adversity such as poverty, so in this situation individuals may perceive the appeals to help others as unreasonable given their own needs. In terms of a health shock, people may become antisocial as they attempt to come to terms with their diagnosis and prognosis. For example, some studies have reported intentional unsafe sex amongst HIV-positive men (e.g. Halkitis and Parsons, 2003); however, this literature acknowledges that this constitutes the actions of the minority. People experiencing a health shock may therefore perceive themselves to be worse off than others and thus worthy of receiving rather than giving support. Up until now, research on 'altruism born of suffering' has not involved analysis of large-scale quantitative data, so there is limited insight into the conditions needed for 'altruism born of suffering'.

2.2. The effect on donations

This discussion suggests a range of ways in which a health shock might impact giving. The changes might impact on total donations (i.e. "lift") and/or on the allocation of donations to different charitable causes (i.e. "shift").[4] There may also be changes in donations over time.

A health shock may have a general (positive or negative) effect across all charitable causes. This would be the case if there was an increase in the degree of sympathy towards all others or if the individual became preoccupied by their own circumstances at the expense of sympathy for others. In both of these cases the (direction of) change in giving would be similar across all charities; giving would go up or down at the expense of other consumption. Note that these changes could be on the extensive margin (i.e. causing people to start or stop giving) and/or the intensive margin. In this case, we would expect to see a "lift" in total donations and no "shift" across different causes.

Alternatively, the health shock may change giving to health charities only, e.g. by making this specific cause more salient and/or directing sympathy towards the new "in-group". In this case, giving to health charities would go up, but what happens to giving to non-health charities depends on substitution between health and non-health charities, as well as between

[4] See Scharf et al. (2017) for a formal discussion of "lift/shift".

charitable donations and other consumption. There may be "shift" and no "lift", i.e. total donations stay the same but the composition of charities given to changes – this would be the case if the increase in giving to health charities comes at the expense of giving to non-health charities. There may also be "shift" with "lift", i.e. there is an increase in total donations and in the share going to health charities – this would be the case if there is an increase in giving to health charities at the expense of other consumption. Note that the degree of shift may not be uniform across different types of non-health charities but will depend on the degree of substitution. In the empirical analysis below, we differentiate religious charities from other non-health charities as these may be impacted differentially. Religious giving is an important component of overall giving in the US (Giving USA, 2018). It may be motivated by different factors to other, non-religious donations. Also, increased religiosity may provide an indirect channel through which charitable giving may increase following a health shock. Individuals may turn (more) to religion following a health shock given that it can be a form of coping, source of support and stress deterrent (Siegel et al., 2001; Pargament and Hahn, 1986; Tix and Frazier, 1998).

Recent studies have drawn attention to the importance of studying the dynamics of charitable giving (Andreoni and Serra-Garcia, 2018; Scharf et al., 2017; Rooney et al., 2019). Models of pure and impure altruism typically assume that individuals exhibit stable behaviour over time (Andreoni, 1990) but the fact that altruistic/warm glow preferences may change following a health shock would be evidence that this is not the case. Some experimental studies have found that pro-social behaviour erodes with repetition (Dawes and Thaler, 1988); others that the effects of major fundraising campaigns fade over time (Scharf et al., 2017; Adena and Huck, 2019). If there is an increase in salience it may be temporary, in which case another "shift" in giving may occur, namely from later periods to the immediate aftermath period after the health shock.

Finally, an adverse health shock could affect giving through the channels of reduced income and increased healthcare expenditure. Any decline in physical or mental health could impact labour force participation and income (Jones et al., 2016; Garcia-Gomez, 2011), and there may be an increase in healthcare expenditure due to out-of-pocket costs associated with ongoing care and treatment such as specialist consultations, diagnostic scans and medication (Narang and Nicholas, 2017; Paez et al., 2009). There may also be an increase in uncertainty about future income which increases precautionary saving at the expense of all spending. We control for these other factors in our analysis.

This discussion shapes the empirical questions that we investigate:

- What is the effect of a health shock on total charitable giving and on giving to different charitable causes after a health shock?
- Are there changes on the extensive margin (i.e. whether people give) and/or on the intensive margin (i.e. amount of giving)?
- Do changes in giving vary across different charitable causes (specifically, health, religious and other non-health)?
- Are any changes permanent or do they fade over time?
- To what extent can changes in giving be attributable directly to the health shock as opposed to other mediating factors (income, spending needs, religiosity)?

We turn now to our empirical analysis, beginning with discussion of the data.

3. Data

3.1. Panel study of income dynamics (PSID)

The PSID is a survey of a nationally representative panel of households in the United States, which began in 1968, containing detailed information on economic, health and social issues. From 2001 to 2015 biennially, the PSID contains a philanthropy module comprising a series of detailed questions relating to charitable giving. Due to the focus on charitable giving, the analysis will be restricted to this period. Our sample consists of households of 'couples' (with or without other household members) where one member of the couple experienced a health shock from 2001 onwards.[5] Because we estimate a within-household analysis and compare households' charitable giving after they experience a health shock with their behaviour prior to a health shock, we only include households who experience a health shock. This is based on two key reasons. First, there is variation in the timing of health shocks and our estimation strategy captures the dynamics of a post-shock response. Second, households that do not experience a health shock are significantly different across a number of key sociodemographic characteristics (age, education, race, household size) compared with households who experience a health shock (refer to Supplement C8), and therefore may provide an inappropriate control group. Our main conclusions are robust to these choices (further details are provided in Supplement C8).

We consider the household head and partner to be jointly responsible for determining household donations so households are excluded if there were changes in the household head or spouse (e.g. due to death) to ensure that household composition remains constant. Households are also excluded if the health shock was not the first health shock (which we

[5] Charitable giving is typically a household decision between the household head and partner. A majority (67%) of households in the PSID are 'couples' and these households are generally more stable over time, which is important for minimising confounding due to changes in household head and partner composition, which may affect charitable giving decisions.

Table 1
Summary statistics of control variables (2001–2015).

	Mean	SD
Demographics		
Age – head	56.0	11.2
Age – partner	53.6	11.0
Household characteristics		
Household size	3.0	1.3
Annual household equivalised income (real 2015, USD '000)	64.7	99.5
Number of children	0.6	1.0
Death of child (=1 if death of child occurred %)	0.2	4.0
Birth of child (=1 if birth of child occurred %)	3.0	17.0
Other unrelated health condition (=1 if has asthma or arthritis %)*	69.0	46.0
Observations	3170	

Note: Asthma and arthritis were selected based on data availability.

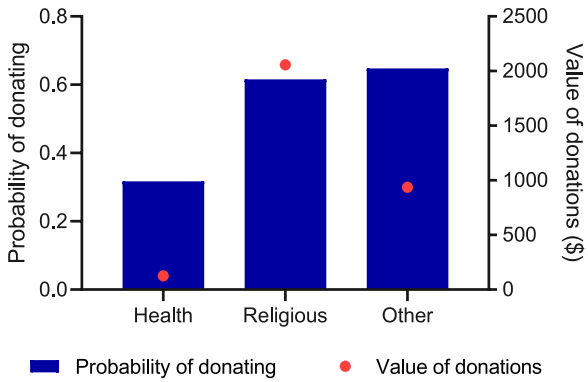

Fig. 1. Average probability of households donating (2001–2015) and value of donations (in 2015 USD), by sector.
Note: Value of donations are in real 2015 USD, based on Consumer Price Index data from World Bank (2019).

observed from 1999 to 2015) to capture changes to charitable giving following an initial adverse health event.[6] The final sample comprises 3133 observations on 452 households.

Table 1 outlines the summary statistics of the key variables used as time varying controls in the analysis. The mean age of the household head and partner is 56 and 54 respectively, with a mean household size of 3.0 and household equivalised income of around $65,000. We also control for other significant events such as the birth or death of a child (a relatively uncommon occurrence), and the presence of an unrelated health condition (69%) which may influence salience of need towards the health sector.

3.2. Charitable giving

Households are asked whether they donated to a charitable organisation and if so, are asked to indicate the total dollar value of donations in the calendar year prior to the survey wave.[7] Both questions are asked for each of the following charity sectors: health, religious, combination, needy, education, youth, cultural, community, environment, international peace and other. Donations are reported at the household level, so it is not possible to ascertain how much each individual in the household donated. In this paper, we focus on the health and religious charity sectors and combine all other sectors to form an 'other' category.[8]

The mean probability of donating to a charity across all households in all years is 82%. Fig. 1 shows that by sector, more households donate to a religious charity (62%) and other charities (65%), compared to health (32%). The distribution of total donations is positively skewed with a number of outliers. Fig. 1 also shows that in terms of mean donations per annum, the religious sector receives the highest donations ($2057) compared to health ($127) and other ($937).

[6] We can only observe health shocks between 1999 and 2015. If any individual in the household experiences at least one health shock during this period, we record the one that occurred first as the health shock, and exclude any other future health shocks observed for that household. Changes in household composition and multiple health shocks are later included in the sample when robustness checks are undertaken (see Section 5.4).

[7] For example, in the 2001 PSID wave, households are asked about charitable giving during 2000.

[8] Health charities are defined as healthcare or medical research organisations such as hospitals, mental health facilities, cancer, heart and lung associations. Religious charities are defined as donations specifically for religious purposes or spiritual development such as churches, mosques or radio ministries.

3.3. Health shocks

Information on health conditions and events are available every two years from 1999 to 2015. Household heads are asked: "has a doctor ever told you that you have had a stroke [heart attack, cancer]?". In terms of the time since health shock, from 1999 to 2003, household heads are asked: "how long have you had this condition?". This differed from 2005 to 2015, and household heads are instead asked: "how old were you the first time you had a stroke [heart attack, cancer]?" and "have you had another stroke [heart attack] at any time in the past 12 months/a second or subsequent stroke [heart attack] since that first one?" All questions were also asked for spouses. Health shocks experienced by children in the household are outside the scope of our investigation due to health questions not asked about other household members. In our sample, of those who experienced a health shock, 62% had cancer, 23% had a heart attack and 15% had a stroke.

The three types of health shocks we consider are all serious and potentially life-threatening health conditions and have the benefit of being generally unanticipated. They are by no means the only conditions which may affect giving, but they provide a more definitive way of identifying the effect of a health shock on giving compared to other conditions (e.g. diabetes, asthma) which may be chronic and anticipated. We acknowledge that our results may not generalise to other types of health conditions or shocks (such as accidents). Excluding other health conditions from our measure of a health shock may underestimate results if these omitted conditions induce greater levels of pro-social behaviour. In Section 5.2 we show that our measure of a health shock corresponds with a decline in self-assessed health.[9]

From these questions, we combine health information on the household head and their spouse to construct two key household health shock variables: (1) whether a household head or spouse had a health shock, and (2) the time since the health shock (relative to when donations were made). For 1999–2003, time since the health shock is taken directly from the question: "how long have you had this condition?". For 2005–2015, time since health shock is calculated as the difference between the household head/spouse's age at the interview date and the age they reported they first had the condition. We then use the time since health shock to calculate the key variable: (3) the date of the health shock. Time of the donations relative to the health shock is then grouped into six categories:

(1) $t<-2$: more than two calendar years prior to the health shock;
(2) $t=-2$: in the calendar year two years prior to the health shock;
(3) $t=-1$: in the calendar year prior to the health shock;
(4) $t = 0$: in the calendar year of the health shock;
(5) $t = 1$: in the calendar year following the health shock; and,
(6) $t>1$: more than one calendar year following the health shock.[10]

An example of how event times are constructed is illustrated in Fig. 2, where the survey wave corresponds to the donation period in the previous calendar year. Panel A provides an example of a health shock that occurred in 2006. This health shock gets reported in the 2007 survey wave, along with the household's donations for the 2006 calendar year. Hence, this period is categorised as $t = 0$ given that donations occur in the same calendar year as the health shock. The remainder of the event times are outlined in Panel A in accordance to the time of donations relative to the health shock in 2006. Panel B provides an example of a health shock that occurred in 2007. This health shock also gets reported in the 2007 survey wave; however, the donation period for the 2006 calendar year corresponds to the year prior to the health shock, so this period is categorised as $t=-1$.

Given that donations are reported for the previous calendar year, there are two potential scenarios at $t=-1$. The first is that a household may report on their donations in the calendar year prior to the health shock year (donations for $t=-1$) *before* their health shock in the current survey year has happened (we only find out they had a health shock in later waves) (Case 1 in Fig. 2, Panel C). The second is that a household may report on their donations in the calendar year prior to the health shock year (donations for $t=-1$) *after* the health shock has already happened in the current survey year (Case 2 in Fig. 2, Panel C). For example, in the 2007 wave an individual may report on their 2007 health shock while also reporting on their 2006 calendar year donations. This may result in reporting bias where those who had their survey after the health shock may inflate their reported donations (i.e. Case 2, Panel C) – they may donate more following their health shock and feel compelled to inflate their 2006 donations to include these recent donations. We account for this by including an interaction term which captures whether the interview date was before or after the health shock at $t=-1$.

Further details on the construction of event times are provided in Supplement B.

[9] We find that compared to individuals who experience a health shock, individuals in our excluded non-health shock sample experience fewer survey-over-survey declines in self-assessed health (see Supplement C8). This suggests that individuals in the non-health shock sample are unlikely to be experiencing other more serious health events and provides support for our health shock measure and sample.

[10] This category was selected to ensure an adequate sample size given the biennial nature of the data and to minimise misclassification impacts for some inconsistent reporting of longer-term durations.

Donation period	2000	2002	2004	2006	2008	2010	2012	2014
corresponds to								
Survey wave	**2001**	**2003**	**2005**	**2007**	**2009**	**2011**	**2013**	**2015**
A. Health shock in 2006	t<-2	t<-2	t=-2	t=0	t>1	t>1	t>1	t>1
	Donations for 2000 and 2002 occurred more than 2 years before the health shock.		Donations for 2004 occurred ~2 years before the health shock.	Household reports donations for 2006 during 2007 survey wave. This period (2006) coincides with the year of the health shock.	Donations during these periods occurred more than 1 year following the health shock.			
B. Health shock in 2007	t<-2	t<-2	t<-2	t=-1	t=1	t>1	t>1	t>1
	Donations during these periods occurred more than 2 years before the health shock.			Household reports donations for 2006 during 2007 survey wave. This period (2006) corresponds to 1 year before the health shock.	Donations for 2008 occurred ~1 year after the health shock	Donations during these periods occurred more than 1 year following the health shock.		
C. Interaction term at t=-1								
Health shock occurred in June 2007:								
• Case 1: interview date (March 2007) occurred before health shock				=0				
• Case 2: interview date (September 2007) occurred after health shock				=1				

Fig. 2. Construction of event time – example.

4. Empirical strategy

We estimate the following empirical model:

$$Y_{it} = \sum_{n=-2}^{n=2} \beta_n HS_{it+n} + X'it\gamma + \alpha_i + \lambda_s + \varepsilon_{it} \tag{1}$$

where Y_{it} is the outcome of interest for household i at time t. In different specifications, this is defined as the probability of donating and the value of donations, both overall and by sector (health, religious or other).[11]

We include a set of indicators, HS_{it+n}, for when charitable giving in a particular calendar year occurred in relation to the health shock. In particular, we consider six different time periods: $t < -2$ (more than two years prior to the health shock); $t = -2$ (one to two years prior to the health shock); $t = -1$ (up to one year prior to the health shock); $t = 0$ (same year as the health shock); $t = 1$ (up to one year following the health shock); and $t > 1$ (more than one year following the health shock). The reference category is $t < -2$, so our model compares household donation behaviours relative to their own behaviour more than two years prior to the health shock.

In addition, α_i are household fixed effects, λ_s are survey year fixed effects and ε_{it} is an error term. $X'$is a vector of time varying control variables affecting charitable giving which includes age, household size, presence of an unrelated health condition and a life event such as the birth or death of a child (as discussed in Section 3.1). It also includes a control for whether a household was reporting on their pre-shock donations after their health shock in order to minimise reporting bias (as discussed in Section 3.3).

The distribution of our donations data is strongly skewed, with a heavy right-hand tail and a relatively large number of zeros. To estimate the impact of a health shock on the value of donations, we consider generalised linear models (GLMs) with fixed effects and alternative links and family distributions and select our preferred specification based on model performance (specification tests and goodness of fit). Values are winsorised at the 5th and 95th percentile to reduce the impact of outliers. Where the log link is used, zero donations are recoded as $1. Where the preferred specification has a log link, robustness tests are undertaken for changes in recoding to $0.10 and $0.01. Our preferred specification for health sector donations is a linear link with Gaussian (normal) distribution, while for total, religious and other sector donations, the log

[11] In Equation (1) we provide a linear specification though in some models examining the value of donations for particular sectors a linear-log specification is estimated.

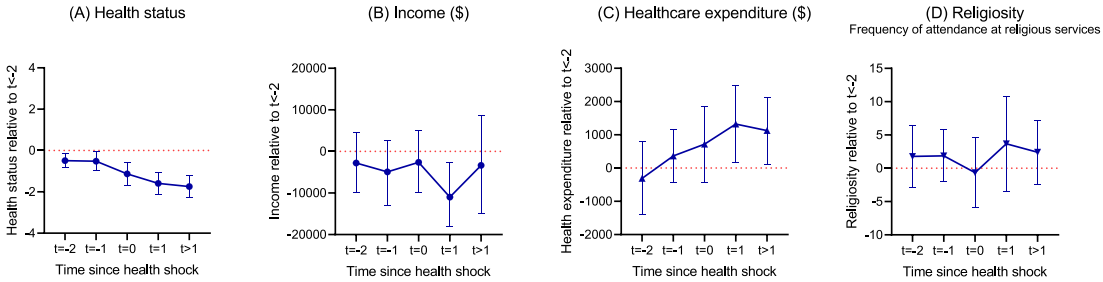

Fig. 3. Impact of a health shock on health status, income, healthcare expenditure and religiosity (potential mediators).
Sample: couples households present in sample from 2001 onwards who experience no changes in couple household composition following a first health shock. Error bars are 95% confidence intervals based on cluster-robust standard errors.
Reference category is more than two years prior to the health shock ($t<-2$).
(A) Fixed effects ordered logit Blow-Up and Cluster Estimator (Baetschmann and Staub, 2015) for self-assessed health status. 1194 individuals (8057 observations) with a health shock dropped because of all the same outcomes. Self-reported health status of the household member who experienced the health shock, measured on a scale of 1 to 5 where a lower value corresponds to poorer health: (1) poor; (2) fair; (3) good; (4) very good; (5) excellent.
(B) Fixed effects estimates of time relative to health shock and household equivalised income ($). Based on 3134 observations of 452 unique households.
(C) Fixed effects estimates of time relative to health shock and healthcare expenditure ($). Based on 3134 observations of 452 unique households.
(D) Fixed effects estimates of time relative to health shock and household frequency of attendance at religious services (number of times of attendance per year). Data is only available for the years 2003, 2005 and 2011. Based on 1224 observations of 442 unique households. There are no changes in religious preference in the sample, so this is not shown.
All models include as covariates: age of head and partner, family unit size, death of child, new birth in household, other unrelated health condition (asthma, arthritis) and time (year) dummies.
Models (B), (C) and (D) additionally include an indicator of whether they were reporting on pre-shock donations after their health shock (interaction between whether had health shock condition and $t=-1$).
Detailed results are provided in Supplement A (Table A1). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

link and gamma family distribution are preferred.[12] We also report on the second preferred specification to explore the robustness of our conclusions.

Because health status, income, healthcare expenditure and religiosity are potential mechanisms through which a health shock could influence charitable giving, we investigate these characteristics further in two ways. First, we estimate the extent to which health status (of the household member experiencing the health shock), household income, healthcare expenditure and religiosity (household frequency of attendance at religious services) are impacted by a health shock. Second, we include them in the main model (1) as covariates and see how they change the estimated impact of the health shock on giving behaviour. In terms of the extent to which they are impacted by a health shock, the impact on health status is estimated using a fixed effects ordered logit Blow-Up and Cluster Estimator (BUC) for self-assessed health status (Baetschmann and Staub, 2015),[13] and the impacts on income, healthcare expenditure and religiosity are estimated using standard linear fixed effects models.

5. Results

5.1. How are health status, income, healthcare expenditure and religiosity impacted by a health shock?

To provide an understanding of the various impacts to the household following a health shock, in Fig. 3 we present estimates of the impact of a health shock on changes in health status (of the household member experiencing the health shock), household equivalised income and religiosity of the household. Panel A shows that compared with more than two years prior to the health shock ($t<-2$), there is a significant worsening of self-assessed health in the year of the health shock ($t = 0$) and in the years following the health shock ($t = 1$ and $t>1$). Importantly, these estimates suggest that the individual is indeed experiencing a health shock, with noticeable changes to their health status during the year of and after the heath shock. Health status also decreases at $t>1$ as health shocks can be associated with different intensities and prognoses. However, we were not able to further explore this due to a lack of data.

[12] We undertake a Link test to determine the appropriate link function (we test the log, square root and linear link). The modified Park test is undertaken to select an appropriate distributional family. Where multiple specifications or distributional families were not rejected, we chose the model on the basis of lower root mean square standard error and mean average prediction error, similar to the approach in Jones (2011). As a robustness check, we undertake a comparison with the next best alternative model (linear link with Gaussian distribution for religious, other and total donations, and log link inverse gaussian for health donations).

[13] When estimating fixed effects ordered logit models such as for self-assessed health status, there are issues associated with unobserved heterogeneity which can result from omitted variables or subjective differences in the anchoring of responses on the ordered response scale. If unaccounted for, heterogeneity will generally bias the estimated effects. The BUC estimator has been found to be efficient and more robust in comparison to other approaches (refer to Baetschmann and Staub, 2015).

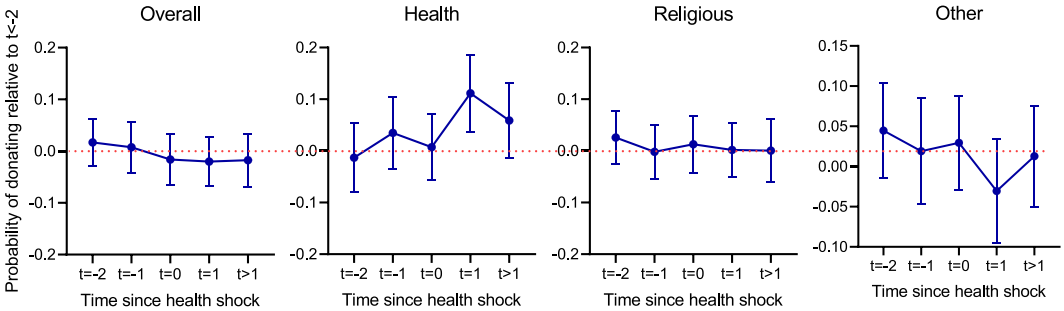

Fig. 4. Dynamics of donating relative to a health shock – probability of donating.
Fixed effects estimates of time relative to health shock and the probability of donating by charity sector.
Reference category is more than two years prior to the health shock ($t<-2$).
All models include fixed effects and covariates: age of head and partner, family unit size, death of child, new birth in household, other unrelated health condition (asthma, arthritis), time (year) dummies, whether they were reporting on pre-shock donations after their health shock (interaction between whether had health shock condition and $t=-1$).
Sample: couples households present in sample from 2001 onwards who experience no changes in couple household composition following a first health shock.
Error bars are 95% confidence intervals based on cluster-robust standard errors.
Detailed results are provided in Supplement A (Table A2). .

Panel B of Fig. 3 shows that compared to $t<-2$, household income reduces at all time periods, though these are generally not statistically significant. An exception is at $t = 1$ (one year following the health shock), where there is a significant and large reduction in household income of around $10,177. This suggests a temporary reduction in employment in the year following the health shock. Additional analyses using data on self-reported healthcare expenditure suggests that these income changes occur alongside a significant increase in healthcare expenditure by around $1324 ($p<0.05$) and $1127 ($p<0.05$) at $t = 1$ and $t>1$ respectively (Panel C). Combined, this suggests that following a health shock, households are likely to have less disposable income to give to charities.

In Panel D of Fig. 3, we show that a health shock has statistically insignificant effects on religiosity (measured by frequency of attendance at religious services) across all time periods. It is therefore unlikely that changes in religiosity play a major role in influencing the decision to donate following a health shock. Religious preference (i.e. whether an individual identified themselves with a religion) did not change over time so could not be examined in our fixed effects models. All coefficient estimates are provided in Table A1 (Supplement A).

5.2. Dynamics of donating relative to a health shock – probability of donating

In Fig. 4, we show the dynamics of the probability of donating relative to the health shock. Panel A shows that there is no effect on the overall probability of donating. There is a small decrease in the probability of donating during and following a health shock, but these estimates are not significant.

While there is little impact on the overall probability of donating, Panel B of Fig. 4 shows that there is a significant positive impact on the probability of donating to health charities. The greatest increase in the probability of donating to health charities occurred at $t = 1$ by around 11% ($p<0.01$), declining at $t>1$ (more than a year following the health shock) although it still remains higher than $t<-2$ (charitable giving more than two years prior to the health shock). There is also a small but insignificant change in the probability of donating to religious (0.2%) and other sectors (−3.1%) at $t = 1$ (Panel C and D). When we break down the 'other' sectors into its respective categories (Table A3, Supplement A), coefficient estimates remain small and imprecisely estimated, ranging from −5% ($p<0.10$) for education to 4% ($p<0.10$) for international peace. Further details are provided in Supplement A, Table A2.

The new givers to the health sector predominantly comprise households that donated to another (non-health) sector prior to their health shock (96%), compared to those that did not donate at all (4%). So, while there is no general increase in the proportion of those giving following an adverse health shock, existing donors appear to be adding health charities to their giving portfolio. We confirm this by estimating the number of sectors donated to as an outcome of the health shock. A fixed effects Poisson model indicates that the number of sectors donated to at $t = 1$ increases by a factor of 1.06 at $t = 1$ (further details are provided in Supplement A, Table A4). These results suggest that there may need to be a baseline level of charitable giving and altruism prior to the health shock for the response to occur.

We also examine heterogeneity of these results by the type of health shock, age, prior health conditions and religiosity (further details in Supplement C). Different health shock conditions could elicit different responses given differences in population affected, treatment and prognosis. Stroke and heart attacks typically affect older people with diagnosed or undiagnosed chronic conditions. In contrast, cancer can affect a greater proportion of younger people, may be associated with

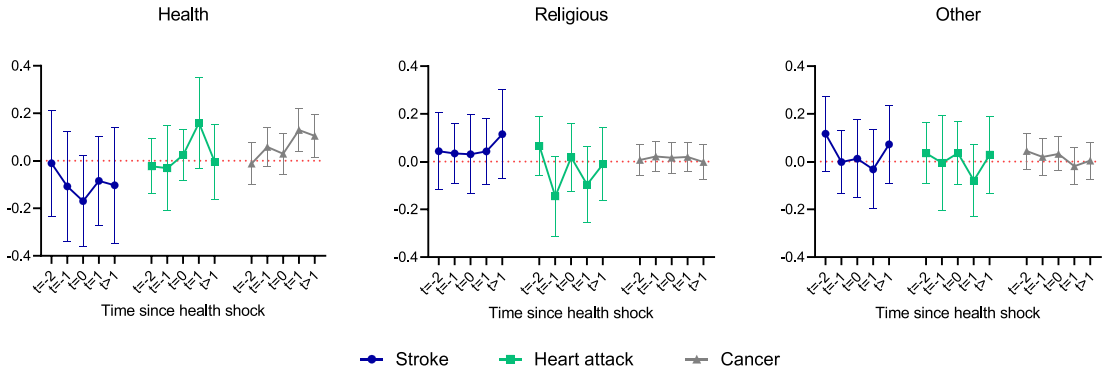

Fig. 5. Dynamics of donating relative to a health shock – probability of donating by health shock condition.
Fixed effects estimates of time relative to health shock and the probability of donating by charity sector and health shock condition.
Reference category is more than two years prior to the health shock ($t<-2$).
All models include fixed effects and covariates: age of head and partner, family unit size, death of child, new birth in household, other unrelated health condition (asthma, arthritis), time (year) dummies, whether they were reporting on pre-shock donations after their health shock (interaction between whether had health shock condition and $t=-1$).
Sample: couples households present in sample from 2001 onwards who experience no changes in couple household composition following a first health shock.
Error bars are 95% confidence intervals based on cluster-robust standard errors.
Detailed results are provided in Supplement C (Table C2).

poor long-term prognosis or be caught early enough and 'cured'. High profile cases like Olivia Newton-John may also influence affect and social presence of the condition in society. In Fig. 5, we show that cancer elicits the strongest response of all the health shocks conditions, with a significant increase in the probability of donating to health by 13% at $t = 1$ ($p<0.01$) which remained at $t>1$ (11%, $p<0.05$). To further investigate the impact of age, we consider the effect according to whether the health shock occurred at less than 55 years compared to more than or equal to 55 years. The results indicate a stronger increase in the probability of donating to health at $t = 1$ for those under 55 years (21%, $p<0.01$). However, differences in effects by health conditions in our sample do not appear to be due to age since the mean ages at which the conditions occur are very similar.[14] Another possible explanation might be the prevalence of cancer and the greater prominence of cancer charities. The recovery from cancer can also be prolonged, aligning with our findings comparing primary and secondary health shocks (Supplement C1) where we find a greater and significant probability of donating to health at $t = 1$ following a primary health shock (7.8%, $p<0.05$); greater variability for a secondary health shock at $t = 1$ (8.4%, $p>0.10$); and a diminished response at $t>1$ (5%, $p>0.10$). These results suggest that charitable giving may fade with recurrences or prolonged shocks as there may be some adaptation in response and the health shock becomes less of a 'shock'.

Prior to a health shock, an individual may have an already diagnosed health condition (e.g. diabetes, hypertension, asthma), so may already be salient towards the needs of the health sector. Our results indicate that these individuals had a significant increase in the probability of donating to health at $t = 1$ (13%, $p<0.01$) and $t>1$ (9%, $p<0.01$) compared to those who did not, although their donation amounts suggest these are token (Supplement C, Table C6). Religiosity may also have an impact on charitable giving. We further investigate heterogeneity by whether the household was religious or not, where religiosity is defined as the frequency of attendance at religious services per annum. Regardless of our definition of 'religious' and 'non-religious' households, the results consistently showed that religious households are more responsive following a health shock with a higher probability of donating and value of donations across all sectors compared to non-religious households (Supplement C, Table C11-Table C14). This may be due to the greater level of baseline pro-social behaviour translating into a higher propensity for charitable giving following a health shock.

A serious childhood health condition may also prime individuals to respond more or less pro-socially when they have a health shock in adulthood. Based on information in the PSID, we define a 'serious' childhood condition as a diagnosis of diabetes, heart trouble, hypertension and respiratory disorder before age 17. We find that when a household member has had a serious childhood health condition, the significant increase in probability of donating to health following a health shock at $t = 1$ (13.4%) is offset (−13.5%), though the interaction term is not statistically significant. Additional analyses indicate that households with a serious childhood health condition were already more likely to be donating to a health charity (6%, $p<0.01$) independently from whether or not they had a health shock in adulthood. Further details are available in Supplement C9. While these findings are limited by the types of childhood health conditions available in the data, they are

[14] The mean age of a health shock is 55. By condition, the mean age is 56 for stroke, 55 for heart attack and 54 for cancer.

Table 2
Dynamics of donating relative to a health shock – impact of health status, income and healthcare expenditure (potential mediators).

	(1) Main model	Impact of single mediator on main model			(5) All mediators
VARIABLES		(2) Health status	(3) Income	(4) Healthcare expenditure	
Time relative to health shock					
Reference category: $t<-2$ (more than 2 years prior)	–	–	–	–	–
$t=-2$ (1 to 2 years prior)	−0.013	−0.012	−0.013	−0.014	−0.013
	(0.034)	(0.035)	(0.034)	(0.034)	(0.035)
$t=-1$ (up to 1 year prior)	0.035	0.037	0.035	0.035	0.037
	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)
$t = 0$ (year of health shock)	0.007	0.005	0.007	0.008	0.005
	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)
$t = 1$ (up to 1 year after)	0.111***	0.116***	0.111***	0.113***	0.117***
	(0.038)	(0.039)	(0.038)	(0.038)	(0.039)
$t>1$ (more than 1 year after)	0.059	0.061	0.059	0.060	0.061
	(0.037)	(0.038)	(0.037)	(0.037)	(0.038)
Potential mediators					
Reference category: Health status: poor	–	–	–	–	–
Health status: fair	–	0.054	–	–	0.053
		(0.044)			(0.044)
Health status: good	–	0.027	–	–	0.026
		(0.047)			(0.047)
Health status: very good	–	0.063	–	–	0.061
		(0.051)			(0.051)
Health status: excellent	–	0.050	–	–	0.047
		(0.058)			(0.058)
Income (10,000s)	–	-	−0.001	–	−0.000
			(0.001)		(0.001)
Healthcare expenditure (1000s)	–	-	-	−0.001	−0.001
				(0.001)	(0.001)
Observations	3126	3009	3126	3126	3009
Unique households	452	425	452	452	425
R-squared	0.016	0.019	0.016	0.017	0.019

Cluster-robust standard errors in parentheses.
Fixed effects estimates of time relative to health shock and probability of donating to health – impact of potential mediator(s) on the main model.
Reference category is more than two years prior to the health shock ($t<-2$).
(1) Main model (as presented in Supplement A, Table A2).
(2) Main model with health status as a control variable.
(3) Main model with income (10,000s) as a control variable.
(4) Main model with healthcare expenditure (1000s) as a control variable.
(5) Main model with health status, income (10,000s) and healthcare expenditure (1000s) as control variables.
Religiosity is not shown given there were no changes in religious preference in the sample and frequency of attendance at religious services data was only available for 2003, 2005, 2011. When comparing the main model and the main model plus the frequency of attendance of religious service for 2003, 2005 and 2011, there were minimal changes in the coefficients (Supplement C).
As an extension of (3), we also consider the impact of welfare income as a control variable. Results indicate very little change to the estimates in the main model (1).
All models include as covariates: age of head and partner, family unit size, death of child, new birth in household, other unrelated health condition (asthma, arthritis), time (year) dummies, whether they were reporting on pre-shock donations after their health shock (interaction between whether had health shock condition and t=-1).Sample: couples households present in sample from 2001 onwards who experience no changes in couple household composition following a first health shock.
*** $p<0.01$

consistent with the results on multiple health shocks which suggest that the effect of further changing donating behaviour fades with subsequent shocks.

5.3. The roles of income, healthcare expenditure and health status

In Table 2, we present estimates of our main model on the probability of donating to the health sector (shown in Panel B of Fig. 4) with income, healthcare expenditure and health status included as additional control variables. Neither income, healthcare expenditure nor health status are statistically significant, and the coefficient of the time periods relative to the health shock change very little with the inclusion of income or health status in the model. This suggests that changes in income and health status have little influence on the effect of a health shock on charitable giving. As expected, we find that including religiosity (refer to Supplement C, Table C15) as a control variable makes little difference to the estimated health shock coefficients. This implies that the health shock itself appears to be directly influencing charitable giving and that there is limited mediation through the pathways of income, healthcare expenditure and health status.

Table 3
Dynamics of donating relative to a health shock – value of donations (marginal effects), winsorised at the 5th and 95th percentile.

	Donations – marginal effects			
VARIABLES	(1) Health ($)	(2) Religious ($)	(3) Other ($)	(4) Total ($)
Time relative to health shock				
Reference category: $t<-2$ (more than 2 years prior)	–	–	–	–
$t=-2$ (1 to 2 years prior)	4.28	107.11	119.50*	169.30
	(5.49)	(138.93)	(62.28)	(190.54)
$t=-1$ (up to 1 year prior)	9.16	9.83	43.63	383.41*
	(6.90)	(142.78)	(62.77)	(216.74)
$t = 0$ (year of health shock)	3.61	203.12	−21.65	4.98
	(5.50)	(143.72)	(58.03)	(187.84)
$t = 1$ (up to 1 year after)	24.27***	79.53	−140.38**	−76.92
	(6.03)	(137.46)	(57.49)	(191.99)
$t>1$ (more than 1 year after)	11.24*	81.71	−76.27	−203.74
	(5.80)	(152.02)	(61.10)	(204.64)
Observations	3098	3096	3130	3130
Unique households	452	452	452	452

Cluster-robust standard errors in parentheses.
Marginal effects and within-households fixed effects estimates of time relative to health shock and donations by charity sector. Values winsorised at the 5th and 95th percentile to reduce the impact of outliers.
Reference category is more than two years prior to the health shock ($t<-2$).
(1) Health donations are estimated using GLM linear link and gaussian distribution.
(2) Religious donations are estimated using GLM log link and gamma distribution.
(3) Non-health donations are estimated using GLM log link and gamma distribution.
(4) Total donations are estimated using GLM log link and gamma distribution.
Marginal effects are shown in (1)-(4). Zero donations are recoded to $1 which is robust to changes in recoding of zero donations to $0.10 and $0.01. Donations are winsorised (bottom and top 5%). In addition, we compare results with the next best alternative model (log link with inverse gaussian distribution for health donations, linear link with gaussian distribution for religious and non-health donations) which had a minimal impact on the results. The marginal effects of these alternative models are provided in Supplement A (Table A5).
All models include as covariates: age of head and partner, family unit size, death of child, new birth in household, other unrelated health condition (asthma, arthritis), time (year) dummies, whether they were reporting on pre-shock donations after their health shock (interaction between whether had health shock condition and $t=-1$).
Sample: couples households present in sample from 2001 onwards who experience no changes in couple household composition following a first health shock.
*** $p<0.01$.
** $p<0.05$.
* $p<0.1$.

5.4. Dynamics of donating relative to a health shock – value of donations

Table 3 presents the estimated marginal effects of time since a health shock on the value of donations.[15] Column 1 presents the marginal effects of health donations using a GLM linear link and gaussian distribution, and Columns 2 to 4 present the marginal effects of religious, other and total donations. Zero donations are recoded to $1 for religious, other and total donations. We winsorise the values (at the 5th and 95th percentile) to reduce the impact of outliers although the results remain imprecisely estimated.

There is no significant change in the total value of donations across all sectors (the negative coefficients are not statistically significant). In line with the increase in the probability of donating to health charities, there is an increase in the value of donations to health charities, albeit small ($24, $p<0.01$). There is a larger increase in religious donations ($80) but this is statistically insignificant ($p>0.10$). Donations to other sectors decreased at $t = 1$ (-$140), significant at the 5% level. Together, these results indicate that there is no "lift" in giving but instead a "shift" in donation dollars from other, non-health sectors into health and potentially religious sectors. These results are robust to including income, healthcare expenditure and health status as additional control variables (refer to Supplement A, Table A6).

Religious donations appear to be more stable across all time periods relative to the health shock, compared to health and other sectors which fluctuate between negative and positive estimates. Given historical trends in charitable giving to the religious sector, this may be reflective of the religious sector being viewed as a core component of a household's charitable giving budget, with health and other sectors viewed as subsidiary that can be adjusted at the margins.

While we do not find any evidence that religiosity is impacted by a health shock, the measures of religiosity in the PSID are limited to religious preference and frequency of attendance at religious services. Studies have also suggested that religion

[15] We further break down the dollar amount of donations according to who had the health shock in the household in Supplement C.

can be a mechanism of coping and support either during or in the immediate aftermath of the health shock (Siegel et al., 2001; Pargament and Hahn, 1986; Tix and Frazier, 1998), which may be reflected in the increase in religious sector donations at $t<-1$, $t = 0$ and $t = 1$.

These results are robust to changes in the recoding of zero donations to \$0.10 and \$0.01, and using the next best alternative specified model (refer to Supplement A, Table A5). In addition, the results are also robust to expanding the sample to include multiple health shocks, changes in household composition (deaths), and including state of residence as a control variable (refer to Supplement C, Table C1, Table C8 and C16).

6. Discussion

We find no significant effect of an adverse health shock on the overall probability of donating or on total donations. Instead, we find that an adverse health shock appears to influence existing donors to change the charities that they support and to add health charities to their giving portfolio. We find both an increase in the probability of giving to health charities and the amount of money given to health charities. There is no evidence of substitution away from religious giving – if anything, religious giving increases after a health shock. Instead, the substitution is away from other, non-health, non-religious charities. Although there is no decline in the probability of giving to these other charities, there is a decrease in amounts donated. Overall, income and health changes associated with a health shock had a limited effect on charitable giving, indicating that the main effect is likely to be driven by the health shock itself.

Our paper focuses on the direct responses of household members following a health shock of the household head or partner. We have not considered what might happen in the event of mortality, nor have we considered any response from family members living outside of the household. Both of these may be interesting avenues for further research.

Further work might also be done with richer religiosity data – which may have revealed ways in which a health shock affected religiosity. This is important given the important role that religiosity plays in religious giving (and the robustness of religious giving through a health shock). It would also be interesting to extend the analysis to other countries, such as the UK or Canada, which have a smaller share of religious giving and also a different mix of private and public provision in healthcare services.

A lack of data also limited our ability to further examine additional factors that may have provided an understanding on why a stronger response was elicited following cancer compared to the other health shock conditions (e.g. prognosis, existing knowledge and resources, degree of social presence and affect towards each health shock condition) and heterogeneity by intensity of the health shock.

Another avenue for further research would be to investigate other forms of pro-social behaviour such as volunteering and the effect of a health shock on the trade-off between charitable giving and volunteering following a health shock, including whether they are mediated differently. In addition, many low-cost fundraising platforms (e.g. GoFundMe) are increasingly being used to solicit donations on behalf of charities. This is beyond the scope of our study due to limited data, but could provide further understanding on the different dimensions of altruism born of suffering.

Nevertheless, our results shed light on the nature of altruism born of suffering. We find no evidence of a general increase in pro-social behaviour (there is no increase in the number of people giving to charity, nor in total donations). Instead, altruism born of suffering appears to manifest as an increase in the desire to support health charities at the expense of other, non-health, non-religious charities. The religious sector has consistently received the greatest donations in the US (Giving USA, 2018), and our results indicate that donations to the religious sector remain an important component of a household's charitable giving budget after a health shock. As a result, while households may view the religious sector as core, the health sector and other sectors may be viewed as substitutes.

We interpret altruism born of suffering as an increase in "salience" of donating to health, similar to the impact of a fundraising campaign. The social psychology literature suggests multiple reasons why this might occur, including an increase in the degree of sympathy for healthcare recipients, the formation of ingroups and feelings of reciprocity. There is also likely to be increased awareness and increased opportunity for donating to health charities. While we find no evidence of an overall lift in donations and only a shift in giving, these findings differ to studies that have investigated the effects of natural disasters on charitable giving. The earlier study by Scharf et al. (2017) found that major disaster fundraising appeals lift total donations and shift donations to other charities across time. Similarly, Deryugina and Marx (2021) found that lethal tornadoes significantly increase total donations, implying that giving to one cause need not come at the expense of another.

One explanation for the different findings could be the differences in event type. Altruism born of suffering makes a distinction between types of suffering in terms of whether the event was experienced individually or collectively, and whether the harm was inflicted intentionally or not. These dimensions determine the scope of effect, ranging from short term interpersonal helping of ingroup members, to long term collective pro-social behaviour benefiting outgroup members. In our case, a health shock, as a very personal event, causes an increase in giving that is limited to ingroups or those suffering from the event type (Vollhardt, 2009). In comparison, suffering that is non-intentional and collective (e.g. natural disasters) or intentional (e.g. violence) is more likely to result in pro-social behaviour towards outgroups and other disadvantaged groups, thereby falling on the higher end of the spectrum (Vollhardt, 2009). Following a disaster appeal, donations increased to both appeal (ingroup) and non-appeal (outgroup) charities (Scharf et al., 2017; Deryugina and Marx, 2021). Another potential explanation is the difference in fundraising and media responses, which is present for a national or international disaster but not for an individual health shock.

The main policy implication is for non-profit organisations concerned with attracting and retaining donors. Efforts by non-profit organisations that support individuals in the immediate aftermath of a health shock may facilitate the foundations for reciprocity. In the shorter term, directed efforts could focus on attracting donors following their recovery period. Further work could be undertaken to better leverage the increase in new donors and translate it into donation dollars that are less token. In the longer term, a diversified strategy could focus on retaining donors when responses are expected to decline.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jebo.2021.09.038.

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