Local Crime and Prosocial Attitudes: Evidence from Charitable Donations*

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Abstract

Combining longitudinal postcode-level data on charitable donations made through a UK giving portal with publicly available data on local crime and neighborhood characteristics, we study the relationship between local crime and local residents' charitable giving and we investigate the possible mechanisms underlying this relationship. An increase in local crime corresponds to a sizeable increase in the overall size of unscheduled charitable donations. This effect is mainly driven by the responses of female and gender unclassified donors. Donation responses also reflect postcode variation in socio-economic characteristics, levels of mental health, and political leanings, but mainly so for female and gender-unidentified donors.

Keywords: Charitable Donations, Prosocial Behavior, Crime.

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1 Introduction

Crime generates a range of economic and social impacts. The directly quantifiable costs of crime include any financial losses incurred by crime victims and the costs associated with deterrence, policing and enforcement. These are sizeable: recent estimates for the UK put them at around 3% of GDP (Heeks et al. 2018). Other costs, such as the long-term effects for victims, the mental health effects from heightened fear of crime, and the indirect effects on private businesses, are difficult to quantify but likely to be very substantial (Anderson 2021).[1] The experience of crime can also shape trust, social attitudes and, ultimately social capital (Troiano 2018), which has been shown to be an important determinant of economic performance (Ponzetto and Troiano 2018).

This study focuses on how the experience of crime affects prosocial attitudes as reflected in charitable donations. Why should we expect the two to be linked? If we associate prosocial attitudes with pure or impure altruism ("warm glow"; Andreoni 1990), the motives that have been traditionally emphasized in the economics literature on giving, we might expect that experiencing more crime, if this is viewed as a symptom of deprivation and social dysfunction, would underscore the need for more social engagement, translating into more giving. Reciprocity-driven prosociality (Gächter and Herrmann 2009) might respond differently.

The psychology literature and the medical literature have also pointed to a link between the experience of crime, mental health, and prosocial behavior. A number of studies suggest that fear of crime is associated with higher prevalence of depression, particularly in older adults, women, an low-income mothers.[2] There is also clear evidence that depression, in turn, feeds into prosocial attitudes, although evidence on the direction of this effect is mixed, with individuals who are experiencing depression being more likely or less likely to engage in prosocial behavior depending on the context studied.[3]

Finally, we can expect the experience of crime to affect giving via the combination of individuals' political attitudes and their beliefs about the causes of crime. Political attitudes and prosocial attitudes appear to be related, with political conservatism generally being negatively correlated with prosocial behavior and attitudes and political liberalism being positively correlated (Farwell and Weiner 2000; Zettler, Hilbig, and Haubrich 2011) – although religiosity is positively associated with both charitable giving and politically conservatism (Margolis and Sances 2017). It is also well known

[1]With reference to the US, this study estimates net costs (without accounting transfers from victims to criminals in property crimes) to be as high as 15% of GDP.

[2]White et al. (1987) show some adverse effect of crime on the mental health of adults. Wilson-Genderson and Pruchno (2013) find that perceptions of neighborhood safety have significant effects on the depressive symptoms experienced by older adults. Stafford, Chandola, and Marmot (2007) report that subjects who experienced fear of crime had poorer mental health, reduced physical functioning, and lower quality of life. Roberts et al. (2012) show that higher fear of crime leads to higher psychological distress in former Soviet Union countries. Dustmann and Fasani (2016) find that crime causes considerable mental distress for residents, primarily driven by property crime. Effects are stronger for females and mainly related to depression and anxiety.

[3]Zhang, Sun, and Lee (2012) find that individuals affected by depression made fewer deceptive and fewer altruistic responses than healthy people in an interpersonal trust-reciprocity game. Haushofer et al. (2023) find that stress hormone causes participants to behave less prosocially in a trust game. In contrast, Caceda et al. (2014) report that depressed male subjects showed increased prosocial behavior in a trust game, whereas the opposite effect was seen for depressed female subjects.

that conservative and liberal individuals hold different views about crime and its causes (Hough and Roberts 1998). How these different attitudes translate into differences in donation *responses* to changes in the salience of crime is not a priori clear.

In this study, we use longitudinal evidence on charitable donations and crimes reported at the UK postcode level to study how crime occurrences at a given location affect charitable donations by local residents. This analysis rests on an underlying assumption that local crime occurrences add to local residents' experience of crime, either directly as victims of crime in a small number of cases or indirectly by making crime more salient to them. Crime, alongside politics and sports, tends to be more salient to individuals than other news items, partly due to the high coverage it receives in media outlets (Curran et al. 2010; Bennett 2023).[4] This extensive coverage exacerbates the public perception of rising crime rates, fear of crime and fear of victimization (Chadee 2001; Duffy et al. 2008; Humphreys et al. 2019).

Our donation data come from the Charities Aid Foundation (CAF), a UK-based giving portal. This is a unique and rich dataset, featuring more than half a million individual donors making close to forty million individual donations to more than 90,000 charities over the 2011-2022 period (twelve years). The data also provides information on donors' postcodes (but is otherwise fully anonymized). Our crime data comes from the UK Home Office and contains information on crimes reported at any given postcode by type of crime at a monthly frequency for England, Wales and Northern Ireland (i.e., all UK postcodes except those in Scotland).

The data includes information on donors' gender, which allows us to study whether responses differ by gender. To carry heterogeneity analysis along further dimensions, we augment our dataset with neighborhood-level information on residents' socio-economic and demographic characteristics from the 2011 and 2021 Office of National Statistics (ONS) Census as well as with postcode-level information on voting behavior from the UK Electoral Commission. Based on this information, we explore empirical specifications that include interactions between local crime occurrences and neighborhood characteristics, such residents' age, educational attainment, their political leanings, and self-reported mental health indicators. These allow us to shed some light on the possible mechanisms underlying the heterogeneity in responses between genders and across crime and donation types.

Donors raise their donations by more than one percentage point on average following occurrences of crime at locations close to their place of residence, with the response being strongest (more than two percent) for crimes against the person. However, when we look separately at responses by male and female donors, we find striking differences between them. Overall, male donors are unresponsive, and so the overall positive response can be attributed to female donors. Moreover, when we break down responses according to the type of crime, we see male donors responding *negatively* to certain forms of crime (e.g., theft) that female donors respond *positively* to. There are also differences in responses across donation types: donations to some categories of charities (e.g., charities whose activities are related to "society") respond positively, while donations to other categories (e.g., charities related to education or childcare) respond negatively. Donation responses are heterogeneous across postcodes with different social-economic characteristics, level of mental health, and political leanings, but only

[4] The significance of crime-related news in public concern is emphasized by the UK's National Union of Journalists, which defines public interest as encompassing the detection or exposure of crime or serious misdemeanors, among other factors (NUJ Code of Conduct: Public Interest).

so for female donors.

Our study contributes to the evidence base on the effects of socio-economic effects of crime. There have been a few studies discussing the link between crime and prosocial behavior, but these have been mostly survey based.[5] An exception is Berrebi and Yonah (2016), who investigate the impact of mass shootings on monetary donations as reported in annual tax returns and aggregated at the state level, also controlling for state-level crimes other than mass shootings. The longitudinal, donor- and postcode-level evidence we use in our study contains considerably more information about the relationship between crime and charitable giving, revealing patterns that are not in evidence in aggregate data. Most notably, by exploiting variation in the demographic and socio-economic characteristics of residents across locations and their political leanings, our analysis sheds light on the mechanisms that mediate the relationship between crime and giving, to the best of our knowledge the first study to do so.

The remainder of the paper is structured as follows. Section 2 describes our data. Section 3 discusses our empirical strategy. Section 4 presents estimates of overall intensive-margin and extensive-margin responses. Section 5 reports results of augmented empirical specifications that can help us pinpoint the sources of heterogeneity in intensive-margin effects. Section 6 concludes.

2 Data

Our crime data comes from the UK Home Office and combines official records from the police forces in England, Wales, Northern Ireland, and the British Transport Police at a monthly level. The information covers types of crime, the months in which they were committed, and their street-level locations. The types of crime include anti-social behavior, bicycle theft, burglary, criminal damage and arson, drugs, other crime, other theft, possession of weapons, public order, robbery, shoplifting, theft from the person, vehicle crime, violence and sexual offences, and unclassified crime. Following internationally recognized crime categorizations (from the US FBI) and previous literature (Dustmann and Fasani 2016), we further classify these crime types into four broad categories, including crimes against society, property crime, crimes against the person, and unclassified crime. More details on our crime categorization are reported in Table A1 in the online appendix.

Donors' exposure to local crime is measured by the number of crimes that occurred near their place of residence. Based on the geographical location – at the level of street coordinates – of each reported crime incident, we compute the monthly number of crimes that occurred within a one-, three- and five-mile radius of the address postcode where donors live.[6] Table 1 gives summary statistics for our crime data, showing the average number of crimes occurring within a one-mile radius over a 144-month period from January 2011 to December 2022 across all donors' postcodes.[7] On average,

[5]An example is Britto, Van Slyke, and Francis (2011), who conducted 2,300 interviews within a single MSA in the US (Atlanta) – a sample that tends over-represent women and the elderly – and examined the impact of fear of crime on charity donation and volunteering. They find that, while fear of crime has no effect on donating to charities by both women and men, it is negatively associated with volunteering for women.

[6]We obtain the longitude and latitude coordinates for donors' postcodes from the Office of National Statistics (ONS). These coordinates allow us to estimate the distance between donors' postcodes and the locations of reported crimes.

[7]Summary statistics for crimes within a three- and five-mile radius are shown in Online Appendix Table A2 and A3.

Table 1: Summary statistics of crime variables occurring within a 1-mile radius

	(1) Min	(2) P25	(3) P50	(4) P75	(5) Max	(6) Mean	(7) SD	(8) N
Crimes against society	0	17	60	141	4,991	119	179	42,491,960
Property crime	0	15	52	131	6,013	114	204	42,491,960
Crimes against the person	0	8	31	81	1,067	64	88	42,491,960
Unclassified	0	6	80	231	8,625	190	317	42,491,960
Total	0	72	247	589	14,129	486	719	42,491,960

Notes: The table presents summary statistics for crime type variables occurring within a 1-mile radius. Columns (1) to (5) show the minimum, 25^{th} percentile, median, 75^{th} percentile, and maximum values respectively; (6) to (8) show the mean, standard deviation, and number of observations, respectively.

there are 486 crimes of all types within a one-mile radius. Among the categorized crimes, crimes against society and property crime have the highest number of cases. The least commonly recorded crime type is crime against the person, with an average of 64 cases per month within a one-mile radius.

For donations, we employ a unique dataset of anonymized donor accounts managed by the Charities Aid Foundation (CAF). These accounts serve as dedicated checking accounts designed for donating funds to charitable organizations. Individuals can establish an account by making a minimum one-off payment of £100 or by setting up a monthly direct debit of £10. Additional contributions can be made at any time, but it is not possible to withdraw funds from the account. The dataset consists of all donations made via the accounts from January 2011 to December 2022. During this period, 505,087 individuals made at least one donation, resulting in a total of 38.8 million donations to 93,400 charities. The average size of a donation transaction is £74.5. Each record provides detailed information about the exact time and date, amount donated, name of the charity, gender and postcode of the donor.

We also have information on CAF account types used for each donation transaction, which includes Charity Account – Individual Gift Aid, Give As You Earn (GAYE), and Individual Trust Income Account. Notably, 79.83% of transactions fall under the GAYE category. CAF's GAYE scheme is the UK's largest payroll giving scheme. It offers a tax-efficient way to donate to charities directly from donors' wages or company/personal pensions. Under this scheme, donations are deducted before income tax is applied, avoiding the need for higher-rate taxpayers to claim a deduction through their tax return.[8] To take advantage of the scheme, employers must receive a request before the payroll date. To mitigate the influence of outliers, we exclude transactions that have contribution amounts exceeding £500 or falling below £0 from the analysis. As a result, we achieve sub-samples of 30,963,254 transactions from GAYE accounts and 7,821,282 transactions from non-GAYE accounts.[9]

[8] In the UK tax system, tax relief for donations by lower rate taxpayers is delivered in the form of a match directly paid by the treasury to donation recipients ("Gift Aid"). Higher-rate taxpayers can additionally claim the difference between the higher rate and the basic rate on their donations, but they can only do so by filing a tax return (tax returns are not compulsory for all UK taxpayers).

[9] In addition to differentiating between GAYE and non-GAYE donations, we also employ an alternative categorization

Table 2: Summary statistics of donation outcome variables

	(1) Min	(2) P25	(3) P50	(4) P75	(5) Max	(6) Mean	(7) SD	(8) N
Panel A: Donation Amount								
Non-GAYE sample	0.01	13	26	60	5,200	61.58	91.55	8,650,562
Non-automatic sample	0.01	20	45	100	2,700	77.91	104.06	4,207,449
GAYE sample	0.01	5	5	10	12,000	13.16	42.06	20,555,697
Automatic sample	0.01	5	6	14	11,500	18.90	49.87	25,153,488
Total	0.01	5	9	20	12,000	27.50	64.96	29,201,052
Panel B: Donated Dummy								
Non-GAYE sample	0	0	0	0	1	0.23	0.42	37,143,970
Non-automatic sample	0	0	0	0	1	0.12	0.33	34,657,474
Total	0	0	0	1	1	0.43	0.50	67,366,505

Notes: The table presents summary statistics for donation outcome variables across sub-samples. Panel A and panel B show statistics for the donation amount variable and the donated dummy variable, respectively. For each panel, columns (1) to (5) show the minimum, 25^{th} percentile, median, 75^{th} percentile, and maximum values respectively. Columns (6) to (8) show the mean, standard deviation, and number of observations, respectively.

Descriptive statistics for the CAF donations data are summarized in Table 2. On average, each donor makes a contribution of £27.5 per month to a particular charity, with the size of individual donations ranging from a minimum of £0.01 to a maximum of £500, with a standard deviation of £64.96, indicating significant variation in contribution amount. The size of individual donations also varies by gender. For payroll (GAYE) donations, the average donation size is lower than the £28 average, at £13.16, compared to non-payroll (non-GAYE) donations with average size of £61.58. The mean monthly count for non-payroll donations is 0.23, implying that, on average, non-payroll donors give to a charity every four months.

In our sample, 51.68% of donors are men, 39.76% are women, and the remaining 8.56% are of unidentified gender. Among female donors, the average donation amount is approximately £15.13, while for male donors, it is approximately £24.02. Male donors also account for a higher proportion of the total transactions, representing approximately 51.70%, while female donors account for 40.03%. Interestingly, when gender is not specified, the average donation amount rises to around £48.66. Overall, the average total yearly donations per donor ID is £935.27. For male donors, it is £748.94, almost triple the corresponding amount for female donors, which is £257.75. Gender-unidentified donors each donate £5,835.86 per year on average.

In our dataset, donations see a general decline over time, with the highest donation amount in 2013 at more than £80.0 million, and the lowest in 2022 at more than £63.2 million. An exception to this trend was 2020, when donations temporarily surged to around £67.7 million – quite possibly due to the heightened needs of economically disadvantaged individuals following the onset of the

criterion, whereby a donation is classified as "automatic" if we observe more than six records with the same donated amount made by the same donor to the same charity (and as non-automatic otherwise). We then only keep the first record within each automatic donation sequence. Using this alternative criterion, we obtain two sub-samples: one consisting of 586,638 automatic donations and another comprising 4,207,449 non-automatic donations.

COVID-19 pandemic.

Among the charities receiving the highest contribution amounts, Cancer Research UK leads with £23.9 million, followed by The National Society for the Prevention of Cruelty to Children with £13.3 million. In the top ten charities, several charitable causes stand out. First, there is a focus on healthcare, particularly cancer, with charities such as Cancer Research UK, Macmillan Cancer Support, and The British Red Cross Society. Additionally, there is a great presence of charities supporting religious causes, such as Christian Aid and The Salvation Army. Child welfare is another prominent cause, with The National Society for the Prevention of Cruelty to Children and The Save the Children Fund receiving donation amounts of £13.3 million and £10.3 million, respectively. Finally, significant attention is directed toward disaster relief, with total contributions of £10.8 million to Disasters Emergency Committee.

To categorize charities according to the causes they pursue, we use information from the UK Charity Classification (Damm and Kane 2022). The matching process involved merging this classification data with the charities in our dataset by their Charity Commission numbers. For charities whose commission number is missing in our dataset, we manually collect it from their websites, focusing on charities having at least 5,000 transactions. As a result, we are able to match with more than 63,500 out of 92,000 charities in our donation data. Merged charities account for nearly 90% of the total donation amount and 94% of transactions. There are in total twenty-four broad charitable causes and one charity can pursue several causes.

We also categorize donations on the basis of the geographical scope of the activities of the recipient charities. For this purpose, we measure, for each charity, the geographic dispersion of its donors as the standard deviation of the latitudes derived from its donors' postcodes. Based on this measure, we then construct a dummy variable, $LOCAL_{it}$, which takes the value of one for donations to charities with a below-median standard deviation measure and a value of zero otherwise.[10] Using this dummy to examine the donation split between local and non-local (national) charities, we observe a substantial number of unique donors 425,676 have made contributions to non-local charities. In contrast, only 102,229 unique donors have donated to local charities. By comparison with their female counterparts, male donors give more to local charities: male donors allocate 21.59% of their donation amount and 15.54% of their transactions to local charities, while the corresponding figures for female donors are 18.23% and 12.37%, respectively. Even though the number of donors contributing to local charities is much smaller by comparison with those supporting non-local charities, total donations are not that much different. Local charities receive a total contribution of £137.4 million, while non-local charities receive a total amount of £588.8 million.

We augment our crime and donation data with information on geographic information on socio-economic and demographic characteristics from the 2021 ONS Census, including information on religion, education, age and occupation at Output Area level, with each Output Area being built from clusters of adjacent unit postcodes.[11] Data on income are collected from the ONS's estimates

[10] To mitigate the influence of outliers, we exclude charities with fewer than six donors and the top 1% of charities located in far north and far south regions.

[11] An Output Area (OA) is the lowest level of geographical aggregation for publicly available UK Census statistics. For reference, the number of individual postcodes in the UK is above 1.7 million, while the number of Output Areas is 181,408. Quoting from the ONS's documentation, "each Output Area is made up of between 40 and 250 households and a usually resident population of between 100 and 625 persons".

Table 3: Correlation between postcode-level socio-demographic characteristics

	FEMALE	*FEMALE_CENSUS*	*RELIGIOUS*	*AGE65PLUS_D*	*HIGH_EDU*
FEMALE_CENSUS	0.0198				
RELIGIOUS	-0.0386	0.0119			
AGE65PLUS_D	-0.0456	0.0626	0.1490		
HIGH_EDU	-0.0570	-0.0515	-0.0077	0.0672	
HIGH_INCOME	-0.0590	0.0129	0.1544	-0.0120	0.5390

Notes: The table presents the correlations among different output area-level socio-demographic characteristics, including gender, religiosity, age, education and MSOA-level income. Correlation coefficients between gender, religiosity, age, and education are reported at the output area level. Correlation coefficients between income and other variables are reported at the MSOA level.

of annual household income at the Middle layer Super Output Area level.[12] We also use subjective well-being data coming from the ONS's UK Annual Population Survey covering the period from 2012 to 2022. This data reports mean ratings of personal well-being, such as life satisfaction, feeling that the things done in life are worthwhile, happiness, and anxiety at the local authority district level. The data is reported at the level of Local Authority Districts.[13] To align all mental health measures with the anxiety indicator, we invert the scores for life satisfaction, worthiness, and happiness. Next, we obtain yearly immigration data at the local authority level from the ONS for the years 2011 to 2020, including measures such as the net internal migration rate and the proportion of non-UK born population. Finally, in relation to political attitudes, we collect the general elections results as reported by the UK Electoral Commission and available at the constituency level for the years 2010, 2015, 2017, and 2019. For years without political elections, the political leaning of an area is based on the latest voting results. Our data on EU referendum voting results are from Hanretty (2017), which provides estimates of the Leave vote at the parliamentary constituency level.

Table 3 reports correlation coefficients for residents' characteristics across different geographical areas. It is noteworthy that the variable *FEMALE* represents the proportion of female donors, while *FEMALE_CENSUS* indicates the proportion of female residents in the area. The positive correlation between these two variables, 0.0198, suggests that the fraction of female donors in our donation data is positively correlated with the ONS output area-level information on gender. Furthermore, the proportion of female donors in an area (*FEMALE*) is negatively correlated with *RELIGIOUS*, *AGE65PLUS_D*, *HIGH_EDU*, and *HIGH_INCOME*. This suggests that in areas with a higher proportion of religious, older, highly educated, and higher-income residents, males are more likely to donate than males in other areas. Regarding output area-level gender and other characteristics, there are positive correlations between *FEMALE_CENSUS*. *RELIGIOUS* and *AGE65PLUS_D*, indicating

[12] A Middle layer Super Output Area (MSOA) comprises between 2,000 and 6,000 households and have a usually resident population between 5,000 and 15,000 persons.

[13] Local Authority Districts (LAD) is an administrative division responsible for local government functions, including local planning, housing, local highways, building, environmental health, refuse collection and cemeteries. As of December 2020, there were in total 379 LADs.

that areas with a higher proportion of females tend to have a higher ratio of religious residents and individuals aged 65 and over. This association may be due to higher religiosity levels and longer life expectancy among women. In contrast, *FEMALE_CENSUS* and *HIGH_EDU* are negatively correlated, revealing that areas with a higher proportion of females tend to have a lower fraction of highly educated people. The high proportion of older residents *AGE65PLUS_D* shows a positive correlation with residents' education level and religiosity. This suggests a tendency for older populations to have a higher level of education attainment and to be more likely to be religious.[14] Similarly, the proportion of high-income residents is positively correlated with residents' education level and religiosity, but negatively correlated with the proportion of older residents.

Comparing the donations in our sample with donations per capita at the UK level, both in terms of the size of individual donations and the overall amount given by each individual, it is clear that our sample is not representative of the population as a whole – the donors in our sample give much more than does the average UK donor. In particular, we would expect it to consist of comparatively higher-income individuals, which in turn implies that the proportion of local residents represented in the sample should vary across postcodes depending on output area-level socio-economic characteristics. And indeed, regressing the (log of) ratio of CAF donors at each postcode to the number of residents at that postcode and regress its log against the log of output area-level 2021 Census characteristics, we find elasticity values of 1.37 and 1.24 respectively for household income and education; i.e., a doubling in household income at a postcode corresponds to a 137% increase in the proportion of residents at that postcode who are represented in our CAF sample. The corresponding elasticity for age is −0.07 – small but still statistically significant. The elasticity for religion is close to zero and statistically insignificant. To measure variation in the gender composition of our sample across postcodes, we compute, for each postcode, the ratio of female donors in the sample to the Census postcode-level gender composition. Elasticity estimates for this ratio with respect to Census socio-demographic characteristics are −0.37 for education, −0.16 for income, −0.12 for age, and −0.21 for religiosity; i.e., female donors are comparatively better represented in our sample at younger, low-income, low-education, low-religiosity postcodes.

3 Empirical Strategy

To estimate donation responses to local crime, we use variants of the following specification:

$$DONATION_{it} = \beta_{mg(i)}\, CRIME_{mp(i),t-1} + \phi_i + \psi_{tr(i)g(i)} + \epsilon_{it} \;, \tag{1}$$

where

$DONATION_{it}$: the natural logarithm of donation amount by individual i at time t (intensive-margin analysis) or a binary variable for whether individual i makes a positive donation at time t (extensive-margin analysis);

[14] The education variable is based on the highest level qualification (including academic, vocational, and professional qualifications) for residents aged 16 or over. Although younger children are excluded from this measure, this mechanically tends to produce some positive correlation between age and educational attainment.

$CRIME_{mpt}$: an indicator for crime of type m within a one-, three- or five-mile radius from postcode p at time t (the natural logarithm of one plus the number of crime occurrences or a binary variable for above- or below- median level);

$p(i)$: the postcode where individual i resides;

$g(i)$: the "treatment group" to which i belongs; depending on the particular specification examined, this is defined by categorical variables based on i's characteristics (e.g., i's gender, categorical variables for characteristics of residents in the area where i resides, relating to demographics, mental health outcomes, voting behavior, or a combination of these);

$r(i)$: the UK region where i resides (Cymru Wales, East Midlands, East of England, London, North East & Cumbria, North West, Northern Ireland, South East, South West, West Midlands, Yorkshire & the Humber);

β_{mg}: the "treatment effect" for group g from occurrences of crime of type m at the postcode where they reside;

ϕ_i: an individual fixed effect;

ψ_{trg}: a treatment group-specific time effect.

Including region and group-specific time effects, ψ_{trg}, controls for regional variation in time trends and ensures that the parallel trends assumption for individuals within a treatment group is satisfied, implying that the estimated β_{mg} measures the average treatment effect across individuals in each treatment group.[15] A treatment group is defined by a combination of characteristics relating to donors and the donations they make, such as gender, socio-demographic characteristics and electoral outcomes for the postcode where they reside, indicators of the geographical scope (national vs. local) of the charities they donate to, with this combination varying depending on the specification considered.

Note that (1) includes lagged crime rather than contemporaneous crime. This is because our crime data is at monthly frequency, and so a non-negligible fraction of the donations in a given month occur prior to the crimes recorded for that month. Using lagged crime ensures that the donation choices we measure are always made subsequent to the crime incidents.

We estimate both intensive-margin responses (amount donated) and extensive-margin responses (whether or not an individual donates). For extensive-margin responses, we handle missing donation records by setting the value of each donor-charity-month cell to zero. Specifically, for each charity, we consider the time period from when a donor first started donating to that charity until the last recorded donation. Any missing cells within this period are assigned a value of zero. We estimate specification (1) separately for each category of crime, including social crime, property crime, violence crime, and unclassified crime as well as the total number of all crimes.

A potential threat to identification is crime and giving being correlated due to some common influences, giving rise to endogeneity, i.e., the error term being correlated with the treatment. An

[15] Denoting with y^u_{it} the outcome of interest for an untreated unit i at t, the parallel trends assumption is met if $y^u_{it} - y^u_{i,t-1}$ is the same for all i's belonging to the same treatment group g.

economic downturn, for example, could make individuals more likely to commit property crimes but would also affect donors' budgets. Or weather conditions could influence the number of crimes committed due to its effect on individuals' daily routines (e.g., walking through a park), which in turn affects opportunities for committing certain forms of crimes (e.g., robbing individuals who walk through a park); but the same weather conditions could also dictate how much time individuals spend indoors and devote to making donations through the giving portal. The region-specific time effects we include in our specifications ensure that our causal estimates are not biased by this channel.[16]

A second potential threat to the identification of causal effects – from the salience of crime to giving – is reverse causation – from giving to crime. Our analysis uses longitudinal data at a monthly frequency and focuses on lagged effects. Even if the donations had some effect on local crime through the activities of the charities that funded by them, the effects could only be felt over the medium or long term, not retrospectively or even simultaneously. To address endogeneity concerns even more systematically, we also investigate specifications where the variation in crime at a given location is instrumented by variation in crime occurring at neighboring locations.

4 Findings

4.1 Payroll and non-payroll donations

As discussed above, payroll (GAYE) donations require employers to act on requests from employees that their donations be directly deducted from pay, making it possible for higher-rate donors to immediately benefit from higher-rate donation reliefs rather than having to claim it through self-assessment. Processing such requests requires time, and changes to payroll arrangements can only take effect according to given payroll schedules. Moreover, the higher administrative cost associated with these requests for both donors and employers means that these will typically be for repeated, regularly-scheduled donations. All of this means that we should expect to see a wider time lag between changes in donor circumstances and changes in donations to charities for payroll donations than for non-payroll donations.

This prior is confirmed by the findings reported in Table 4 from an exploratory specification that incorporates multiple lagged effects of crime on amounts donated, i.e.,

$$DONATION_{it} = \sum_{l=1}^{3} \beta_l \, CRIME_{p(i),\,t-l} + \phi_i + \psi_t + \epsilon_{it} \ , \tag{2}$$

which we run separately for payroll and non-payroll donations. For non-payroll donations, we find that first lagged responses are highly significant. Second lagged responses in columns (2) and (3) are also significant, albeit at a lower significance level. Moreover, the results in columns (1)-(3), with the first-lagged coefficient losing significance in (2) and (3), are indicative of a systematic positive serial correlation (hence, collinearity) among lagged variables. Given this pattern, our focus for

[16]The inclusion of lagged crime rather than contemporaneous crime in our empirical specification also helps mitigate concerns that crime and donations may be spuriously correlated through contemporaneous channels, such as weather conditions.

Table 4: Lagged donation responses to crime – intensive margin

	(1) Non-GAYE	(2) Non-GAYE	(3) Non-GAYE	(4) GAYE	(5) GAYE	(6) GAYE
Lagged logcrime	0.150***	0.073	0.078	-0.065***	-0.083***	-0.035
	(0.054)	(0.064)	(0.066)	(0.020)	(0.030)	(0.032)
Second lagged logcrime		0.135**	0.149**		0.029	0.112***
		(0.065)	(0.070)		(0.030)	(0.035)
Third lagged logcrime			-0.034			-0.173***
			(0.067)			(0.032)
Obs	8,145,969	8,066,317	8,009,915	18,219,560	18,067,820	17,905,565
R^2	0.722	0.722	0.722	0.857	0.857	0.857

Notes: The table presents results for lagged donation responses to total crime. The dependent variable is the donated amount multiplied by 100, taking a value of one if the donor contributes to a particular charity during the month and zero otherwise. The crime variable is the natural logarithm of one plus the number of crimes in the previous month. Columns (1) to (3) show results for non-payroll donations in models that include lagged crime, lagged crime along with the second lag, and lagged crime along with the second and third lags, respectively. Columns (4) to (6) show results for payroll donations in models that include lagged crime, lagged crime along with the second lag, and lagged crime along with the second and third lags, respectively. In all regressions, donor, charity, and *region* × *month* fixed effects are included but not reported. Robust standard errors are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

non-payroll donations remains on the first lag, as it can also serve as a proxy for subsequent lags. In contrast, for payroll donations, adding further lags does not reveal a clear pattern. Responses are negative when a single lag or two lags are included (albeit smaller in absolute value than for those for non-payroll donations), but the second-lag coefficient becomes positive and significant when a third lag is included, and inconsistent pattern that is likely to be the associated, at least in part, with set payroll dates and payroll processing lags for payroll requests.[17]

4.2 Intensive-margin and extensive-margin responses

Estimation results for the response of donation to crime at the intensive margin are reported in Table 5. For non-payroll, a doubling of crime at the postcode would translate into a 0.132%–0.268% increase in the donation amount, suggesting a positive association between fear of crime and charitable giving. This positive association between fear of crime and donation holds for all crime types, including crimes against society, property, and the person. Notably, the effect is largest for crimes against society. Extensive margin responses for non-payroll donations (Table 6) are mostly insignificant.

Responses for payroll donations are presented in the next two tables. As can be seen from Table 7, there is a negative association between crime and the donation amount for property crime and crimes against the person, and a positive association for crimes against society. As noted above, however, the administrative processing lags associated with payroll donations cast doubt on the interpretation of this coefficient. Effects of local crime on the duration of payroll donation spells (Table 8) are insignificant with the exception of the effect of crimes against society, which is positive and significant at the 5%

[17]Results for "non-automatic" and "automatic" are available in an online appendix.

Table 5: Intensive-margin donation responses for non-payroll donations

	(1)	(2)	(3)	(4)
	Total crime	Crimes against society	Property crime	Crimes against the person
Lagged logcrime	0.150***	0.268***	0.132**	0.148***
	(0.054)	(0.055)	(0.053)	(0.052)
Obs	8,145,969	8,145,969	8,145,969	8,145,969
R^2	0.722	0.722	0.722	0.722

Notes: The table presents results for donation responses to different crime type variables for non-payroll transactions. The dependent variable is the natural logarithm of donation amount multiplied by 100. The crime variable is the natural logarithm of one plus the number of crimes in the previous month. Columns (1) to (4) show results for total crime, crimes against society, property crime, and crimes against the person, respectively. In all regressions, donor, charity, and *region* × *month* fixed effects are included but not reported. Robust standard errors are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table 6: Extensive-margin donation responses for non-payroll donations

	(1)	(2)	(3)	(4)
	Total crime	Crimes against society	Property crime	Crimes against the person
Lagged logcrime	-0.018	-0.007	0.009	0.025*
	(0.014)	(0.014)	(0.014)	(0.013)
Obs	35,304,938	35,304,938	35,304,938	35,304,938
R^2	0.437	0.437	0.437	0.437

Notes: The table presents results for donation responses to different crime type variables for non-payroll transactions. The dependent variable is the donated dummy multiplied by 100, taking a value of one if the donor contributes to a particular charity during the month and zero otherwise. The crime variable is the natural logarithm of one plus the number of crimes in the previous month. Columns (1) to (4) show results for total crime, crimes against society, property crime, and crimes against the person, respectively. In all regressions, donor, charity, and *region* × *month* fixed effects are included but not reported. Robust standard errors are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table 7: Intensive-margin donation responses for payroll donations

	(1) Total crime	(2) Crimes against society	(3) Property crime	(4) Crimes against the person
Lagged logcrime	-0.065***	0.067***	-0.067***	-0.301***
	(0.020)	(0.021)	(0.021)	(0.020)
Obs	18,219,560	18,219,560	18,219,560	18,219,560
R^2	0.857	0.857	0.857	0.857

Notes: The table presents results for donation responses to different crime type variables for payroll transactions. The dependent variable is the natural logarithm of donation amount multiplied by 100. The crime variable is the natural logarithm of one plus the number of crimes in the previous month. Columns (1) to (4) show results for total crime, crimes against society, property crime, and crimes against the person, respectively. In all regressions, donor, charity, and *region* × *month* fixed effects are included but not reported. Robust standard errors are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table 8: Duration response for payroll donations

	(1) Total crime	(2) Crimes against society	(3) Property crime	(4) Crimes against the person
Lagged logcrime	0.186	0.702**	-0.283	0.222
	(0.303)	(0.311)	(0.291)	(0.304)
Obs	202,815	202,815	202,815	202,815
R^2	0.900	0.900	0.900	0.900

Notes: The table presents results for donation responses to different crime type variables for payroll transactions. The dependent variable is the donation duration in months. The crime variable is the natural logarithm of one plus the number of crimes in the previous month. Columns (1) to (4) show results for total crime, crimes against society, property crime, and crimes against the person, respectively. In all regressions, donor, charity, and *region* × *month* fixed effects are included but not reported. Robust standard errors are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

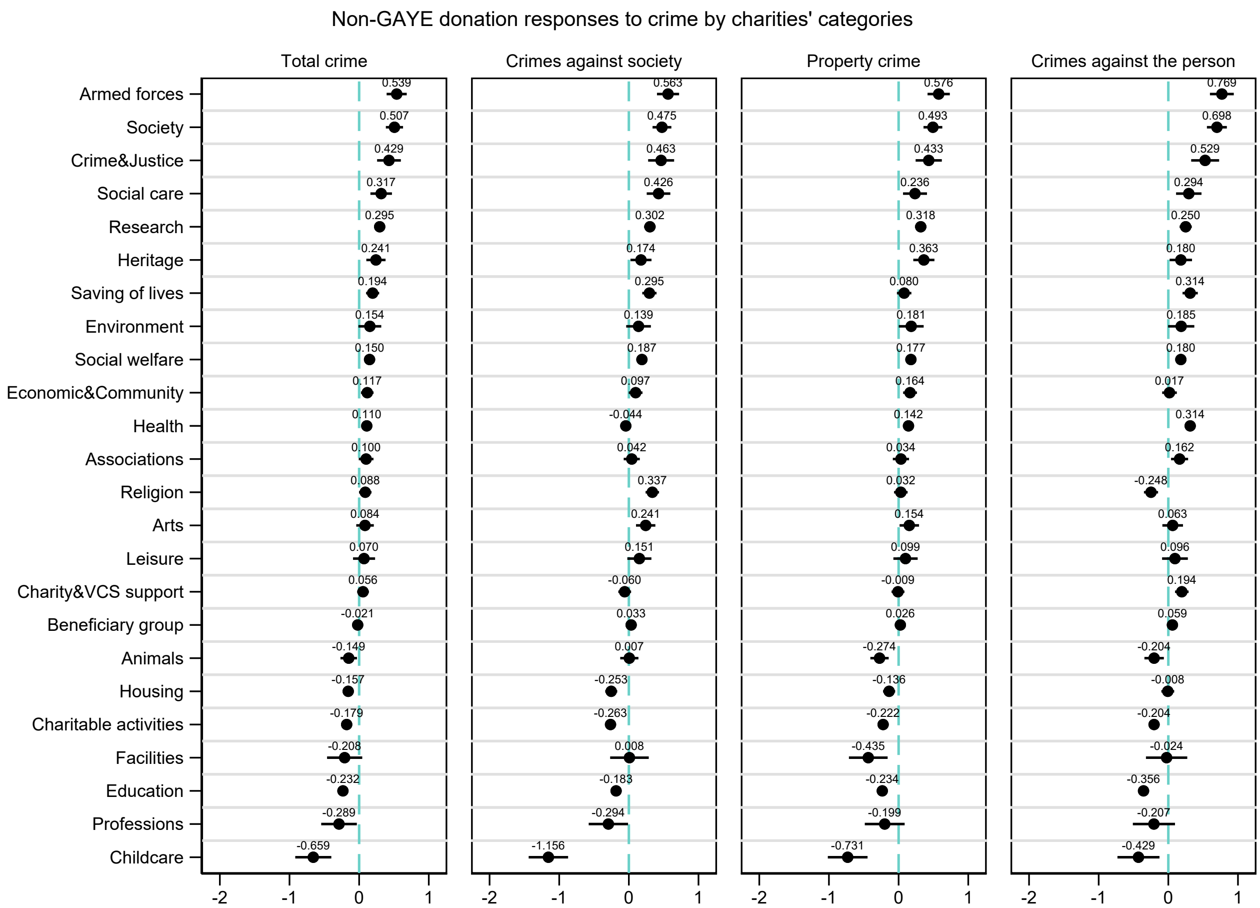
level. The difference in the responses to crime between payroll and non-payroll donations might also be driven by planning considerations and psychological factors. Regular donations reflect a long-term commitment to a cause and are more likely to be driven by a sense of commitment and consistency, whereas non-payroll donations can reflect unplanned, short-term/one-off decisions that are more likely to be influenced by donors' current attitudes and state of mind and by how these are affected by short-run variation in local crime.

We further investigate more specifically which charitable causes receive increased or decreased contributions when local crime increases. We include to interaction terms between $CRIME_{p(i)t-1}$ and each charitable cause dummy into model (1). As can be seen from Figure 1, donations increase the most for Armed Forces, Society, Crime and Justice, and Social Care causes when local crime rises. Notably, a twofold increase in crime can lead to an increase of up to 0.698 percent in giving amount to Society causes. It makes intuitive sense that donations would increase towards causes related to addressing crime, social issues, economic needs, and community welfare when local crime rates rise. Donors tend to target causes that could help alleviate the problems signaled by higher local crime. Donations also increase, though to a lesser extent, for Research, Heritage, Saving Lives, Social Welfare, Economic and Community, Health, Associations, and Religion causes. Conversely, contributions decrease for Animals, Housing, Charitable Activities, Education, Professions, and especially Childcare causes as fear of crime rises. For other causes, such as Arts, Leisure, Charity and VCS support, Beneficiary group, Facilities, and Environment, local crime has no effect on charitable contributions to these causes.

We also explore how responses differ between donations to charities with a comparatively more local geographical scope (as defined in Section 2) and donations to national charities. Donors may view local donations as benefiting comparatively more those local communities that the individuals committing the crimes belong to, implying that responses in local donations should be comparatively more reciprocity driven than responses in national donations. Results are shown in Figure 2 and seem to be in line with this interpretation: donations to local charities respond negatively for all crime types, whereas donations to national charities respond positively for all crime types.

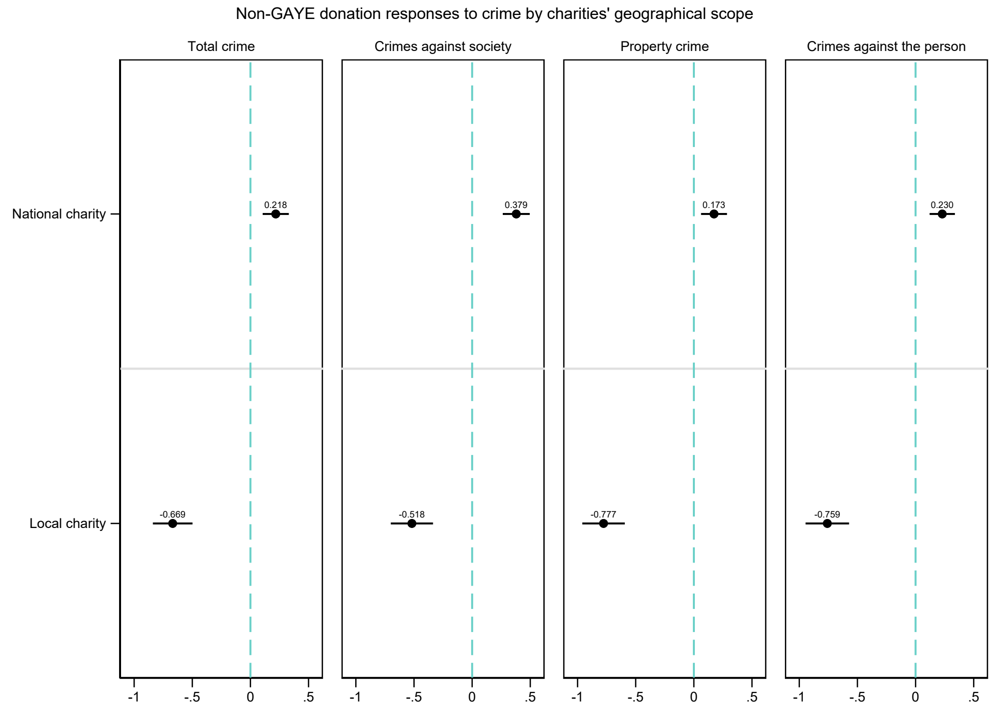
To address any remaining endogeneity concerns, we also employ a Two-Stage Least Square Instrumental Variable (2SLS IV) approach. Specifically, the local crime (within one-mile radius) is instrumented with the difference in number of crimes between a five-mile radius and a one-mile radius. The rationale behind this choice is that crime in the outer circle is more likely to be correlated with crime in close neighborhoods but is less likely to have a direct impact on residents' giving behavior. In the first stage, for each type of crime, the number of crimes within a one-mile radius is regressed on the difference in the number of crimes within a five-mile radius and the number of crimes within a one-mile radius, and then the projection from the first stage is included in the second stage. Table 9 reports regression results from 2SLS IV estimations, which are consistent with findings from our main specification but deliver quantitatively larger response coefficients (roughly double) for all crime types except for property crime, which has an insignificant coefficient. The first-stage results reported in Table A7 in the online appendix indicate that higher crime rate in the neighboring areas is associated with higher close-neighbor crime rate. In addition, under-identification and weak identification tests, respectively the Lagrange Multiplier (LM) test and the F test, reveal that the instrument is relevant.

Figure 1: Donation responses for non-payroll donations across charity causes



Notes: The figure presents estimated coefficients for non-payroll transactions by charity causes, with 95% confidence intervals. The dependent variable is the natural logarithm of donation amount multiplied by 100. The crime variable is the natural logarithm of one plus the number of crimes in the previous month. In all regressions, donor, charity, and *region* × *month* fixed effects are included but not reported.

Figure 2: Donation responses for non-payroll donations by charities' geographical scope



Notes: The figure presents estimated coefficients for non-payroll transactions by charities' geographical scope, with 95% confidence intervals. The dependent variable is the natural logarithm of donation amount multiplied by 100. The crime variable is the natural logarithm of one plus the number of crimes in the previous month. In all regressions, donor, charity, and *treatment group* × *region* × *month* fixed effects are included but not reported.

Table 9: Donation responses for non-payroll donations using 2SLS-IV estimator

	(1)	(2)	(3)	(4)
	Total crime	Crimes against society	Property crime	Crimes against the person
Lagged logcrime	0.336***	0.414***	0.178	0.466***
	(0.098)	(0.135)	(0.135)	(0.149)
Obs	8,145,969	8,145,969	8,145,969	8,145,969
R^2	0.000	0.000	0.000	0.000

Notes: The table presents results for donation responses to different crime type variables for non-payroll transactions using IV estimators. The dependent variable is the donated dummy multiplied by 100, taking a value of one if the donor contributes to a particular charity during the month and zero otherwise. The crime variable is the natural logarithm of one plus the number of crimes in the previous month. Columns (1) to (4) show results for total crime, crimes against society, property crime, and crimes against the person, respectively. In all regressions, donor, charity, and *region* × *month* fixed effects are included but not reported. Robust standard errors are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

5 Correlates of donation responses

To help shed light on some of the possible mechanism underlying donation responses to local crime, in this section we investigate how responses vary across donors depending on their characteristics and the characteristics of the areas where they reside. Based on our discussion in Section 2 and our findings in Section 3, we restrict attention to intensive-margin responses in non-payroll donations (less likely to be planned), as these can provide a clearer and more reliable reflection of how pro-social attitudes responds to variation in local crime than do extensive-margin responses and responses in payroll donations (more likely to be planned).

5.1 The role of religiosity, age, education, income, and gender

Economic theories of giving often distinguish between two primary motivations explaining why people give: pure altruism and impure altruism (Ottoni-Wilhelm, Vesterlund, and Xie 2017). Pure altruism is a selfless motive whereby individuals give to improve outcomes for other individuals without expectation of return. In contrast, impure altruism involves giving to alleviate givers' mental distress or gain personal rewards, such as social approval, inner satisfaction, and self-esteem. To try to distinguish between the effects of crime on donations when these are driven by pure versus impure altruism, we proxy altruism with religiosity (Einolf 2011; Bennett and Einolf 2017), based on the notion that donors people living in areas with a high proportion of religious residents as more likely to be pure altruism-driven donors (since most religious faiths emphasize altruism). Education and age can also shape individuals' altruism or prosocial behavior. Prior literature show that higher education attainment is positively associated with higher propensity to do volunteer work and charitable donations (Dur and van Lent 2018). Older adults also exhibit more altruistic behaviors than younger adults (Sze et al. 2012; Freund and Blanchard-Fields 2014; Hubbard et al. 2016). Finally, donors with lower incomes or those residing in lower-income areas are more affected by and concerned about local crime (Vauclair and Bratanova 2017).

To proxy for variation in donors' characteristics across postcodes, we use data on residents' religiosity, age and education at the Output-Area level from the 2021 Census. For religion, we create the dummy variable $RELIGIOUS_{p(i)}$, which takes the value of one if the proportion of religious individuals at the donor's postcode is above the median proportion across all local areas and a zero value otherwise. For age, we define a dummy variable $AGE65PLUS_{p(i)}$, which is assigned a value of one if the proportion of individuals aged 65 or more at the donor's postcode is above the median proportion across all local areas, and zero otherwise. For education, we define a dummy variable $HIGH\_EDU_{p(i)}$, which equals one if the proportion of secondary-educated people at the donor's postcode is above the median proportion across all local areas and is zero otherwise. For income, we create the dummy variable $HIGH\_INCOME_{p(i)}$, which takes the value of one if the proportion of high-income households at the donor's postcode is above the median proportion across all local areas and is zero otherwise.

Unlike for religion, age, education, and income for which we must use Output Area-level Census information to proxy for donor characteristics, the gender of donors can be obtained from our donation data (a dummy variable $FEMALE_i$ associated with each individual donation from donor i). Prior research (e.g., DellaVigna et al. 2013) suggests that women are more malleable, more sensitive and hence more responsive to social cues. Marginal givers (those who are close to indifferent between donating and not donating) are more frequently women. This higher proportion of marginal donors among women results in increased donations in certain situations with an extra push. However, in other cases, they may decline to donate if given an easy option to do so. For instance, Lilley and Slonim (2016) show that the increase in donations after the 2009 Victorian Bushfires in Australia, in comparison to periods without disasters, is significantly greater for women than men. Similarly, we expect that female donors respond more to increased local crime than their male counterparts.

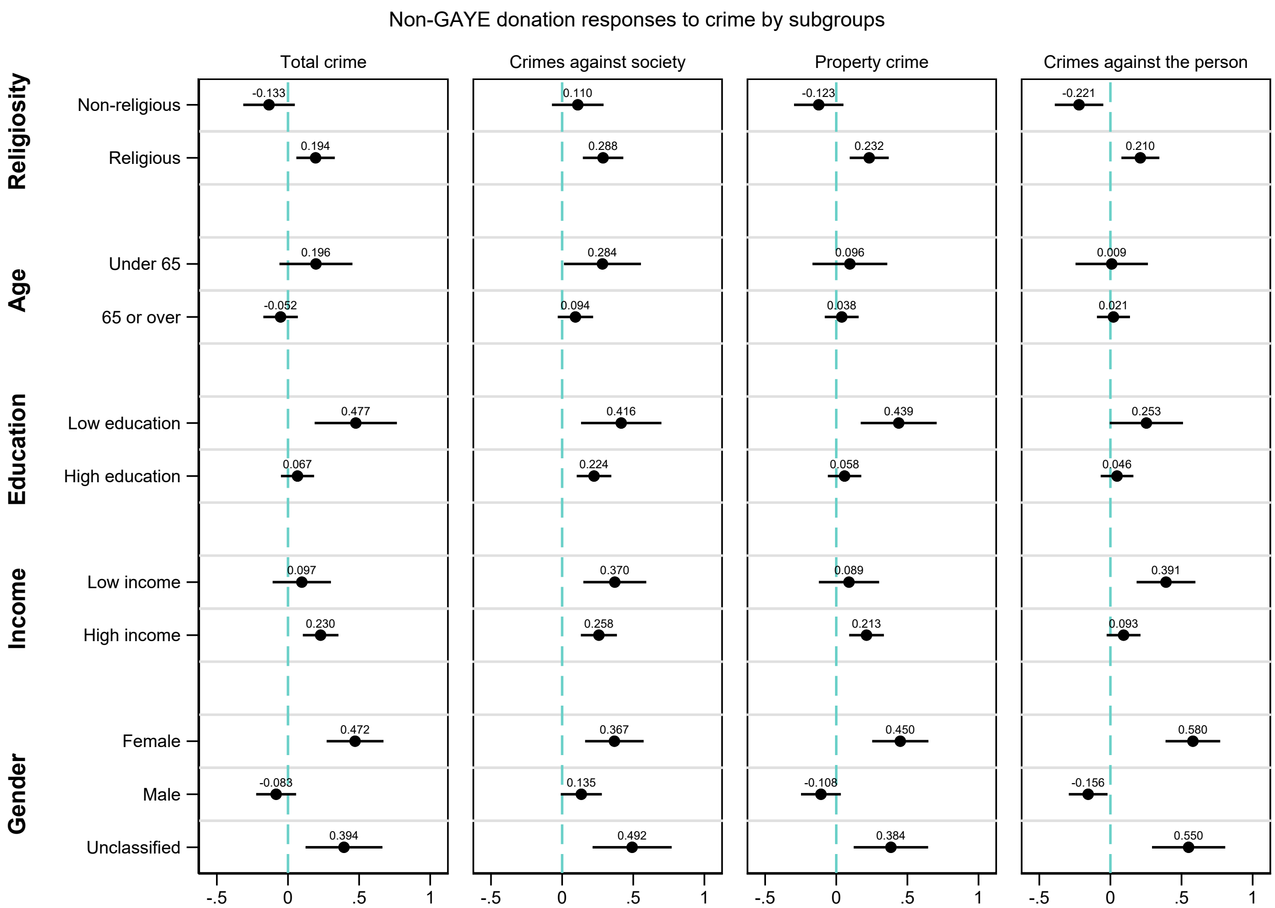
To examine how differences in religiosity, age, education, income and gender translate into differences in donation responses to crime, we introduce an interaction term involving the relevant dummy variable and lagged crime ($CRIME_{p(i),t-1}$) into model (1). Figure 3 reports estimation results. Some caution should be exercised when interpreting estimates of coefficients on interaction terms with area-level characteristics, as these do not necessarily reflect donor characteristics at that postcode. This is for two reasons. First, as discussed in the previous section, donors in the sample residing at a given postcode are not fully representative of the population at that postcode – and the extent to which they are varies depending on postcode characteristics (with CAF donors being comparatively more numerous at high-income, high-education locations). Second, we may be concerned that the effect of postcode-level characteristics on donations may come from how donors perceive the characteristics of other residents at that location rather than from their own characteristics (as shown in Panel D of Figure 3). So, for example, donations to local charities may be comparatively higher at low-income postcode because of a higher perceived need on the part of non-donors rather than because donors at that postcode have comparatively lower incomes. However, because of the high level of granularity of the Output Area code information – it seems quite plausible that these characteristics would reflect, to some extent at least, the characteristics of donors in that area. No such doubt can arise in relation to gender, as we can directly observe the gender of donors in our data.

Overall, donors at non-religious postcodes are less responsive to local crime than those at religious postcodes, but the opposite is true when it comes to crimes against the person (top panel of Figure 3). Results in the second panel on the donation responses to crime by age show that donors at "older" postcodes are less responsive to local crime compared to their younger counterparts. While people in "older" areas are generally non-responsive to crime, donors in "younger" areas raise their giving amount by 0.387%–0.620% following a twofold rise in crime depending on crime type.

With regard to education – the third panel of Figure 3 – donors at postcodes with lower education attainment levels tend to be more responsive to crime. It is possible that individuals in higher education areas are more likely to understand the benefits of prosocial behaviors or to have the resources to help others. Moreover, higher education is associated with higher permissive attitudes towards crime, lower fear of crime, and lower punitive attitudes toward criminals (Costelloe, Chiricos, and Gertz 2009; Scarborough et al. 2010). Prior research provides evidence that emotionally triggered donations decrease when donors process quantitative or deliberative information. For instance, people are less likely to donate to help feed a malnourished child when shown information that places the child within the broader context of famine in Africa (Small, Loewenstein, and Slovic 2007). Our findings on education are in line with these previous studies in showing that, when donations are made by comparatively more informed donors, as proxied by the level of educational attainment at the postcode where donors reside, they become less responsive to emotional stimuli.

As can be seen from the bottom panel, donations by female donors tend to respond significantly

Figure 3: Donation responses for non-payroll donations across subgroups



Notes: The figure presents estimated coefficients for non-payroll transactions by religiosity, age, education, and gender subgroups, from top to bottom, with 95% confidence intervals. The dependent variable is the natural logarithm of the donation amount multiplied by 100. The crime variable is the natural logarithm of one plus the number of crimes in the previous month. In all regressions, donor, charity, and *treatment group* $\times$ *region* $\times$ *month* fixed effects are included but not reported.

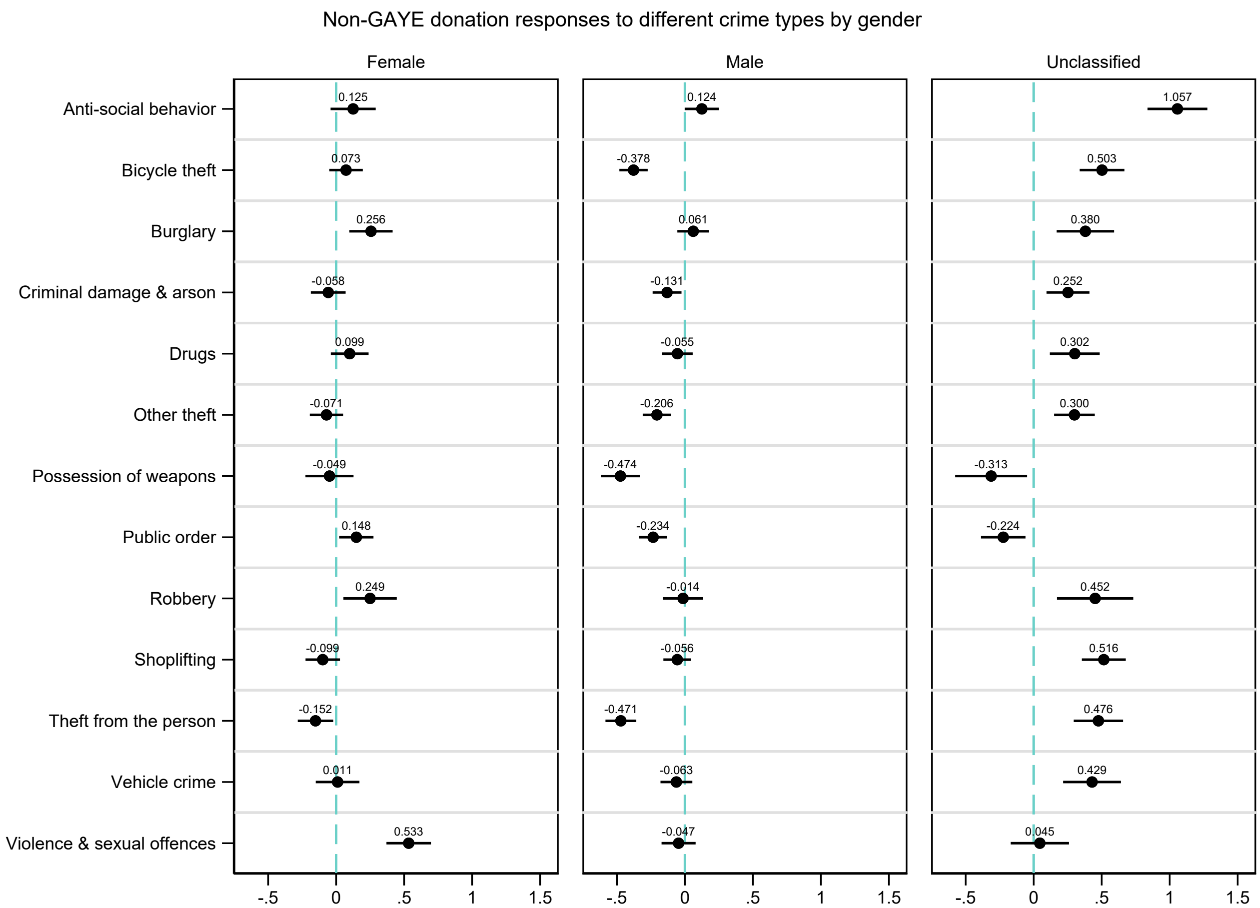
(positively) to increases in local crime than do those by male donors, particularly for crimes against the person. On average, a 100% increase in local crime corresponds to a 0.472% increase in donation amount among women. In contrast, there is no significant change in donation size among men as a result of increasing crime. This finding is consistent with those documented in previous studies (see, e.g., Seo and Torabi 2004) suggesting that women may be more emotionally focused or more vulnerable, hence more affected by fear of crime. Donations by gender unclassified donors are nearly equally responsive: a 0.394% increase for a 100% increase in local crime.

In interpreting these results, one should consider the possibility that gender might be collinear with other donor characteristics, particularly religiosity (Trzebiatowska and Bruce 2012) and political leaning, i.e., female donors' responses may differ not (solely) due to their gender but because of other characteristics that are associated with gender. The correlation coefficients in Table 3, however, indicate that UK women are not more religious than men. But we see a negative correlation between female and conservative leaning, in line with findings of studies suggesting that women generally lean towards left-wing political views (Van Ditmars 2023). Additionally, Table 3 reveals that the postcode-level gender composition of donors in our sample is not representative of the overall gender composition as reported in the ONS census: the correlation between the two measures is very weak leading to a sign reversal in the sign of correlations between the gender measure in our sample with postcode-level religiosity and age.

More detailed results for gender differences in the effects of crime types are reported in Figure 4. Female donors tend to increase their donation amount when there are increases in the number of burglary, public order, robbery, and particularly violent and sexual offences. The sensitive nature of violent and sex crimes appears to motivate increased charitable giving among women the most, possibly driven by greater fear of victimization and empathy. Specifically, a doubling in violence and sex offences would lead to a 0.533% rise in amount donated for women. When we break down responses by male donors according to the type of crime, we see some statistically significant responses – for bicycle theft, other theft, possession of weapons, and theft from the person. Unlike for female donors, however, these responses are negative. Neither gender reacts significantly to disorder crimes such as anti-social behavior, criminal damage and arson, or shoplifting offenses. Donations by gender-unclassified donors – those making the largest donations – are much more responsive for most types of crime (for anti-social behavior, the elasticity of donations with respect to local crimes is close to unity), a notable exception being violence and sexual offences. Gender-unclassified donors are more responsive (positively) than either female or male donors, particularly in relation to anti-social behavior.

A possible interpretation of these gender differences in responses is that they reflect gender differences in actual or perceived rates of crime victimization, which would in turn lead to gender differences in the extent to which men and women respond to a heightened fear of crime. Fear of victimization can affect individuals' behavior in different ways. The vulnerability argument suggests that fear of crime should be related to avoidance behaviors and lower levels of volunteering for women more than for men (Nellis 2009; Britto, Van Slyke, and Francis 2011). In contrast, alternative arguments suggest that fear of crime may lead to a larger increase in charitable giving among women compared to men. Firstly, societal norms may encourage men to suppress their fear, making them less likely to respond to it. Secondly, fear of crime is associated with women being more inclined to seek information related to crime and terrorism events, whereas fear of crime affects men but

Figure 4: Donation responses for non-payroll donations across genders



Notes: The figure presents estimated coefficients for non-payroll transactions responses to different crime sub-types, by gender, with 95% confidence intervals. The dependent variable is the natural logarithm of the donation amount multiplied by 100. The crime variable is the natural logarithm of one plus the number of crimes in the previous month. In all regressions, donor, charity, and *region* × *month* fixed effects are included but not reported.

does not prompt active attempts to seek out information (Nellis 2009). And when seeking relevant information, women are more affected, and consequently more likely, to respond to crime. Finally, as noted by Nellis (2009), women are more concerned about repeated terrorist attacks compared to men. This concern about future crime may be linked to a higher sense of community responsibility regarding the crime problem (Garland 2001), or it may lead to preventive actions such as donations among women.

UK crime statistics, however, show that men have a higher risk of being victims of crime, although women are more likely to be victims of certain types of crimes, especially intimate violence including domestic abuse and sexual assault (ONS, 2020[18]). In particular, cases of sexual assault against females in 2019/20 were over four times more numerous than those against males, and the proportion of females reporting domestic abuse was twice that of males (i.e., 7.3% vs. 3.6%). On the other hand, studies also highlight the fear of crime paradox where, despite higher crime victimization rates among men, women are more afraid of being victims of crime than men (Fisher and Sloan 2003; Nellis 2009; Lane and Fox 2013). If fear of crime and the actual risk of victimization were perfectly correlated, we would expect women to be especially fearful of domestic abuse and sexual assault, given their higher risk of experiencing these crimes compared to men; but findings show that women often express higher fear across all crime types.

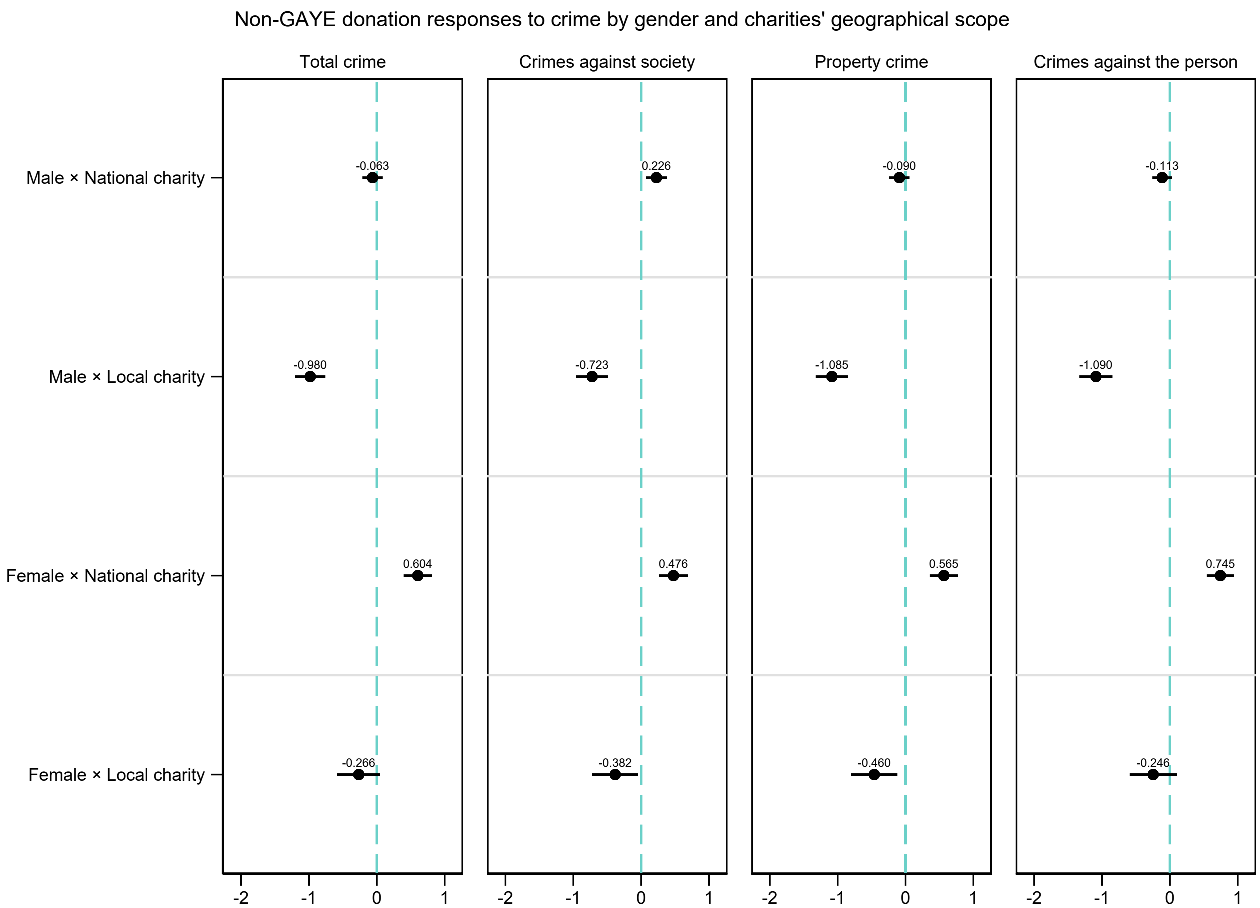
The direction of the differential response across genders also seems to contradict one of our previous findings. In Section 3, we showed that donations to local charities tend to respond negatively to local crime. Since female donors give comparatively more to local charities (as documented in Section 2), if local donations by male and female donors responded in the same way, this should mechanically translate into overall donation responses by female donors being more negative rather than more positive as we find here. To understand where this differential response comes from, we run regressions with a specification that interacts crime with both gender and charity scope indicators. Estimated coefficients are shown in Figure 5. Male donors exhibit negative responses in their local donations, whereas female donors do not. However, the overall positive response by female donors relates to national donations only.

We further investigate how the effect of gender on donation responses to crime interacts with other characteristics, including religiosity, age and education. To do this, we introduce triple interaction terms, $FEMALE_i \times \textit{<local characteristic>}_{p(i)} \times CRIME_{p(i),t-1}$, into specification (1) to estimate how these factors combine. The results from this analysis are shown in Figure 6.

First, with regard to the interaction between gender and religiosity, male donors at high-religiosity postcodes are the most unresponsive group to crime. Female donors remain most responsive to crime overall. Female donors at non-religious postcodes tend to reduce giving, while those at high-religiosity postcodes tend to increase their donations following increased fear of crime. Second, regarding the interaction between gender and age, only females at "younger" postcodes are responsive (positively). In terms of the interaction between gender and education, male donors at high-education postcodes are the least responsive group to crime. Female donors across all education levels tend to increase donations but more so at low-education postcodes, with an elasticity as high as 0.873% for crimes against the person.

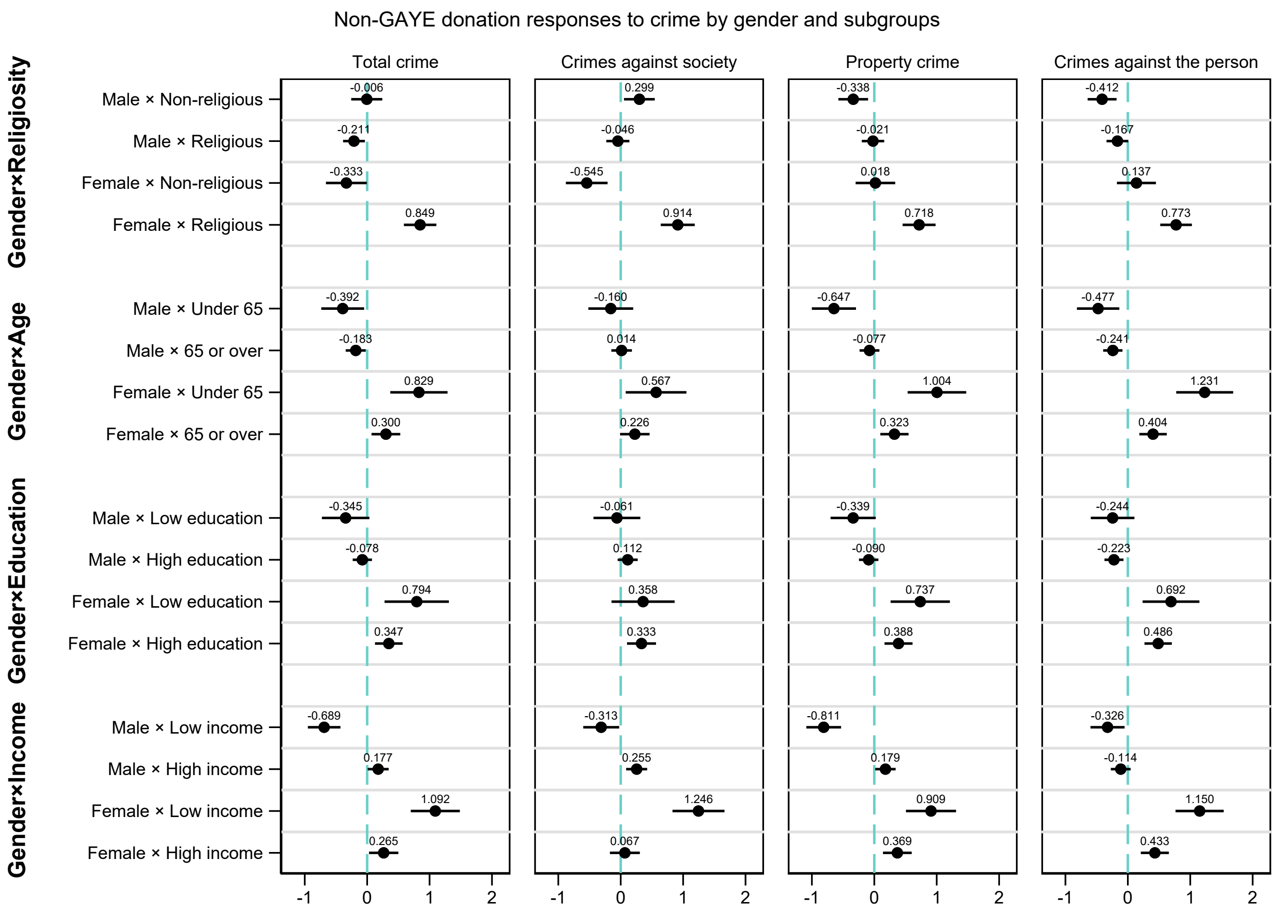
[18]Sources: https://www.gov.uk/government/statistics/women-and-the-criminal-justice-system-2019/women-and-the-criminal-justice-system-2019#victims

Figure 5: Donation responses for non-payroll donations by gender and charities' geographical scope



Notes: The figure presents estimated coefficients for non-payroll transactions by gender and charities' geographical scope, with 95% confidence intervals. The dependent variable is the natural logarithm of donation amount multiplied by 100. The crime variable is the natural logarithm of one plus the number of crimes in the previous month. In all regressions, donor, charity, and *treatment group* × *region* × *month* fixed effects are included but not reported.

Figure 6: Donation response for non-payroll donations across interactions of subgroups



Notes: The figure presents estimated coefficients for non-payroll transactions by gender interacted with religiosity, age, and education subgroups, from top to bottom, with 95% confidence intervals. The dependent variable is the natural logarithm of the donation amount multiplied by 100. The crime variable is the natural logarithm of one plus the number of crimes in the previous month. In all regressions, donor, charity, and *treatment group* × *region* × *month* fixed effects are included but not reported.

Finally, in relation to the interaction of gender and income, we know that female donors are comparatively underrepresented in higher-income areas, and thus comparatively over-represented in lower income areas (as shown in Section 2). This, in conjunction with the high level of granularity in the categorization of geographical areas by household income (2,000 to 6,000 residents in each area, allowing for significant variation at relatively short distances), means that coefficient estimates for the gender $\times$ income interactions can be reliably understood as measuring how donors respond depending on their own income rather than on the income of their neighbors. By comparison with donations by their higher-income counterparts, donations by lower-income donors tend to respond more positively, particularly so for female donors, for whom a 100% increase in local crime corresponds to an increase in the amount donated by roughy 1% across all donation types.

5.2 *Fear of crime, mental health, and giving*

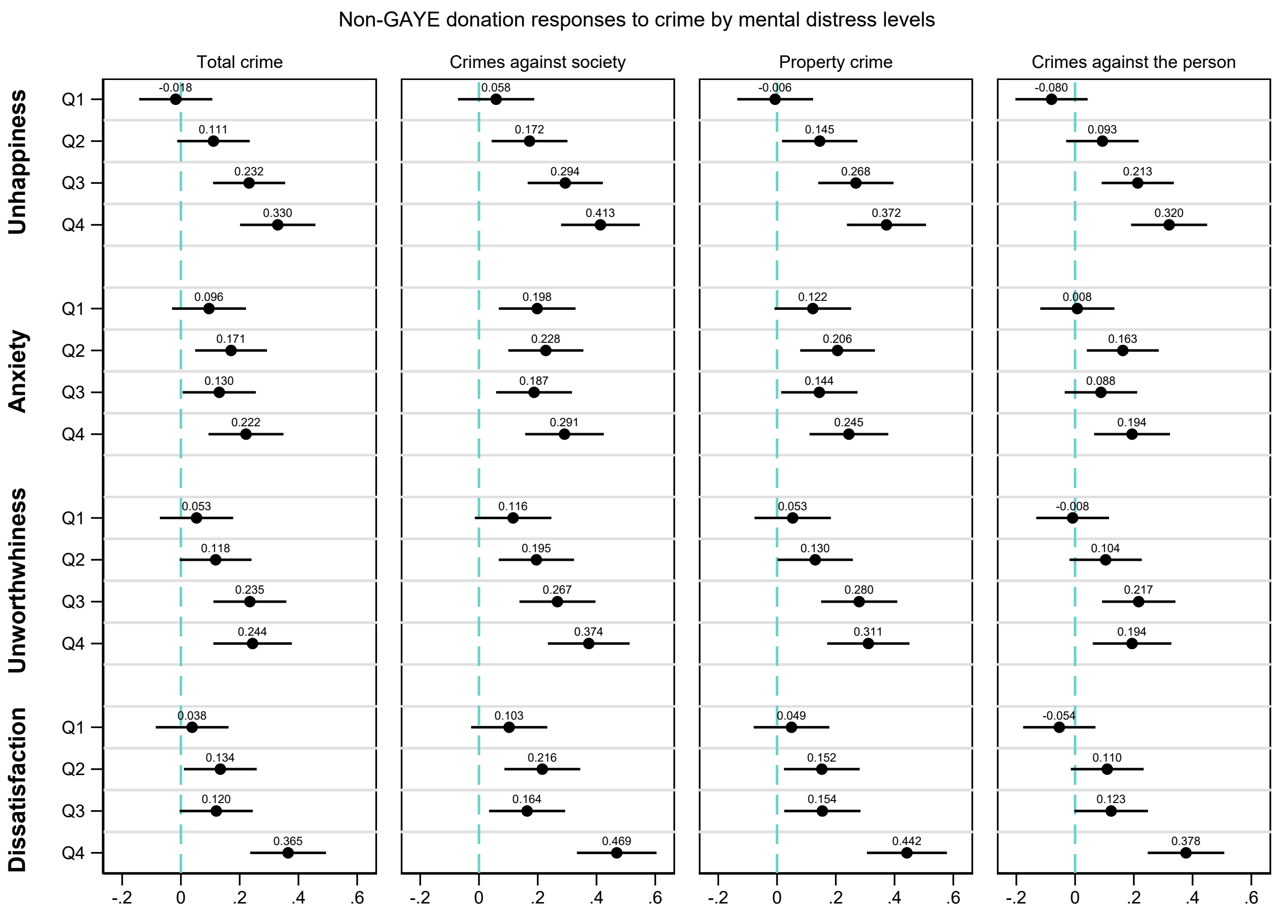
Previous studies suggest that crime as well as perceived neighborhood safety and fear of crime are associated with lower mental well-being and higher levels of depressive feelings (see, e.g., Whitley and Prince 2005; Stafford, Chandola, and Marmot 2007). For the UK, Dustmann and Fasani (2016) find a negative effect of overall local crime rates on the mental distress experienced by residents in urban areas. The effect of a one-standard-deviation increase in the local crime rate is about twice to four times as large as the effect of a one-standard-deviation decrease in the area's employment rate on mental distress. In turn, mental distress can lead to increased prosociality, including donations, as a way of relieving that distress and improving mood (Anik et al. 2009; Ong, Zaki, and Gruber 2017; Sabato and Kogut 2021). In other words, donating may act as a coping mechanism, which enables distressed residents to manage negative feelings and the distress caused by local crime.

To shed light on this mechanism, we include in our specification an interaction term between $CRIME_{p(i),t-1}$ and quartiles of mental health indicators, including unhappiness, anxiety, unworthiness, and dissatisfaction with life, into model (1). We would expect that when local crime increases, donors living in lower mental well-being areas are more likely to raise their charitable giving, in contrast to those in areas with better mental well-being.

Results are shown in Figure 7. Overall, we find that the effect of local crime on charitable donations increases at postcodes with higher levels of mental distress. Those in the lowest distress quartile show little to no response to crime, while those in the highest distress quartile exhibit the largest response. This pattern holds for total crime as well as individual crime types, and is consistent across indicators of mental distress, including unhappiness, anxiety, unworthiness, and dissatisfaction with life. More specifically, a doubling of local crime is associated with a change in amount donated of 0.111%, 0.232%, and 0.33% for donors living in areas with Q2, Q3 and Q4 unhappiness levels, respectively. For other indicators, higher local crime is associated with 0.13-0.222% increased donations for higher anxiety quartiles, 0.118-0.244% increased donations for higher unworthiness quartiles, and 0.134-0.365% increased donations for higher dissatisfaction with life quartiles.

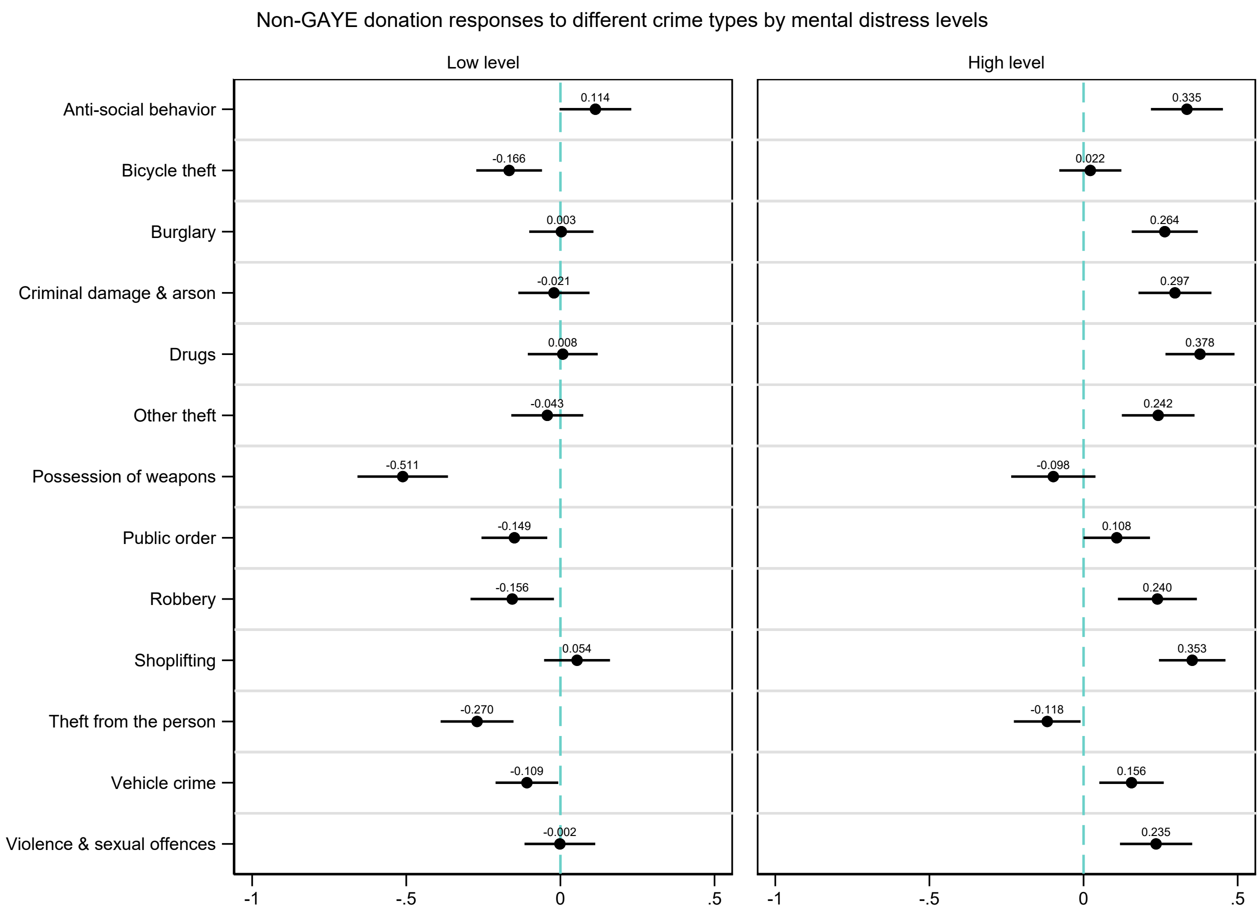
When breaking down responses for donors at postcodes with better mental health by crime type (Figure 8), we observe statistically significant (negative) responses for several types of crime – property crimes, such as bicycle theft, possession of weapons, public order, robbery, theft from the person, and vehicle crime. In contrast, donors at postcodes showing a higher level of mental distress show statistically significant (positive) responses across almost all crime types.

Figure 7: Donation responses for non-payroll donations by postcode mental distress level



Notes: The figure presents estimated coefficients for non-payroll transactions by mental distress level, including unhappiness, anxiety, unworthiness, and dissatisfaction with life, from top to bottom, with 95% confidence intervals. The dependent variable is the natural logarithm of donation amount multiplied by 100. The crime variable is the natural logarithm of one plus the number of crimes in the previous month. In all regressions, donor, charity, and *region* × *month* fixed effects are included but not reported.

Figure 8: Donation responses for non-payroll donations across mental distress levels and crime types



Notes: The figure presents estimated coefficients for non-payroll transactions by low and high mental distress level, using unhappiness indicator, across crime types, with 95% confidence intervals. The dependent variable is the natural logarithm of donation amount multiplied by 100. The crime variable is the natural logarithm of one plus the number of crimes in the previous month. In all regressions, donor, charity, and *region* × *month* fixed effects are included but not reported.

As suggested by Kort-Butler and Hartshorn (2011), crimes occurring at a greater distance have a relatively lower direct impact on the fear of crime. Accordingly, we should expect them to have a lower influence on donations. If we re-run our baseline specification including crimes within a three-mile and five-mile radius, we find that, in general, the response coefficient becomes larger in magnitude when we include crime at farther locations.[19] Given that the coefficients represent elasticities, this pattern should not be interpreted as implying that responses are stronger for crimes at farther locations – the median total crime within a three-mile radius is six times higher than that within a one-mile radius, and so the same proportional increase in crime at three miles and at one mile translates into a much larger increase in the number of crimes at three miles. Rather, the pattern indicates that crime has a cumulative effect in space and matters to individuals even when it occurs farther from their place of residence – e.g., by affecting individuals' daily routines away from home, such as commuting to work (Dustmann and Fasani 2016).

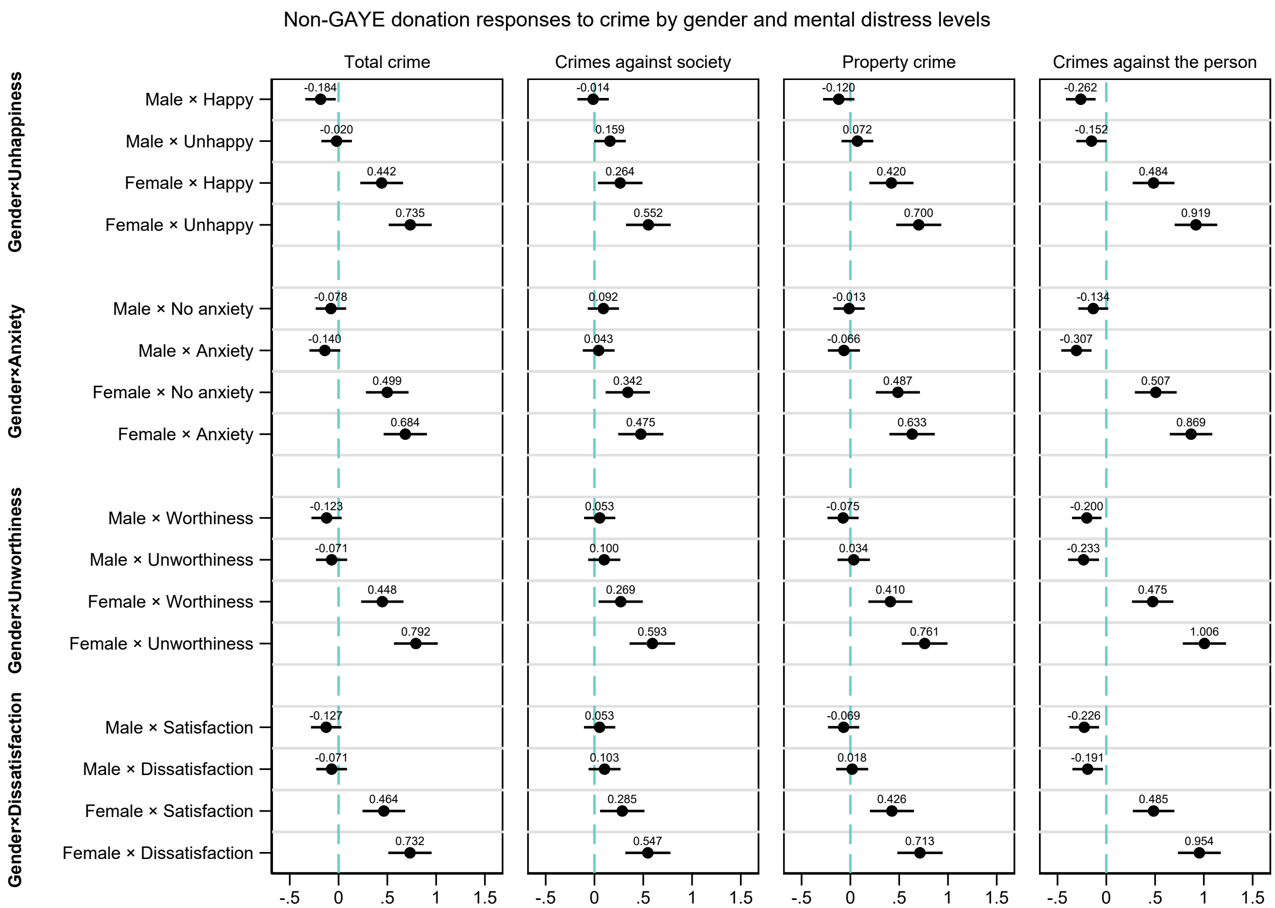
As discussed earlier, there is some consensus that women tend to experience more fear in response to similar local crime levels than men. Consistent with this, Dustmann and Fasani (2016) find clear gender differences in the impact of local crime on mental health, where crime affects women's mental health more than twice as much as men's. This gender disparity is consistent across property crime and total crime, while the effects of violent crime are driven only by women. In the same vein, we explore whether donation responses to crime vary along the gender and mental distress dimensions by introducing the interaction terms between $CRIME_{p(i),t-1}$ and $FEMALE_i$ as well as mental health indicators into the model. The results are reported in Figure 9. Male donors at all postcodes are not responsive to local crime. In contrast, all female donors are responsive, with the effect being larger among donors at postcodes with high mental distress levels. Notably, the effects of crime on female donors are largest for crimes against the person and smallest for crimes against society.

Previous literature has also documented a positive relationship between heightened fear of crime or death from mass murders and prosocial behavior at the aggregate level. Steinberg and Rooney (2005) find that the mean difference in non-tragedy giving before and after the 9/11 terror attack by white donors is \$2.65, compared to an average contribution of \$1,442 pre-event. A similar magnitude for the mean increase in donation is observed among other socio-demographic groups. In the same vein, Berrebi and Yonah (2016) show that a one-unit increase in the number of mass shootings within a US state can result in a 5% increase in the donation amount in the subsequent year. Considering the average annual occurrence of mass shooting incidents across the 49 sampled states, a doubling of the number of mass shooting incidents corresponds to a 0.645% increase in donation amount.

To relate our estimated responses to these earlier findings, we examine how donations in our sample were affected by the suicide bombing that occurred on 22 May 2017 at the Manchester Arena following a music concert. The terrorist attack, the deadliest in the UK since the 7/7 London bombings twelve years earlier, triggered widespread mental distress and anxiety. The time window we consider is four months before and four months after the event. Treated areas are those located in Greater Manchester. Control areas include all other areas except for London (since other terrorist events occurred in London in March and June 2017). We report results of our event study estimates in Figure 10. We find that donation amounts increase gradually within three months after the bombing. The largest increases of 2.1% and 3% occurred at two and three months after the event, respectively.

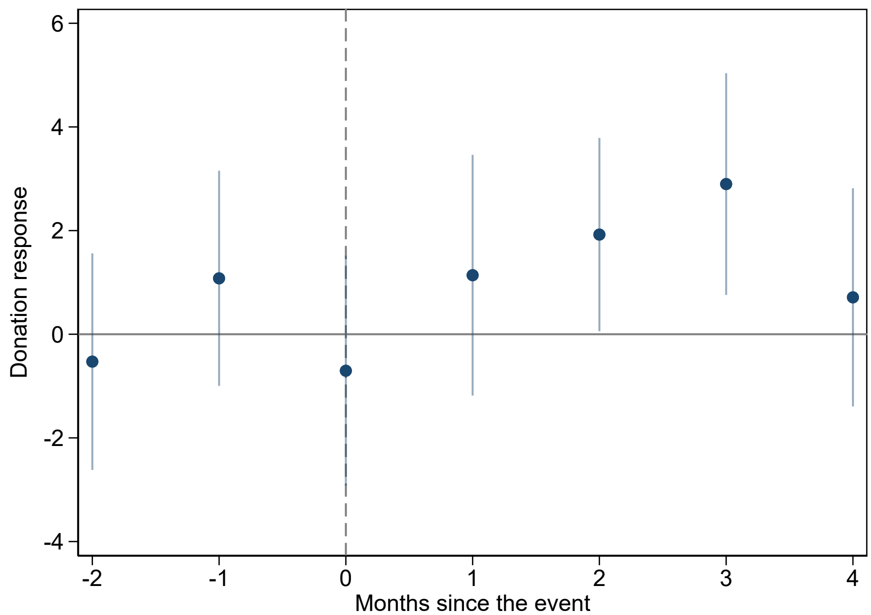
[19]Results are shown in Tables A8 and A9 of the online appendix.

Figure 9: Donation responses for non-payroll donations across mental distress level and gender



Notes: The figure presents estimated coefficients for non-payroll transactions by gender and mental distress level, including unhappiness, anxiety, unworthiness, and dissatisfaction with life, from top to bottom, with 95% confidence intervals. The dependent variable is the natural logarithm of donation amount multiplied by 100. The crime variable is the natural logarithm of one plus the number of crimes in the previous month. In all regressions, donor, charity, and *treatment group* × *region* × *month* fixed effects are included but not reported.

Figure 10: Donation response around a terrorist attack



Notes: The figure presents estimated coefficients for non-payroll transactions around Manchester Arena terrorist event in May 2017, with 90% confidence intervals. The dependent variable is the natural logarithm of the donation amount multiplied by 100. The covered time period is four months before and four months after the event. Coefficients of the Lead 4 and Lead 3 (four and three months before the event) are normalized. Treated areas are in Greater Manchester. Control areas include all other areas except for London (since there are other terrorist events in London in March and June 2017). $Donor \times charity$, and month fixed effects are included but not reported.

5.3 The role of social capital and political attitudes

A large literature has stressed the idea that differences across communities of individuals in their ability to sustain cooperation stem from differences in "social capital" – social connections, trust, reciprocity bonds – and that, more broadly, social capital has a positive impact on social and economic outcomes by reducing transaction costs, facilitating collective action, and lowering opportunistic behavior. In particular, communities with robust social capital tend to be more effective in maintaining public goods, such as soil and water conservation (Bouma, Bulte, and Van Soest 2008), or exhibit higher rates of volunteering and charitable giving (Glanville, Paxton, and Wang 2016).

To look for evidence of a link between donation responses to crime and social capital, we extend our analysis by examining how they vary across areas that are heterogeneous in terms of resident turnover and of the cultural homogeneity of their residents. For this purpose, we rely on information from UK migration statistics, namely, for each postcode, the internal UK migration flow for the district where the postcode is located and the number of non-UK born residents in that district, and use this information to construct binary above- and below-median indicator variables, $MIGRATION_p$ and $NON\_UK\_BORN_p$, which we use in single interactions with $CRIME_{p(i),t-1}$ as well as in double interactions with $CRIME_{p(i),t-1}$ and an indicator of recipient charities' geographical scope ($LOCAL_{it}$). We would expect that areas that experience higher resident turnover have a lower level of social cohesiveness, whereas the opposite might be true for areas with a large fraction of non-UK born residents, who must rely comparatively more on interpersonal connections and local social capital to navigate an environment and a social system that they are comparatively less acquainted with.

Estimates of responses by group, shown in Figures 11 and 12, are in line with this prior: donors in locations experiencing above-median levels of internal migration respond comparatively more negatively to local crime in their donations to local charities and comparatively more positively in their donations to national charities, while the opposite applies to locations with an above-median proportion of foreign-born residents.

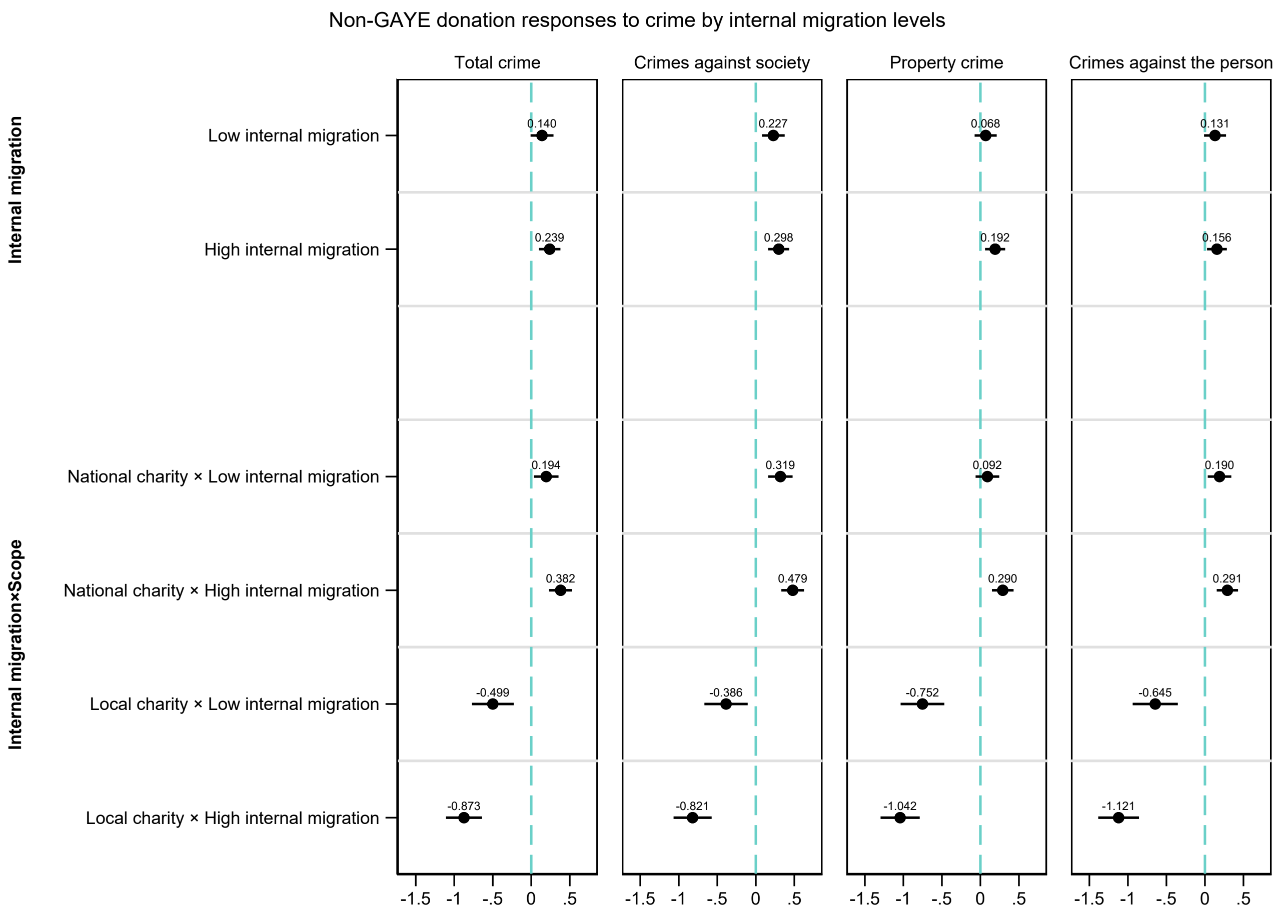
Next, we consider variation in political attitudes. To this end, we use postcode-level information from the UK electoral commission to create $CONSERVATIVE_p$, a dummy variable that equals unity if the number of votes for the Conservative Party is higher than that for the Labour Party and zero if the number of votes for the Conservative Party is less than that for the Labour Party.[20] We drop three constituencies where the number of votes between the two parties is the same.

Results in the top panel of Figure 13 show that donors in areas with different political leanings areas respond to different crime types. Specifically, in areas with a Labour leaning, donors increase the contribution amount by more than 0.32% as a result of a two-fold increase in crimes against society. In addition, a doubling of crimes against the person at the postcode is associated with a 0.29% higher donation amount in Labour leaning areas. Donors in Conservative leaning areas are much less responsive.

When further breaking down the analysis by gender in the lower panel of Figure 13, we find that female donors in Labour leaning areas are more likely to increase their donation in response to crime, while their Conservative-leaning counterparts show a smaller increase. However, among

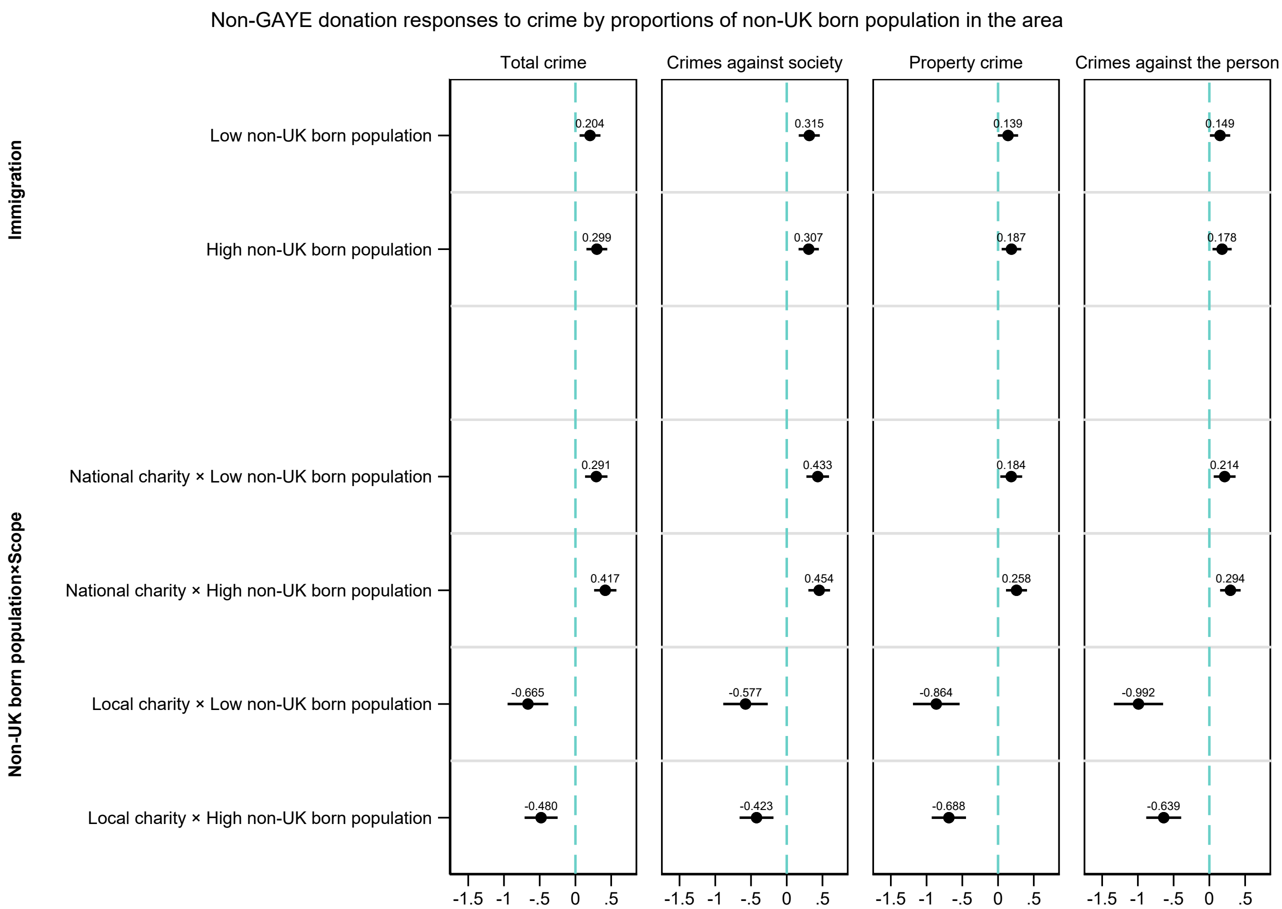
[20] We only consider the Conservative and Labour parties due to the dominance of these two parties in the UK (Wager, Bale, Cowley, and Menon 2022).

Figure 11: Donation responses for non-payroll donations by internal immigration and charities' scope



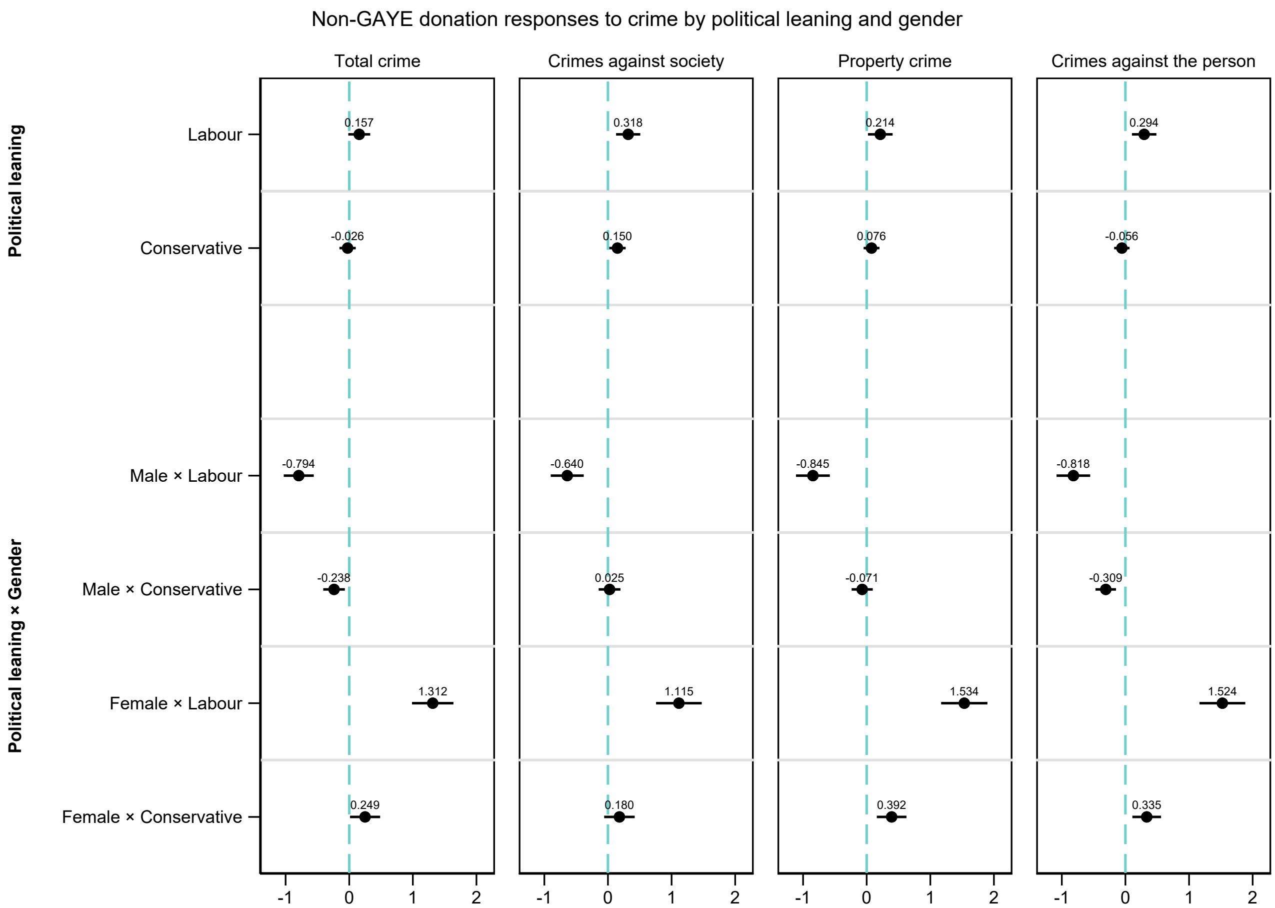
Notes: The figure presents estimated coefficients for non-payroll transactions by internal migration levels and charities' scope, with 95% confidence intervals. The dependent variable is the natural logarithm of donation amount multiplied by 100. The crime variable is the natural logarithm of one plus the number of crimes in the previous month. In all regressions, donor, charity, and *treatment group* × *region* × *month* fixed effects are included but not reported.

Figure 12: Donation responses for non-payroll donations by non-UK born population levels and charities' scope



Notes: The figure presents estimated coefficients for non-payroll transactions by non-UK born population levels and charities' scope, with 95% confidence intervals. The dependent variable is the natural logarithm of donation amount multiplied by 100. The crime variable is the natural logarithm of one plus the number of crimes in the previous month. In all regressions, donor, charity, and *treatment group* × *region* × *month* fixed effects are included but not reported.

Figure 13: Donation responses for non-payroll donations across political leaning and gender



Notes: The figure presents estimated coefficients for non-payroll transactions by political leaning and gender, with 95% confidence intervals. The dependent variable is the natural logarithm of donation amount multiplied by 100. The crime variable is the natural logarithm of one plus the number of crimes in the previous month. In all regressions, donor, charity, and *treatment group* × *region* × *month* fixed effects are included but not reported.

male donors, we find the opposite pattern, with Labour-leaning men being more likely to decrease their donation when crime increases, while their Conservative-leaning counterparts show a smaller decrease. As previously mentioned, the intersection of gender differences in political attitudes and religious beliefs may contribute to these gender differences in responses. While religion is associated with conservatism, this connection is weaker among women and stronger among men (Tolleson Rinehart and Perkins 1989). Therefore, the observed pattern among men may be influenced by the strong religiosity among conservative male donors, resulting in a lower anti-immigrant sentiment in their response to crime. In contrast, conservative women, who are not necessarily more religious, appear to show a stronger anti-immigrant sentiment in their response.

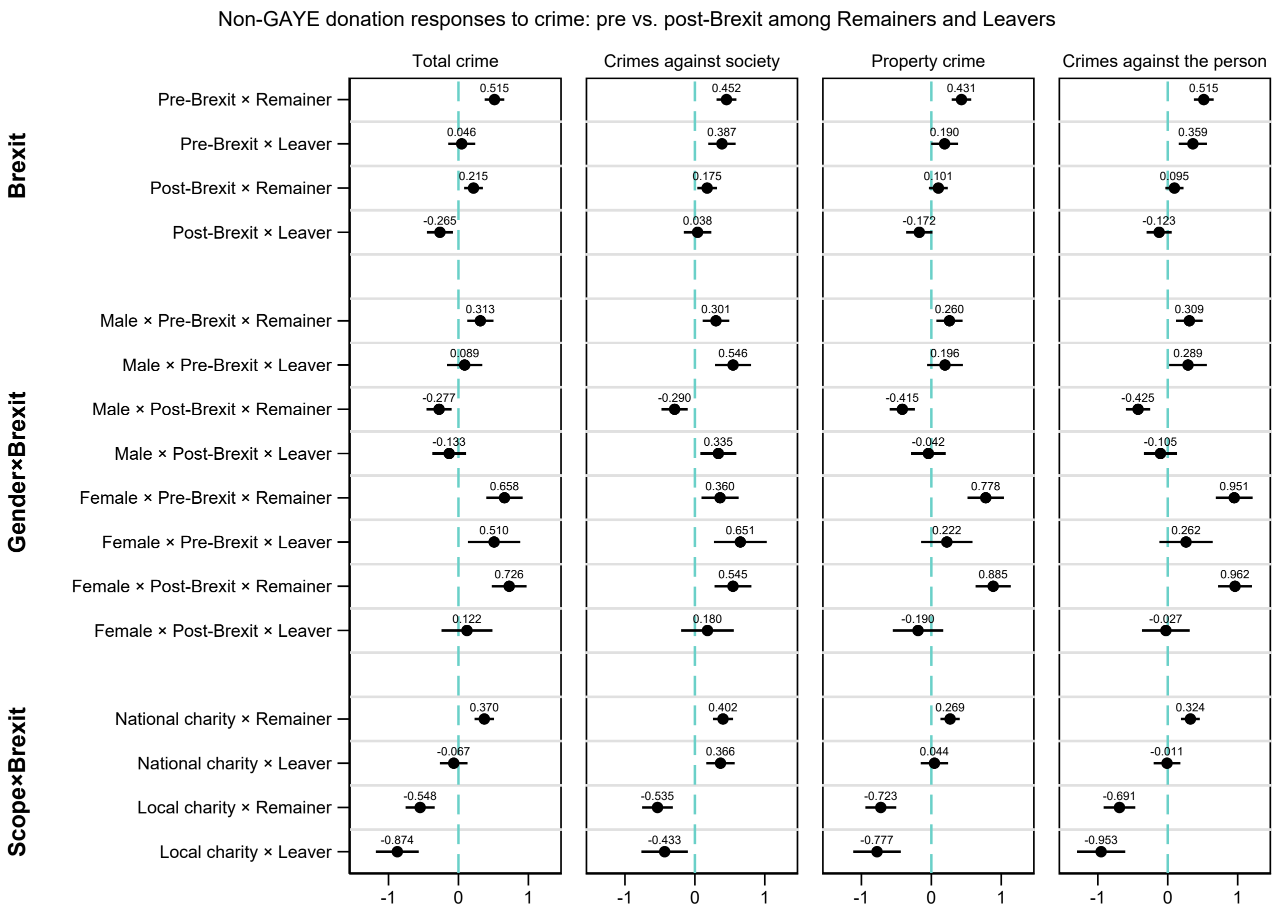
We also draw upon the growing "criminalization of immigration" debate (Ajzenman, Dominguez, and Undurraga 2023), which refers to individuals' tendency to blame crime on immigrants and on specific racial groups. We hypothesize that individuals with anti-immigrant sentiment are more likely to blame immigrants for crime. Consequently, when there is a rise in crime rates, they might respond by reducing their contributions to charities that they perceive as disproportionately benefiting immigrants, who can be economically weaker and more reliant on external support. Following Kaufmann and Harris (2015), we might expect residents living in areas with a Conservative-leaning more likely to hold stronger opposition to immigration compared to those residing in Labour-leaning areas. Our results in Figure 13 seem to be in line with this interpretation, but only so for female donors: donation responses for male donors are negative but larger in absolute size at Labour-leaning postcodes than at Conservative-leaning postcodes.

There is also some consensus that anti-immigration attitudes played a significant role in shaping voter preferences in the EU referendum, particularly among Leave voters (Prosser, Mellon, and Green 2016; Clarke, Goodwin, and Whiteley 2017). Yet, the question of whether anti-immigrant sentiments decline after Brexit remains controversial. Some studies (e.g., Ford 2018; Schwartz et al. 2021) find that anti-immigration attitudes softened after the referendum. This finding, however, is contradicted by in-depth interviews with Polish women migrants who reported a growing hostility towards them post Brexit (Rzepnikowska 2019). In the same vein, Creighton and Jamal (2022) conjecture that anti-immigrant sentiments may not have declined but rather became "masked" after Brexit. This concealed anti-immigrant sentiment might also reveal itself in how donations respond to crime.

We use the June 2016 EU referendum date and variation in the voting outcome at different locations as a second proxy for variation in anti-immigration attitudes. We create the *POST* dummy variable that equals unity if the donation was made between July 2016 and December 2022 and zero otherwise. $LEAVE_p$ is a dummy variable that equals unity if the proportion of Leave votes is above the median proportion of Leave votes at all postcodes and zero otherwise.

The results in the top panel of Figure 14 show that, in general, donors living in pro-Brexit areas are less likely to respond positively to local crime than those living in anti-Brexit areas, with the difference becoming less pronounced post EU referendum. However, when we break down responses by gender (the second panel of the figure), we find that this pattern is reversed for overall donations made by female donors – although female non-leavers respond more strongly to crimes against the person. Finally, donations to local charities in leavers dominated areas respond significantly more negatively to crime than those in non-leavers dominated areas (the bottom panel of the figure), suggestive of a link between crime blaming and anti-immigration views.

Figure 14: Donation responses for non-payroll donations before and after Brexit



Notes: The figure presents estimated coefficients for non-payroll transactions by political leaning and gender, with 95% confidence intervals. The dependent variable is the natural logarithm of donation amount multiplied by 100. The crime variable is the natural logarithm of one plus the number of crimes in the previous month. In all regressions, donor, charity, and *treatment group* × *region* × *month* fixed effects are included but not reported.

6 Conclusion

Our study has focused on the relationship between local crime and local residents' charitable giving and the possible mechanisms underlying this relationship. The most striking and more consistent pattern in our findings is a systematic difference between the responses of male donors and those of female and gender unassigned donors, not just in the direction and size of the response but also in terms of how these responses vary with other indicators, such as the scope of operation of recipient charities, religiosity, age, education, income, indicators of mental health, political leanings.

For crime, a plausible explanation for these patterns is that individuals' vulnerability to crime – be it actual or perceived – varies systematically with their gender, particularly for certain form of crime, such as crimes against the person. A natural question for further research is whether these gender differentials in donation responses extend to other triggers beyond local crime.

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A Online Appendix

Table A1: Types of crime

Type	Description
Anti-social behavior	personal, environmental and nuisance anti-social behavior
Bicycle theft	taking without consent or theft of a pedal cycle
Burglary	offences where a person enters a house or other building with the intention of stealing
Criminal damage and arson	damage to buildings and vehicles and deliberate damage by fire
Drugs	offences related to possession, supply and production
Other crime	forgery, perjury and other miscellaneous crime
Other theft	theft by an employee, blackmail and making off without payment
Possession of weapons	possession of a weapon, such as a firearm or knife
Public order	offences which cause fear, alarm or distress
Robbery	offences where a person uses force or threat of force to steal
Shoplifting	theft from shops or stalls
Theft from the person	crimes that involve theft directly from the victim (including handbag, wallet, cash, mobile phones) but without the use or threat of physical force
Vehicle crime	theft from or of a vehicle or interference with a vehicle
Violence and sexual offences	offences against the person such as common assaults, Grievous Bodily Harm and sexual offences
Unclassified	unclassified crimes

Table A2: Summary statistics of crime variables occurring within a three-mile radius

	(1) Min	(2) P25	(3) P50	(4) P75	(5) Max	(6) Mean	(7) SD	(8) N
Crimes against society	0	102	359	911	17,959	803	1,299	42,491,960
Property crime	0	83	306	855	13,191	809	1,445	42,491,960
Crimes against the person	0	50	183	524	4,622	434	635	42,491,960
Unclassified	0	54	502	1,458	25,103	1,302	2,249	42,491,960
Total	0	400	1,487	3,745	43,907	3,348	5,231	42,491,960

Notes: The table presents summary statistics for crime type variables occurring within a three-mile radius. Columns (1) to (5) show the minimum, 25^{th} percentile, median, 75^{th} percentile, and maximum values respectively. Columns (6) to (8) show the mean, standard deviation, and number of observations, respectively.

Table A3: Summary statistics of crime variables occurring within a five-mile radius

	(1) Min	(2) P25	(3) P50	(4) P75	(5) Max	(6) Mean	(7) SD	(8) N
Crimes against society	0	102	360	913	32,174	811	1,342	42,491,960
Property crime	0	83	306	857	20,700	818	1,487	42,491,960
Crimes against the person	0	50	184	525	9,281	438	656	42,491,960
Unclassified	0	54	503	1,461	46,777	1,315	2,318	42,491,960
Total	0	400	1,490	3,753	80,744	3,382	5,400	42,491,960

Notes: The table presents summary statistics for crime type variables occurring within a five-mile radius. Columns (1) to (5) show the minimum, 25^{th} percentile, median, 75^{th} percentile, and maximum values respectively. Columns (6) to (8) show the mean, standard deviation, and number of observations, respectively.

Table A4: Exploratory results for non-automatic samples

	(1)	(2)	(3)	(4)	(5)	(6)
	Non-Automatic	Non-Automatic	Non-Automatic	Automatic	Automatic	Automatic
Lagged logcrime	0.268***	0.112	0.109	-0.006	-0.023	0.000
	(0.086)	(0.098)	(0.101)	(0.019)	(0.028)	(0.030)
Second lagged logcrime		0.293***	0.312***		0.029	0.073**
		(0.099)	(0.106)		(0.028)	(0.032)
Third lagged logcrime			-0.060			-0.095***
			(0.103)			(0.030)
Obs	3,891,612	3,823,893	3,774,753	22,586,424	22,421,306	22,250,585
R^2	0.749	0.748	0.746	0.882	0.882	0.882

Notes: The table presents results for lagged donation responses to total crime. The dependent variable is the donated dummy multiplied by 100, taking a value of one if the donor contributes to a particular charity during the month and zero otherwise. The crime variable is the natural logarithm of one plus the number of crimes in the previous month. Columns (1) to (3) show results for non-automatic donations in models that include lagged crime, lagged crime along with the second lag, and lagged crime along with the second and third lags, respectively. Columns (4) to (6) show results for automatic donations in models that include lagged crime, lagged crime along with the second lag, and lagged crime along with the second and third lags, respectively. In all regressions, donor, charity, and $region \times month$ fixed effects are included but not reported. Robust standard errors are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table A5: Non-automatic and automatic donation responses to crime, intensive margin

	(1)	(2)	(3)	(4)
	Total crime	Crimes against society	Property crime	Crimes against the person
Panel A: Non-automatic donation				
Lagged logcrime	0.268***	0.452***	0.278***	0.188**
	(0.086)	(0.088)	(0.082)	(0.081)
Obs	3,891,612	3,891,612	3,891,612	3,891,612
R^2	0.749	0.749	0.749	0.749
Panel B: Automatic donation				
Lagged logcrime	-0.006	0.123***	-0.016	-0.277***
	(0.019)	(0.020)	(0.020)	(0.019)
Obs	22,586,424	22,586,424	22,586,424	22,586,424
R^2	0.882	0.882	0.882	0.882

Notes: The table presents results for donation responses to different crime types for non-automatic donations (Panel A) and automatic donations (Panel B). The dependent variable is the natural logarithm of donation amount multiplied by 100. The crime variable is the natural logarithm of one plus the number of crimes in the previous month. Columns (1) to (4) show results for total crime, crimes against society, property crime, and crimes against the person, respectively. In all regressions, donor, charity, and $region \times month$ fixed effects are included but not reported. Robust standard errors are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table A6: Non-automatic and automatic donation responses to crime, extensive margin

	(1)	(2)	(3)	(4)
	Total crime	Crimes against society	Property crime	Crimes against the person
Panel A: Non-automatic donation				
Lagged logcrime	-0.050***	-0.029**	-0.041***	0.011
	(0.014)	(0.014)	(0.014)	(0.013)
Obs	32,819,395	32,819,395	32,819,395	32,819,395
R^2	0.147	0.147	0.147	0.147
Panel B: Automatic donation				
Lagged logcrime	0.262	0.164	0.403**	0.374**
	(0.192)	(0.189)	(0.164)	(0.175)
Obs	306,598	306,598	306,598	306,598
R^2	0.87	0.87	0.87	0.87

Notes: The table presents results for extensive donation responses to different crime types for non-automatic donations (Panel A) and donation duration response for automatic donation (Panel B). The dependent variable is the natural logarithm of donation amount multiplied by 100. The crime variable is the natural logarithm of one plus the number of crimes in the previous month. Columns (1) to (4) show results for total crime, crimes against society, property crime, and crimes against the person, respectively. In all regressions, donor, charity, and $region \times month$ fixed effects are included but not reported. Robust standard errors are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table A7: First stage results for 2SLS-IV regressions

	(1)	(2)	(3)	(4)
	Log_Total crime	Log_Crimes against society	Log_Property crime	Log_Crimes against the person
Log_Δcrime	0.672***	0.445***	0.450***	0.382***
	(0.000)	(0.000)	(0.000)	(0.000)
CD Wald F	3,274,240	1,565,311	1,430,433	1,088,924
LM test	<0.001	<0.001	<0.001	<0.001
Obs	8,145,969	8,145,969	8,145,969	8,145,969
R^2	0.629	0.610	0.666	0.629

Notes: The table presents results for the first stage of IV regressions. The dependent variable is the natural logarithm of donation amount multiplied by 100. The crime variable is the natural logarithm of one plus the number of crimes in the previous month. Columns (1) to (4) show results for total crime, crimes against society, property crime, and crimes against the person, respectively. In all regressions, donor, charity, and $region \times month$ fixed effects are included but not reported. Robust standard errors are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table A8: Donation responses to crime occurring within a three-mile radius

	(1)	(2)	(3)	(4)
	Total crime	Crimes against society	Property crime	Crimes against the person
Lagged logcrime	0.218***	0.167***	0.117*	0.210***
	(0.070)	(0.064)	(0.065)	(0.061)
Obs	8,145,969	8,145,969	8,145,969	8,145,969
R^2	0.722	0.722	0.722	0.722

Notes: The table presents results for donation responses to different crime types occurring within a three-mile radius for non-payroll donations (Panel A) and non-automatic donations (Panel B). The dependent variable is the natural logarithm of donation amount multiplied by 100. The crime variable is the natural logarithm of one plus the number of crimes in the previous month. Columns (1) to (4) show results for total crime, crimes against society, property crime, and crimes against the person, respectively. In all regressions, donor, charity, and *region* $\times$ *month* fixed effects are included but not reported. Robust standard errors are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table A9: Donation responses to crime occurring within a five-mile radius

	(1)	(2)	(3)	(4)
	Total crime	Crimes against society	Property crime	Crimes against the person
Lagged logcrime	0.229***	0.180***	0.123*	0.215***
	(0.070)	(0.064)	(0.065)	(0.061)
Obs	8,145,969	8,145,969	8,145,969	8,145,969
R^2	0.722	0.722	0.722	0.722

Notes: The table presents results for donation responses to different crime types occurring within a five-mile radius for non-payroll donations (Panel A) and non-automatic donations (Panel B). The dependent variable is the natural logarithm of donation amount multiplied by 100. The crime variable is the natural logarithm of one plus the number of crimes in the previous month. Columns (1) to (4) show results for total crime, crimes against society, property crime, and crimes against the person, respectively. In all regressions, donor, charity, and *region* $\times$ *month* fixed effects are included but not reported. Robust standard errors are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table A10: Donation responses among non-payroll donations across charity causes

	(1)	(2)	(3)	(4)
	Total	Crimes against society	Property crime	Crimes against the person
Armed forces×Lagged logcrime	0.539***	0.563***	0.576***	0.769***
	(0.074)	(0.081)	(0.082)	(0.088)
Animal×Lagged logcrime	-0.149**	0.007	-0.274***	-0.204***
	(0.061)	(0.067)	(0.067)	(0.071)
Arts×Lagged logcrime	0.084	0.241***	0.154**	0.063
	(0.064)	(0.071)	(0.071)	(0.076)
Associations×Lagged logcrime	0.100*	0.042	0.034	0.162***
	(0.054)	(0.059)	(0.059)	(0.063)
Beneficiary group×Lagged logcrime	-0.021	0.033	0.026	0.059*
	(0.029)	(0.031)	(0.031)	(0.033)
Charitable activities×Lagged logcrime	-0.179***	-0.263***	-0.222***	-0.204***
	(0.032)	(0.035)	(0.035)	(0.037)
Childcare×Lagged logcrime	-0.659***	-1.156***	-0.731***	-0.429***
	(0.132)	(0.145)	(0.146)	(0.154)
Crime&Justice×Lagged logcrime	0.429***	0.463***	0.433***	0.529***
	(0.087)	(0.095)	(0.096)	(0.102)
Charity&VCSsupport×Lagged logcrime	0.056	-0.060	-0.009	0.194***
	(0.043)	(0.047)	(0.047)	(0.050)
Economic&Community development×Lagged logcrime	0.117**	0.097*	0.164***	0.017
	(0.046)	(0.051)	(0.051)	(0.054)
Education×Lagged logcrime	-0.232***	-0.183***	-0.234***	-0.356***
	(0.032)	(0.035)	(0.035)	(0.037)
Environment×Lagged logcrime	0.154*	0.139	0.181**	0.185*
	(0.084)	(0.091)	(0.091)	(0.096)
Facilities×Lagged logcrime	-0.208	0.008	-0.435***	-0.024
	(0.129)	(0.141)	(0.142)	(0.151)
Health×Lagged logcrime	0.110***	-0.044	0.142***	0.314***
	(0.030)	(0.033)	(0.033)	(0.035)
Housing×Lagged logcrime	-0.157***	-0.253***	-0.136***	-0.008
	(0.040)	(0.044)	(0.044)	(0.047)
Heritage×Lagged logcrime	0.241***	0.174**	0.363***	0.180**
	(0.070)	(0.077)	(0.077)	(0.082)
Leisure×Lagged logcrime	0.070	0.151*	0.099	0.096
	(0.081)	(0.088)	(0.089)	(0.094)
Professions×Lagged logcrime	-0.289**	-0.294**	-0.199	-0.207
	(0.131)	(0.144)	(0.146)	(0.154)
Religion×Lagged logcrime	0.088*	0.337***	0.032	-0.248***
	(0.046)	(0.049)	(0.050)	(0.052)
Research×Lagged logcrime	0.295***	0.302***	0.318***	0.250***
	(0.039)	(0.042)	(0.042)	(0.045)
Social care×Lagged logcrime	0.317***	0.426***	0.236***	0.294***
	(0.079)	(0.086)	(0.088)	(0.093)
Saving of lives×Lagged logcrime	0.194***	0.295***	0.080	0.314***
	(0.048)	(0.052)	(0.053)	(0.056)
Society×Lagged logcrime	0.507***	0.475***	0.493***	0.698***
	(0.063)	(0.069)	(0.069)	(0.073)
Social welfare×Lagged logcrime	0.150***	0.187***	0.177***	0.180***
	(0.033)	(0.037)	(0.037)	(0.039)
Obs	7,532,862	7,532,862	7,532,862	7,532,862
R^2	0.720	0.720	0.720	0.720

Notes: The table presents results for donation responses to crime for non-payroll transactions by charity causes. The dependent variable is the natural logarithm of donation amount multiplied by 100. The crime variable is the natural logarithm of one plus the number of crimes in the previous month. Columns (1) to (4) show results for total crime, crimes against society, property crime, and crime against the person, respectively. In all regressions, donor, charity, and *region*×*month* fixed effects are included but not reported. Robust standard errors are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.