Does Online Salience Predict Charitable Giving? Evidence from SMS Text Donations*

Carlo Perroni§
University of Warwick

Kimberley Scharf††
University of Birmingham and CEPR

Oleksandr Talavera‡‡
University of Birmingham

Linh Vi‡
University of Birmingham

February 2022

Abstract

We explore the link between online salience and charitable donations. Using a unique dataset on phone text donations that includes detailed information on the timing of cash gifts to charities, we link donations to time variation in online searches for words that appear in those charities' mission statements. The results suggest that an increase in the online salience of the activities pursued by different charities affects the number and volume of donations made to those charities and to charities that pursue different goals. We uncover evidence of positive "own-salience" effects and negative "cross-salience" effects on donations.

KEY WORDS: Charitable Donations, Online Search, News Shocks

JEL CLASSIFICATION: H41, D12, D64

---

*We are grateful to the National Funding Scheme, particularly William Makower and David Wright, for making SMS donations data available to us (in anonymized form); and to Minjung Kim, Ayse Yemiscigil, other participants to the 2020 SPI conference, and two anonymous reviewers for their helpful comments. All views and opinions expressed in this paper are our own, and do not reflect the views and opinions of the National Funding Scheme.

§University of Warwick, Gibbet Hill Road, Coventry, CV4 7AL, UK; e-mail: c.perroni@warwick.ac.uk

††**CORRESPONDING AUTHOR**. University of Birmingham, Edgbaston, Birmingham, B15 2TT, UK; e-mail: k.scharf@bham.ac.uk

‡‡University of Birmingham, Edgbaston, Birmingham, B15 2TT, UK; e-mail: o.talavera@bham.ac.uk

‡University of Birmingham, Edgbaston, Birmingham, B15 2TT, UK; e-mail: nxv991@student.bham.ac.uk

1 Introduction

The jury is still out as to why people make charitable donations. Irrespective of what the motives for giving might be, useful insights into giving responses can be gained by examining donation choices through the lens of demand theory. For example, if we think of tax reliefs on donations as lowering the "price of giving", then theoretical insights into donation responses to tax changes can be obtained by borrowing predictions derived from a standard model of consumer choice, which tells us how the expenditure on a particular good varies in dependence of its own price (Clotfelter 1990).[1]. Similarly, the effects of selective charitable donation tax reliefs on those donations that do not benefit from the relief can be understood as cross-price effects on expenditures.

While monetary prices remain central to the study of demand responses, in recent years the literature on consumer demand has gone beyond classical price theory to stress the role of salience (Bordalo et al. 2013; Bordalo et al. 2016; Bordalo et al. 2020).[2] The basic notion here is that when consumers' attention is drawn to certain attributes of the goods available to them, consumers respond disproportionately to variation in those attributes. The same idea can be extended to charitable giving choices: greater salience of a particular social issue or goal—which constitutes an attribute of what individuals "buy" when they make a donation to charities pursuing activities related to that issue or goal—can attract donations to those charities (an *own-salience effect*) while lowering donations made to other charities (a *cross-salience effect*).

In this paper, we investigate the role of salience in charitable giving. We use a unique dataset on phone text donations that provides detailed information on the timing of cash gifts to different charities at the daily level. The timing information contained in our data offers a unique opportunity to study how an increase in the salience to donors of the activities pursued by different charities affects the number and volume of donations made to those charities and to charities that pursue different goals.[3]

[1]Examples of applications of this approach are Karlan and List (2007), Uler (2011), Almunia et al. (2020), and Sheremeta and Uler (2021)

[2]Theoretical microfoundations for the role of salience in consumer demand, based on notions of selective or costly attention, are presented in Kőszegi and Szeidl (2013) and in Gossner et al. (2018).

[3]According to the Institute of Fundraising and fast.MAP's Fundraising Media DNA report, the top three channels for generating immediate donations in the UK are telephone, street-fundraising and SMS text (`https://tinyurl.com/cd63bhfk`, accessed on October 1, 2021). In terms of the volume

The charities in the dataset are grouped into categories, and donations to charities in any given category are then linked to Google Trends search scores based on leading keywords in those charities' mission statements. Clearly, online searches are not themselves a source of exogenous variation, but they are a close proxy for exogenous events that would affect the salience of certain issues to donors, which in turn may have an effect on donations (as well as online searches). Thus, using this proxy to measure online salience necessarily entails some degree of measurement error.

The method we use for extracting keywords and linking categories of charities to measures of online search intensity specifies single keywords for searches, rather than more precisely targeted (but potentially more arbitrary) word combinations. The approach is also fully agnostic about the nature of the sentiment, positive or negative, that may be associated with variations in search intensity. Despite the semantic coarseness of this mapping, our analysis uncovers evidence of a statistically significant association, at the weekly level, between online search intensity and donations, i.e., evidence of a positive own-salience effect on donations. Similar patterns are also in evidence when the mapping between charities and keywords in online searches is obtained through a LASSO procedure ("letting the data speak for itself"). The aforementioned analogy with price effects suggests that an increase in the salience of attributes associated with certain charities may increase donations towards those charities *and* reduce donations towards other charities—a *crowding out* or "cannibalization" effect.[4] However, if we interpret salience effects as being equivalent to changes in salience-adjusted "quality" (i.e., in the quality-adjusted price of giving), demand theory gives us a less clear-cut answer: if donations as a whole are sufficiently more substitutable for private consumption than they are for one another, then, in principle, cross-effects may even be positive.[5]

These predictions are in line with our findings on cross salience effects. The results

of donations, a survey made by the Charities Aid Foundation in 2018 lists text giving as the 9th most common way of donating to charities in the UK with 7% of the total, with the bulk of donations consisting of direct cash/bank donations, purchases of goods, raffle or lottery tickets, and membership fee/subscriptions (`https://tinyurl.com/2nfa9cvw`, accessed on October 1, 2021).

[4]In the literature on fundraising, this question has been characterized in terms of asking whether interventions targeted to specific forms of donations can produce a "lift" in total donations instead of a "shift" in donations from other charities or from the future (Cairns and Slonim 2011; Reinstein 2011; Edwards and List 2014; Meer 2017; Filiz-Ozbay and Uler 2019; Ottoni-Wilhelm et al. 2022).

[5]This ambiguity is also discussed by Filiz-Ozbay and Uler (2019), who show that standard demand theory could be adopted to explain both a cannibalization effect but also a demand expansion.

paint a mixed picture: with a few exceptions, cross-salience effects are either negative or statistically insignificant depending on the charity grouping we consider.

Our study contributes to a longstanding debate on how donors respond to prompting. This debate has mainly revolved around charities' fundraising activities and the effects of inter-charity competition on giving (Rose-Ackerman 1982; Klar and Piston 2015; Krieg and Samek 2017), but some of this literature has focused more specifically on crisis fundraising, i.e., how donors respond to unanticipated events such as natural disasters (Simon 1997; Eisensee and Strömberg 2007; Brown et al. 2012; Ottoni-Wilhelm et al. 2022; Deryugina and Marx 2020).[6] Our paper is closely related to these studies but departs from them by focusing on online salience, as proxied by variation in online search intensity, rather than on charities' disaster appeals. It also differs from these studies by studying effects on general donations rather than just on crisis fundraising.

Changes in donations exhibit a significant degree of persistence beyond the period in which the change in the intensity of online searches for relevant keywords occurred. The strength of the relationship between searches and donations is heterogeneous across different areas of activity, but there is little indication that, within given areas of activity, it is different for charities that have different organizational characteristics—whether charities are large or small, whether they are London-based, whether or not their activities have a local focus—suggesting that the patterns we observe are not the result of systematic differences in charity characteristics across different areas of activity. Estimated effects are stronger for donations made during weekdays rather than on weekends; they are stronger for donations that are made in the evening; and they are stronger for younger donors.

Data on online search behavior have been widely used in several areas of economics research. Some studies have used indicators of online job searches to examine the link between job search activity and changes in unemployment insurance (Baker and Fradkin 2017); to forecast unemployment (Fondeur and Karamé 2013; D'Amuri and Marcucci 2017; Dilmaghani 2019); and to predict unemployment insurance claims (Choi and Varian 2012). Other studies have used Google Trends data as a proxy for investor attention, which can predict future stock price (Da et al. 2011a), or as a proxy for demand for stock market information, which increases with the level of stock market volatility (Vlastakis and Markellos 2012). Google Trends data have also been employed

[6]An exception is Connolly-Ahern and Ahern (2015), which focuses on gun control in the US and related nonprofit organizations.

to generate forecasts of inflation expectation, cinema demand, housing price and sales, and foreign exchange rate volatility—see e.g. (Guzman 2011; Hand and Judge 2012; Smith 2012; Wu and Brynjolfsson 2015). Our paper contributes to this line of literature by showing that online search activity can also be a predictor of variation in routine charitable giving. To the best of our knowledge, this is the first study to offer evidence on this.[7]

The rest of the paper is structured as follows. Section 2 describes the data and how we use it to link measures of search intensity with charities. Section 3 describes our empirical strategy. Estimation results are presented in Section 4. Section 5 concludes.

2 Data collection and aggregation

The data we use come from two main sources. For donations, we employ a unique dataset of daily SMS text giving over the period between 2013 and 2019 from the National Funding Scheme (NFS), the largest fundraising platform in the UK. The NFS is a charity that operates as an intermediary to facilitate the fundraising activities of UK-based charitable organizations, offering subscribers a facility for making cash donations via SMS to a fundraising campaign of their choice.[8] The dataset covers a total of 44,371 text donations to more than 500 charities, each record giving detailed information about the exact time, the date, the amount donated, the campaign code, the name of the charity, and the approximate age of the donor.

This rich level of detail, particularly with regards to the timing of the donations, allows us to study how text donations to certain types of charities vary in time with changes in online search activity on certain topics—over the full sample as well as for donations sub-samples (morning donations vs. evening donations, weekend dona-

[7]Scharf and Smith (2016) study the relationship between the size of online peer groups and the level of donations to online fundraisers. Korolov et al. (2016) focus on the relationship between donations and social media activity (rather than online salience more generally), describing a model of information diffusion via Twitter chats, and test it using data on donations to disaster relief. A related theoretical analysis of how information diffusion in social groups is reflected in charitable donations is Scharf (2014).

[8]According to the Phone-paid Services Authority's 2018 annual report, the total amount of text donations was £37.5 million in 2017, reaching £49.6 million in 2018 (`https://tinyurl.com/4hpbfst2`, accessed on October 1, 2021). Donations in NFS data, totalling £118,500 and £170,339 respectively in 2017 and 2018, represent approximately 0.316% and 0.343% of the UK text donation pool in 2017 and 2018, respectively.

tions vs. weekdays donations, recurring donations vs. occasional donations, donations by older donors vs. donations by younger donors). We drop from the data all unauthorized and failed donations (e.g., if the SMS contained a typo), and use the donor's hashed mobile phone number as the donor ID.

Descriptive statistics for our donations data are summarized in Table 1. On average, we observe a higher volume of donations on weekdays than on weekends. The average amount of donations per transaction on a weekend is £17.17 in comparison with £30.83 on a weekday. Donors tend to give more often in the evening (28,817 transactions) than in the morning (8,254 transactions), but the average amount donated per transaction in the morning is higher at £34.10 as compared to £23.93 in the evening.

There are notable differences in the amounts donated by donors of different characteristics. More specifically, older donors (those who belong to the 45-54 and 55+ age ranges) on average give four times more than do younger donors (those who belong to the under 25, 25-34, 35-44 age ranges), £100.29 vs. £23.80, respectively. The average donation size for non-habitual givers (those for whom we observe fewer than three donation records) is just slightly lower than that for habitual givers—£5.98 vs. £5.99.

To group charities into homogeneous categories, we proceed as follows. For each charity appearing in the dataset, we retrieve a mission statement in text form from the charity's own website. As our analysis focuses on donation aggregates by charity type, we manually categorize organizations into groups at two different levels, based on their mission statements and on any other information that was available to us. The more narrowly defined categorization includes 134 separate groups of charities, while the more broadly-defined categorization includes four groups of charities.[9] The lists of categories is presented in Table 2.

We link our donations data with information collected by the Charity Commission for England and Wales and the Scottish Charity Regulator for the year 2018.[10] This allows us to categorize charities by size (revenues) and location (based on their headquarters' address). We also categorize charities based on their geographical areas of

[9]Our empirical strategy relies on panel data methods. This allows us to control for unobserved heterogeneity by incorporating fixed effects for different categories of charities, and this is more effective the more narrowly defined such categories are. However, when looking at heterogeneity across different categories of charities, focusing on narrowly defined categories can result in too little longitudinal sample variation within categories. To strike a balance between these two issues, we use both broadly and narrowly defined categories in our analysis.

[10]`https://tinyurl.com/pznzvubs` and `https://tinyurl.com/pak3a9h4`, accessed on October 1, 2021.

Table 1: Descriptive statistics for donations data

	Mean Donation (£)	Std. Dev.	Number of Donations
	(1)	(2)	(3)
Weekends	17.17	121.21	12,596
Weekdays	30.83	248.99	24,475
Mornings	34.10	273.90	8,254
Evenings	23.93	193.96	28,817
Younger donors	23.80	55.36	715
Older donors	100.29	537.68	661
No age data	24.87	205.49	35,695
Habitual donors	5.99	3.40	1,983
Non-habitual donors	5.98	3.85	25,402
Unidentified donors	83.32	414.09	9,686
All	26.19	214.39	37,071

Notes: The table shows summary statistics for the whole sample and sub-samples of our donations data. Columns (1) and (2) show the mean and standard deviation of donation amount per transaction, respectively. Column (3) shows the total number of donation transactions. *Weekends* includes donation transactions made on a weekend and *Weekdays* includes those made on a weekday. *Mornings* includes donation transactions made in the morning and *Evenings* includes those made in the evening. *Younger donors* includes donation transactions made by young donors (age < 55), *Older donors* includes those made by older donors, and *No age data* includes those without age information. *Habitual donors* includes donation transactions made by habitual donors, *Non-habitual donors* includes those made by non-habitual donors, and *Unidentified donors* includes those made by donors that cannot be identified. *All* includes all donation transactions in our dataset.

Table 2: Categorization of charities

Broad	Narrow
Arts/Culture/Education	Architecture, Art education, Art galleries, Art museums, Arts and culture, Ballet, Black history and culture, Children and art, Children education, Cinema, Circus, Contemporary art, Contemporary art festivals, Crafts, Cricket, Cultural education, Dance, Film, Gymnastics, Heritage, Libraries, Medical museums, Modern music, Music festivals, Musical organizations, Opera, Orchestras, Other arts, Other museums, Other culture, Other education, Other galleries, Other music, Other performing arts, Other sports, Painting, Photography, Printmaking, Puppets, Regimental museums, Research, Science education, Science museums, Theatre, Windmill museums
Family/Women/Health	Abortion, Adrenoleukodystrophy, Attention deficit hyperactivity disorder, Autism, Birth trauma, Blood cancer, Brain injury, Breast cancer, Breastfeeding, Carers, Charcot-Marie-Tooth disease, Children in violence, Children's health, Chronic illness, Cleft palate, Drugs and alcohol addiction, Dyslexia, Elderly, Family, HIV, Health care coastal, Heart disease, Hyper IgM, Idiopathic intracranial hypertension, Learning disability, Other cancers, Other children, Other disabilities, Other healthcare, Other women, Women's childbirth injuries, Women's mental health, Youth
Religious/Professional Orgs.	Armed forces, Baptist churches, Cathedrals, Catholic churches, Catholic youth, Charity assistance, Christian refugee assistance, Church community, Church groups, Civil servants, Evangelical churches, Farmers, Other churches, Pharmacists, Police
Others	Animals, Botanical gardens, Bulldogs, Conservation, Earning income, Environment, Foodbanks, Forests, Homeless, Hunger, Kenyan community, LGBT, Natural disasters, Other communities, Other dogs, Other drugs, Parks, Plants and fungi, Rescue service

Notes: The table shows the classification of narrowly defined categories into four broadly-defined categories.

operations (local vs. national) using information obtained from their websites.

Aggregate measures of charitable giving for each charity category are derived as follows:

$$V_{It}^{A} = \sum_{j \in I} v_{jt}. \tag{1}$$

where V_{It}^{A} is an aggregate donation outcome for charities in category I in week t at level of aggregation $A \in \{Narrow, Broad\}$, and v_{jt} is the donation outcome for charity j in week t. We use two different measures of aggregate donation outcomes: number of donations and total amount donated—i.e., $v \in \{Frequency, Amount\}$. Donations data are aggregated to a weekly frequency to match the Google Trends data, which has a weekly frequency (Sunday to Saturday). While news items are more likely to appear during weekdays, the daily number of transactions is greater during weekends,[11] when donors are not working and have more time to pay attention to budgeting and spending choices (paying bills, shopping, making charitable donations). Given this, we pair the Sunday-to-Saturday Google Trends aggregate with weekly donations aggregates where the donation week starts on the following Friday. A systematic comparison of different time aggregation criteria (shown in Table 17 in the appendix) lends support to this choice.[12]

We use the Google Trends platform to measure the variation in online search activity by topic. After removing stop words from the mission statements of charities in our dataset, we extract from each of these the unstructured text statements the ten most frequent keywords using the *Python NLTK* library.[13] These keywords are then sorted by frequency and by order of occurrence. For any of these keywords, the Google Trends website reports the weekly frequency of Google engine searches originating from a specific geographical region. Since weekly Google Trends data is not available before the end of 2014, we only keep donations data from week 49 of 2014 to week 41 of 2019, obtaining a final sample of 10,869 unique observations.

[11]This can be seen by dividing the total number of weekday donations by the number of weekdays ($24,475/5 = 4,895$) and comparing this figure with the corresponding figure for weekends ($12,596/2 = 6,298$).

[12]The table reports regression results from our main specification using different time shifts (0 to 7 days). In line with the above discussion, although results are qualitatively similar for the different time windows when we use different weekly donation windows, the link between variation in online salience and variation in donations effect is strongest when we set the donation week to start on the following Friday (i.e., $t = 5$).

[13]See `https://www.nltk.org/` for more details, accessed on October 1, 2021.

Google Trends does not report the absolute number of weekly searches for each keyword for the selected time period and location. Rather, the weekly search index for a particular word reflects the share of searches for that word relative to the total number of searches on all topics in the selected geographical area during that week. For each word in the same location, this measure is then normalized in the range 0 to 100 over a moving time window (involving multiple weeks) so that the highest value of the search index within that time window is 100.

We use the search index for individual words as reported by Google Trends to construct an aggregate measure of variation in online salience for each category of charities. This composite search intensity measure is defined as the mean of average changes in the log of weekly search frequency of the set of keywords across all charities belonging to the same category, which takes the following form:

$$\Delta GT_{It}^{Ak} = \frac{1}{\#I} \sum_{j \in I} \frac{1}{k} \sum_{h=1}^{k} \Big(\log GT_t(w_{hj}) - \log GT_{t-1}(w_{hj}) \Big), \tag{2}$$

where ΔGT_{It}^{Ak} denotes the composite search intensity index for charity category I at the level of aggregation $A \in \{Narrow, Broad\}$ in week t using the k most important keywords in charities' mission statements, with k taking values of 10, 5 or 3; $\log GT_t(w_{hj})$ denotes the natural log of search frequency for keyword w during week t; and $\#I$ denotes the total number of charities that belong to category I.

The above mechanical aggregation procedure is fully agnostic about how keywords feature in online searches (e.g., whether with a positive or with a negative connotation). A disadvantage of this approach is that it necessarily produces a noisy semantic matching between charities' missions and online searches. But there are also clear advantages: it is easy to document and is methodologically parsimonious; more importantly, it is methodologically conservative, in that it minimizes the role played by the researcher in defining semantic connections.

To study cross-salience effects, we also construct a measure of cross-category search intensity. This is the mean of average changes in the log of weekly search frequency of the set of keywords across other categories' charities:

$$\Delta OGT_{It}^{Ak} = \frac{1}{\#\{I' \neq I\}} \sum_{I' \neq I} \Delta GT_{I't}^{Ak}. \tag{3}$$

where ΔOGT_{It}^{Ak} denotes the composite search intensity index for charity categories other than I at level of aggregation A in week t using k keywords, $\Delta GT_{I't}^{Ak}$ is the corresponding composite measure for category I', and $\#\{I' \neq I\}$ is the total number of categories other than I. We also use an alternative measure that incorporates the numbers of charities in the sample as category weights:

$$\Delta OGT_{It}^{Ak} = \frac{1}{\sum_{I' \neq I} \# I'} \sum_{I' \neq I} \# I' \Delta GT_{I't}^{Ak}. \tag{4}$$

Table 3 shows the summary statistics of the Google Trends-based variables in our sample. As a result of the normalization method used by Google Trends in information reporting, the sample mean values of the composite search intensity variables, ΔGT^{Ak} and ΔOGT^{Ak}, are all close but not exactly equal to zero.[14]

Table 4 reports correlations amongst all the variables in our analysis. Correlation patterns suggest positive links between search intensity and the number and volume of donations. The negative correlation between the cross-category search intensity measure and donation frequency and amount suggests an inverse relationship between donations to one group and search frequencies of keywords of the other groups. Additionally, the positive correlation of own- and cross-category search intensity measures implies that there is a similar trend in changes of search volumes for keywords in one group and in the others over time.

3 Empirical strategy

To investigate the link between salience and text donations, we employ the following baseline specification:

$$\ln V_{It}^{A} = \beta_0 + \beta_1 \Delta GT_{It}^{Ak} + \tau_t + \gamma_I + \epsilon_{It}, \tag{5}$$

where $\ln V_{It}^{A}$ is the natural logarithm of aggregate donation outcome for category I at the level of aggregation A in week t; ΔGT_{It}^{Ak}, the key variable of interest, is the composite search intensity index for category I in week t using k keywords; and τ_t and γ_I are respectively time and category fixed effects.

Given that we focus on short-run (weekly) variation in salience, and that charities' missions change much more slowly than salience does (and are time-invariant in our sample), any reverse causation from charities' missions to variation in online searches for the words they include can be ruled out. And although the keywords that we observe in charities' mission statements may be the endogenous result of competitive selection amongst charities, our empirical strategy does not hinge on variation

[14] This is the result of how Google normalizes the index. Several papers also document an approximately zero mean: e.g., Nasir et al. (2019), Swamy et al. (2019).

Table 3: Descriptive statistics for Google Trends-based indicators

				Percentile				
	Mean	Std. Dev.	Min	25%	50%	75%	Max	Obs
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ΔGT^3	0.000	0.081	-0.771	-0.031	-0.001	0.030	0.678	10,869
ΔGT^5	0.000	0.066	-0.718	-0.029	-0.002	0.027	0.516	10,869
ΔGT^{10}	0.000	0.059	-0.504	-0.027	-0.002	0.023	0.495	10,869
ΔOGT^3	0.000	0.040	-0.171	-0.019	-0.002	0.016	0.257	10,869
ΔOGT^5	0.000	0.040	-0.162	-0.018	-0.002	0.014	0.260	10,869
ΔOGT^{10}	0.000	0.044	-0.180	-0.020	-0.003	0.015	0.279	10,869

Notes: The table shows summary statistics for our Google Trends-based variables. Columns (1) to (7) show the mean, standard deviation, min, 25^{th} percentile, median, 75^{th} percentile, and max respectively. Column (8) reports the number of observations.

Table 4: Correlations

	ΔGT^3	ΔGT^5	ΔGT^{10}	ΔOGT^3	ΔOGT^5	ΔOGT^{10}	log Freq.
ΔGT^5	0.8694						
ΔGT^{10}	0.7220	0.8320					
ΔOGT^3	0.4596	0.5726	0.7138				
ΔOGT^5	0.4683	0.5818	0.7274	0.9891			
ΔOGT^{10}	0.4718	0.5878	0.7371	0.9736	0.9886		
log Frequency	0.0051	0.0017	0.0025	−0.0126	−0.0113	−0.0120	
log Amount	0.0072	0.0033	0.0009	−0.0135	−0.0122	−0.0128	0.8803

Notes: The table shows the Pearson's Correlation coefficients for the main variables.

in keywords across charities being exogenous: all our empirical specifications include charity sector fixed effects, meaning that they only exploit time variation in donations within charity groups, not cross-sectional variation in donations across different charity groups.

We estimate model (5) for two different measures of text giving, i.e., frequency of donations and volume of donations. Furthermore, to deal with the fact that we observe zero donations over several weeks, we re-estimate the equation (5) using a standard Tobit model (Tobin 1958) and compute its unconditional marginal effects. Using an alternative specification, we select keywords by the Least Absolute Shrinkage and Selection Operator (LASSO)—a variable selection technique (described in more detail in Appendix A.2). We start from a specification which, for each charity categories, potentially allows for the separate inclusion of all the individual keywords (between 450 and 750 for each broad category) that are used to construct the aggregate measures of variation in online search (2) included in our main empirical specification. I.e., we focus on the following specification:

$$\ln V_{It}^{A} = \beta_0 + \sum_{h \in H(I)} \beta_h \left(\log GT_t(w_h) - \log GT_{t-1}(w_h) \right) + \tau_t + \gamma_I + \epsilon_{It}, \tag{6}$$

where I is a broad donations category (i.e., $A = \mathit{Broad}$) and $H(I)$ is the set of keywords for category I (the union of the sets of ten most used keywords for each charity in category I). Using this specification, separately for each charity category, we then apply a LASSO procedure to determine for which of those keywords variation in online searches best predicts variation in donations. Finally, we run regressions with a version of (6) that only includes the three or the five most important keywords at the broadly-defined category level.

We additionally carry out regressions with several augmented specifications. To account for possible persistence effects, we add lagged dependent variables into the equation (5). To examine cross-salience effects, we estimate the following specification:

$$\ln V_{It}^{A} = \beta_0 + \beta_1 \Delta GT_{It}^{k} + \beta_2 \Delta OGT_{It}^{Ak} + \tau_t + \gamma_I + \epsilon_{It}, \tag{7}$$

where ΔOGT_{It}^{Ak} is the composite search intensity index for charity categories other than category I in week t using k keywords. We again estimate model (7) for two different measures of giving: number of donations and volume of donations. Category-specific coefficient estimates (for the more broadly defined categories) are obtained by including interaction terms between the search intensity measures and charitable categories.

Other dimensions of heterogeneity are explored by splitting the sample by donor age (older vs. younger donors), by whether donations originate from active donors (habitual vs. occasional donors), and by time of day (mornings vs. evenings) and by day of the week (weekends vs. weekdays).

A question that naturally arises in relation to our empirical strategy relates to the interpretation of results. In particular, can we legitimately take variation in the online salience of certain issues as being exogenous to variation in charitable donations to causes related to those issues? While we do not wish to claim that results from the above regressions specifications can conclusively demonstrate causation from online salience to donations, it should be noted that most of the search keywords used to construct our explanatory variables do not directly refer to charitable behavior; rather they refer to themes that can become more topical or less topical in online discussions irrespective of any changes in charitable behavior. Moreover, charity-related motives represent a relatively small subset of all the motives that drive variation in online word searches as measured by Google Trends. For example, the number of people who process online information related to education is far greater than the number of people who make donations to charities whose activities are focused on education. Accordingly, variation in Google searches on education-related issues can be expected to be driven comparatively more by education-related news and events than it is driven by any independent variation in donations to education-focused charities. This is precisely the assumption made in a number of other studies that employ Google searches as an exogenous explanatory variable for a more narrowly focused outcome.[15]

To provide further validation, we carry out regressions using a Two-Stage Least Square Instrumental Variable (2SLS IV) variant of our baseline specification where the composite measure of variation in UK online search intensity is instrumented with the corresponding measure for US online search intensity (i.e., GT^{10}_{US}). The rationale behind this is that US online search activity (taken as a proxy for the salience of certain topics to US-based individuals) is likely to be correlated with UK online search activity (taken as a proxy for the salience of certain topics to UK-based individuals) but is comparatively less likely to have a direct effect on donations by UK donors to UK charities. We first regress the UK Google Trends index on the corresponding US Google Trends

[15]Examples are Da et al. (2011b), who use Google Trends variation as a proxy for variation in investor attention and show that an increase in searches predicts higher stock prices in the short term and a price reversal in the long term; and Stephens-Davidowitz (2014), who uses it as a proxy for regional variation in racial animus and shows that it predicts the observed regional variation in Obama's vote share.

index for each keyword to obtain predicted values of the UK Google search index. Next, we aggregate those fitted values to obtain predicted values of the composite measures of search intensity that we use in our main specification and carry out a second-stage estimation by regressing charitable donations on the predicted composites.

4 Estimation results

Estimation results from the baseline specification, using the narrow level of aggregation, are reported in Table 5. Column (1) shows estimates of own salience effects on donations frequency from a fixed-effects estimation. The coefficients on ΔGT^{10} and ΔGT^{3} are positive and statistically significant (the superscripts here refer to k, the number of the most prominent keywords used to construct our mapping). According to the estimates, a one-unit increase in search intensity for all 10 keywords can lead to a 33.8% rise in the number of donations. For a one-unit increase in search intensity for the first three keywords, the number of donations can increase by around 13.9%. For ΔGT^{5}, we find a positive but statistically insignificant coefficient.

Column (2) presents estimation results for the effect of changes in online search activity on the volume of donations using the fixed-effects model. The coefficients on our variables of interest, ΔGT^{10}, ΔGT^{5} and ΔGT^{3} are all positive and statistically significant. The regression coefficients show that a one-unit rise in search intensity for all ten keywords may result in a 113.5% increase in the amount of donations. For a one-unit increase in search intensity for the first five and three keywords, the donated amount can increase by around 59% and 60%, respectively.

Since we are mainly concerned with the relationship between online search activity on donation behavior in all observed weeks, we report the Tobit model's marginal effects on the unconditional log Frequency in column (3) and log Amount in column (4). The results indicate that an increase in search intensity for all ten keywords by one unit leads to a 76.1% increase in the number of donations and a 249.6% increase in the volume of donations. A one-unit increase in search intensity for the first three keywords is associated with a 41.3% rise in donation frequency and a 148.8% rise in the amount donated. These results are consistent with those of fixed-effects models in showing a positive association between online search intensity and charitable donations.

Because of the purely mechanical procedure through which we derive our measures of search intensity, our regressions are based on a semantically coarse mapping

Table 5: Baseline regression results

	log Frequency		log Amount	
	(1)	(2)	(3)	(4)
ΔGT^{10}	0.338***	1.135*	0.761***	2.496*
	(0.128)	(0.602)	(0.254)	(1.440)
Obs	10,869	10,869	10,869	10,869
R^2	0.087		0.068	
	log Frequency		log Amount	
ΔGT^{5}	0.151	0.590	0.467**	1.483
	(0.095)	(0.434)	(0.232)	(1.059)
Obs	10,869	10,869	10,869	10,869
R^2	0.087		0.068	
	log Frequency		log Amount	
ΔGT^{3}	0.139*	0.600*	0.413**	1.488*
	(0.080)	(0.320)	(0.181)	(0.781)
Obs	10,869	10,869	10,869	10,869
R^2	0.087		0.068	

Notes: The table presents results for the baseline regressions for different shock variables. The dependent variable is the natural logarithm of the number of donations in columns (1) and (2), and the natural logarithm of the amount donated in columns (3) and (4). Results of fixed effects models are shown in columns (1) and (3). Unconditional marginal effects of Tobit models are shown in columns (2) and (4). In all regressions, constant and time dummies are included but not reported. Robust standard errors are shown in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

between charities' missions and search topics. Despite this, we find convincing evidence of positive salience effects. One possible interpretation of the estimates is that an increase in online searches around a particular topic proxies for greater salience of that topic to donors. Loosely speaking, greater salience can be thought of as lowering the "salience-adjusted price" of giving to donors—which, if the price elasticity of giving is high enough in absolute value, raises the level of giving (Meer 2014; Karlan and List 2007; Almunia et al. 2020).[16] This result is robust to using different measures of online search intensity and estimation methods.

Columns (2) and (3) of Table 6 report regression results from 2SLS IV estimations, which are consistent with findings from our main specification. The first-stage results reported in column (1) indicate that higher online search intensity in the US is associated with higher online search intensity in the UK for the same topic. In addition, under-identification and weak identification tests, respectively the Lagrange Multiplier (LM) test and the F test, reveal that the instrument is relevant.

The larger coefficient found in the IV estimates, when compared to that obtained in our main specification, suggests that proxying variation in salience to UK donors by the variation in searches by UK residents involves more measurement error that focusing on the component of that variation that can be predicted (through the first stage of our IV specification) by variation on searches elsewhere, resulting in a stronger attenuation bias for the non-IV estimates. A plausible interpretation for this finding is that the measure of variation in non-UK searches, which is based on a large sample of Internet users, is a comparatively less noisy indicator of news-induced shocks to the salience of certain topics to UK donors than the corresponding UK-based measure is, with the latter incorporating a comparatively larger component of idiosyncratic variation in searches about topics that remain consistently salient to UK donors.[17]

A statistically significant relationship between online salience and donations is also

[16] As mentioned earlier, the notion of "salience-adjusted price" can be best understood by analogy with the idea of "quality-adjusted price". E.g., if the price of one unit of good 1 is the same as the price of one unit of good 2, but good 2 is of higher quality, then the effective price of good 2, adjusted for quality is lower than that for good 1. Likewise if the salience of a particular charitable cause increases, with the same £1 donated to that cause a donor can now "buy" donations towards a cause that has greater salience, and so the salience-adjusted price of giving decreases.

[17] Comparing the serial correlation of the Google Trends based UK measure with that of the corresponding US measure (our instrument) provides some corroboration for this interpretation: serial correlation is negative for both measures but it is stronger for the UK measure, indicating higher-frequency fluctuations.

Table 6: IV regression results

	ΔGT^{10}	log Frequency	log Amount
	(1)	(2)	(3)
	0.371***	0.642*	2.559**
	(0.010)	(0.381)	(1.086)
Obs	420,710	10,869	10,869
R^2	0.213	0.103	0.074
First-stage LM test		<0.001	<0.001
First-stage F statistic		1420.56	1420.56

Notes: The table presents 2SLS IV regression results corresponding to our main specification (Table 5). Column (1) reports results for the first stage, where the dependent variable is the UK Google search index for individual keywords. Columns (2) and (3) present IV regression results respectively for the natural logarithm of the number of donations and the natural logarithm of the amount donated. The US Google search index for individual keywords is the main independent variable in column (1), while the UK composite search intensity measure for ten keywords, as predicted from the first stage, is the main independent variable in columns (2) and (3). In all regressions, constant and time dummies are included but not reported. Robust standard errors are shown in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

in evidence if we allow the data to tell us which keyword searches we should focus on as being predictors of variation in donations to charities in a particular category. Results of regressions on LASSO-selected keywords from specification (6) are presented in Table 7. They suggest that out of all keywords of each category, only the first keyword selected by LASSO has a positive and significant association with text donations. Specifically, a one-unit increase in online search intensity of the first keyword would lead to an increase of 135.1% in the frequency of donation, and a rise of 99.2% in the volume of donations in the regression with three keywords.

Table 8 provides evidence of dynamic effects with respect to the number of donations (column (1)) and the amount donated (column (2)) obtained by System-GMM estimation. The lagged dependent variable is treated as endogenous, while search intensity is assumed to be predetermined. The instrument set includes $t-3$ and $t-4$ lags for both difference and level equations. Coefficients on lagged variables are positive and significant at the 1% level. Estimated effects of variation in search intensity on the number of donations remain positive and significant—at the 1% level using ten and five search keywords, and at the 5% level using three search keywords.

Table 9 reports results of estimates of cross-salience effects on frequency (in column (1)) and amount of donations (in column (2)), for the cross-salience measure defined in (3). The coefficients on ΔOGT^{10} on both estimations are negative and statistically significant. More specifically, a one-unit increase in the cross-category search intensity measure for ten keywords can decrease the number of donations and the donated amount by 42.2% and 80.4%, respectively. A possible explanation is that a surge in the salience of other causes can reduce the comparative salience of the cause of interest. In other words, donations towards a particular charitable cause do not only respond to changes in own salience-adjusted price of giving but also to the salience-adjusted prices of giving of other causes. This result shows evidence of a "crowding out" effect across charitable categories, which has also been well documented in Reinstein (2011), Cairns and Slonim (2011), and Filiz-Ozbay and Uler (2019). When we repeat the same exercise using the weighted cross-salience measure defined in (4), we obtain very similar results (Table 10). To investigate whether this heterogeneity reflects heterogeneity in charity organizational characteristics, we use financial information on charities' total income in 2018 to classify charities into separate groups, those above median income and those below median income. We then run a regression on a pooled specification that includes interactions with a category-specific indicator variable that takes the value of one if that charity category contains an above median share of charities that are classified as being large. The same approach is used to ob-

Table 7: Regression results for keywords selected by LASSO

	Three keywords		Five keywords	
	(1)	(2)	(3)	(4)
$\Delta GT\_keyword_1$	1.351*	0.992	1.297*	1.037
	(0.742)	(1.116)	(0.747)	(1.104)
$\Delta GT\_keyword_2$	-0.220	-0.498	-0.255	-0.410
	(0.393)	(0.704)	(0.386)	(0.689)
$\Delta GT\_keyword_3$	0.371	0.303	0.386	0.245
	(0.592)	(0.732)	(0.625)	(0.740)
$\Delta GT\_keyword_4$			-0.138	-0.368
			(0.355)	(0.575)
$\Delta GT\_keyword_5$			0.187	-0.113
			(0.276)	(0.481)
Obs	2,336	2,336	2,336	2,336
R^2	0.148	0.129	0.148	0.129

Notes: The table presents results for the fixed-effects models with search intensities for most important keywords as selected by LASSO. The dependent variable is the natural logarithm of the number of donations in columns (1) and (3), and the natural logarithm of the amount donated in columns (2) and (4). Results of models with three keywords are shown in columns (1) and (2). Results of models with five keywords are shown in columns (3) and (4). In all regressions, constant and time dummies are included but not reported. Robust standard errors are shown in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

Table 8: Dynamic effects

	log Frequency			log Amount		
	(1)	(2)	(3)	(4)	(5)	(6)
ΔGT^{10}	0.292***			0.327		
	(0.100)			(0.225)		
ΔGT^{5}		0.269***			0.438*	
		(0.101)			(0.250)	
ΔGT^{3}			0.188**			0.306
			(0.083)			(0.207)
log Frequency $_{t-1}$	0.720***	0.719***	0.724***			
	(0.177)	(0.177)	(0.178)			
log Amount $_{t-1}$				0.565***	0.565***	0.569***
				(0.167)	(0.167)	(0.168)
Obs	10,734	10,734	10,734	10,734	10,734	10,734
AR(2)	0.762	0.758	0.757	0.923	0.929	0.925
Hansen	0.103	0.107	0.108	0.364	0.366	0.367

Notes: The table presents results for the dynamic-effect regressions using two-step system GMM for different shock variables. The dependent variable is the natural logarithm of the number of donations in columns (1) to (3), and the natural logarithm of the amount donated in columns (4) to (6). We treat the lagged dependent variable as endogenous, while search intensity is assumed to be predetermined. Constant and time dummies are included, but not reported. Standard errors are shown in parentheses. Hansen (p-value reported) is the test for over-identifying restrictions. AR(2) (p-value reported) is the test for second-order serial correlation. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

Table 9: Cross-salience effects

	log Frequency			log Amount		
	(1)	(2)	(3)	(4)	(5)	(6)
ΔGT^{10}	0.328**			0.741***		
	(0.128)			(0.253)		
ΔGT^{5}		0.146			0.459**	
		(0.096)			(0.228)	
ΔGT^{3}			0.134*			0.407**
			(0.081)			(0.180)
ΔOGT^{10}	−0.422**			−0.804*		
	(0.193)			(0.423)		
ΔOGT^{5}		−0.267			−0.535	
		(0.173)			(0.401)	
ΔOGT^{3}			−0.242			−0.455
			(0.159)			(0.368)
Obs	10,869	10,869	10,869	10,869	10,869	10,869
R^2	0.074	0.073	0.073	0.050	0.050	0.050

Notes: The table presents results for the cross-salience effect regressions for different specifications of ΔGT and ΔOGT. The dependent variable is the natural logarithm of the number of donations in columns (1) to (3), and the natural logarithm of the amount donated in columns (4) to (6). Constant and time dummies are included but not reported. Robust standard errors are shown in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

Table 10: Cross-salience effects with weighted ΔOGT variable

	log Frequency			log Amount		
	(1)	(2)	(3)	(4)	(5)	(6)
ΔGT^{10}	0.326**			0.730***		
	(0.128)			(0.254)		
ΔGT^{5}		0.144			0.452**	
		(0.096)			(0.228)	
ΔGT^{3}			0.134			0.403**
			(0.081)			(0.180)
ΔOGT^{10}	−0.425**			−0.793*		
	(0.196)			(0.433)		
ΔOGT^{5}		−0.267			−0.521	
		(0.176)			(0.409)	
ΔOGT^{3}			−0.242			−0.443
			(0.161)			(0.376)
Obs	10,869	10,869	10,869	10,869	10,869	10,869
R^2	0.074	0.073	0.073	0.050	0.050	0.050

Notes: The table presents results for the cross-salience effect regressions for different specifications of ΔGT and ΔOGT. The dependent variable is the natural logarithm of the number of donations in columns (1) to (3), and the natural logarithm of the amount donated in columns (4) to (6). Constant and time dummies are included but not reported. Robust standard errors are shown in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

tain indicators for whether a charity category includes an above median proportion of London-headquartered charities and whether it includes a below-median proportion of charities that operate at the national level rather than only locally (i.e., they are observed to be active in at least three distinct geographical regions). Estimation results from these specifications (Table 11) give no indication that variation in these organizational characteristics plays a significant role.

Table 12 presents estimates of heterogeneous salience effects on giving to different causes obtained from a specification where the search intensity measures are interacted with indicators of charity categories. According to the estimates, Arts, Culture & Education is the most salience-sensitive category, followed by Religious & Other Professional Organizations. The category least sensitive to salience is Women, Family & Health. Giving to Other Social Issues and to Animal & Nature causes do not seem to correlate with changes in the intensity of relevant online searches (at least, in the way we measure them). There are several possible reasons for this heterogeneity. It may reflect genuine substitution patterns in donors' preferences. Or it may reflect differences in online attention across the types of donors who give to different causes; or differences across charity types in the degree of semantic ambiguity of the mapping that we use.

These differences may also reflect other dimensions of heterogeneity across charities. In particular, larger organizations may have a comparatively stronger marketing focus and produce mission statements that are better aligned with how individuals carry out online searches. In this case, a comparatively higher concentration of larger charities in certain areas could account for the heterogeneity in estimated effects.

Each donation in our data has a timestamp that can be used for splitting sample by the timing of donations. Estimates in Panel A of Table 13 show that the relationship between donations and variation in online search is stronger during weekdays than on weekends. More specifically, a one-unit increase in search intensity corresponds to an increase of 28.4% in donation frequency during weekdays, compared with 14.9% during weekends. In the same vein, changes in amounts donated during weekdays are roughly double those donated during weekends. Moreover, the results in Panel B indicates that estimated effects for donations made in the evening are statistically significant, while they are insignificant for those made in the morning.

Our donations data allow us to track the same donor over time. Furthermore, some donors also report their age category. Given this information we can single out older donors (45+ years old) and habitual donors (those with at least of three donations records). Table 14 reports results for sub-samples split by these characteristics. With

Table 11: Estimates of heterogeneous effects by charity characteristics

	log Frequency		log Amount	
	(1)	(2)	(3)	(4)
	Panel A: charity's size			
ΔGT^{10}	0.300*	0.301	0.825***	0.748
	(0.158)	(0.194)	(0.301)	(0.479)
$LARGE \times \Delta GT^{10}$	0.085	0.021	-0.146	-0.108
	(0.159)	(0.220)	(0.355)	(0.544)
Obs	10,869	10,869	10,869	10,869
R^2	0.087		0.068	
	Panel B: charity's location			
ΔGT^{10}	0.361**	0.301	0.880***	0.703
	(0.164)	(0.204)	(0.336)	(0.505)
$LONDON \times \Delta GT^{10}$	-0.042	0.021	-0.213	-0.008
	(0.172)	(0.222)	(0.368)	(0.549)
Obs	10,869	10,869	10,869	10,869
R^2	0.087		0.068	
	Panel C: charity's operating areas			
ΔGT^{10}	0.357**	0.388**	0.908***	0.943**
	(0.151)	(0.190)	(0.286)	(0.463)
$REGIONAL \times \Delta GT^{10}$	-0.056	-0.187	-0.415	-0.598
	(0.164)	(0.225)	(0.390)	(0.558)
Obs	10,869	10,869	10,869	10,869
R^2	0.087		0.068	

Notes: The table presents evidence on heterogeneous effects for a Google Trends composite regressor based on ten keywords. Panels A, B and C show heterogeneous effects across charity sizes, charity locations and charity regions, respectively. The dependent variable is the natural logarithm of the number of donations in columns (1) and (2), and the natural logarithm of the amount donated in columns (3) and (4). Results of fixed-effects models are shown in columns (1) and (3). Unconditional marginal effects of Tobit models are shown in columns (2) and (4). In all regressions, constant and time dummies are included but not reported. Robust standard errors are shown in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

Table 12: Heterogeneity of responses across broad donation categories

	log Frequency			log Amount		
	ΔGT^{10}	ΔGT^{5}	ΔGT^{3}	ΔGT^{10}	ΔGT^{5}	ΔGT^{3}
	(1)	(2)	(3)	(4)	(5)	(6)
Arts/Culture/Education	0.572***	0.417***	0.356***	1.129***	1.011***	0.851***
	(0.155)	(0.107)	(0.070)	(0.343)	(0.324)	(0.238)
Women/Family/Health	0.030	0.102	0.543*	0.515	0.174	0.954**
	(0.204)	(0.156)	(0.303)	(0.421)	(0.418)	(0.470)
Religious/Professional Orgs.	−0.032	−0.041	0.462***	0.164	−0.111	1.019***
	(0.136)	(0.102)	(0.166)	(0.269)	(0.190)	(0.363)
Others	−0.104	−0.014	0.266	0.063	0.107	0.403
	(0.172)	(0.134)	(0.197)	(0.353)	(0.325)	(0.486)

Notes: The table presents results for linear combinations of categorical-effect regressions for different shock variables. The dependent variable is the natural logarithm of the number of donations in columns (1) to (3), and the natural logarithm of the amount donated in columns (4) to (6). Constant and time dummies are included but not reported. Robust standard errors are shown in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

Table 13: Results for sub-samples by timing of donation

Panel A: Weekend vs. weekday donations

	Weekend donations		Weekday donations	
	log Frequency	log Amount	log Frequency	log Amount
	(1)	(2)	(3)	(4)
ΔGT^{10}	0.149*	0.396*	0.284*	0.710***
	(0.079)	(0.203)	(0.148)	(0.271)
Obs	7,893	7,893	10,262	10,262
R^2	0.092	0.081	0.080	0.062

Panel B: Morning vs. evening donations

	Morning donations		Evening donations	
	log Frequency	log Amount	log Frequency	log Amount
	(1)	(2)	(3)	(4)
ΔGT^{10}	0.133	0.488	0.308**	0.784***
	(0.107)	(0.303)	(0.133)	(0.282)
Obs	8,980	8,980	10,076	10,076
R^2	0.096	0.080	0.083	0.063

Notes: The table presents results for regressions of sub-samples split by donation timing for a Google Trends composite regressor based on ten keywords. Panels A and B show results for a sub-sample of weekend vs. weekday and morning vs. evening donations, respectively. The dependent variable is the natural logarithm of the number of donations in odd columns (1), (3), and the natural logarithm of the amount donated in even columns (2), (4). Constant and time dummies are included but not reported. Robust standard errors are shown in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

Table 14: Results for sub-samples by donor characteristics

Panel A: Younger vs. older donors

	Younger donors		Older donors	
	log Frequency	log Amount	log Frequency	log Amount
	(1)	(2)	(3)	(4)
ΔGT^{10}	0.385*	0.662	0.258*	0.694
	(0.190)	(0.484)	(0.146)	(0.507)
Obs	1,792	1,792	3,490	3,490
R^2	0.132	0.139	0.091	0.093

Panel B: Habitual vs. non-habitual donors

	Habitual donors		Non-habitual donors	
	log Frequency	log Amount	log Frequency	log Amount
	(1)	(2)	(3)	(4)
ΔGT^{10}	-0.004	0.135	0.174	0.286
	(0.103)	(0.207)	(0.114)	(0.199)
Obs	4,759	4,759	9,134	9,134
R^2	0.116	0.112	0.101	0.103

Notes: The table presents results for regressions of sub-samples split by donor characteristics for a Google Trends composite regressor based on ten keywords. Panels A and B show results for a sub-sample of young vs. old and habitual vs. non-habitual donors, respectively. The dependent variable is the natural logarithm of the number of donations in odd columns (1), (3), and the natural logarithm of the amount donated in even columns (2), (4). Constant and time dummies are included but not reported. Robust standard errors are shown in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively. The categorization of donors as habitual or non-habitual is only possible for observations where we have donor ID information, which is why the number of observations in Panel B falls short of the total.

regards to donors' ages (Panel A), younger donors are more likely to be salience-sensitive than older givers, in line with a prior that younger donor should be comparatively heavier users of online searches—the coefficient on the main variable of interest (search intensity) for young donors is larger than that found for older donors. With regards to whether donations are from habitual and occasional donors (Panel B), we do not find statistically significant coefficients for either group.[18]

5 Conclusions

We study the relationship between online salience and charitable giving. We employ a unique dataset on SMS donations from 2013 to 2019, which includes information on the time and date when donations were made, to examine how time variation in the intensity of online search for topics that are related to the activities pursued by different charities is reflected in variation in the frequency and volume of donations made to those charities and to charities that pursue different goals. The charities in the dataset are grouped into categories, and donations to charities in any given category are then linked to Google Trends search scores based on keywords extracted from charities' mission statements.

Our findings are as follows. First, donations correlate with changes in the online salience of the activities pursued by charities (even when these changes are imprecisely measured). The number and volume of donations to a particular charitable cause is positively associated with the intensity of online search activity on topics related to such a cause and negatively associated with online search frequencies on topics related to other causes. Second, there is substantial heterogeneity in salience sensitivity across different categories, timings of donations and types of donors. Donations to charities pursuing Arts & Culture causes are more salience-sensitive than others, while giving to causes related to Women, Family & Health exhibits the least salience sensitivity. Estimated effects are stronger for donations that are made during weekdays rather than on weekends; they are stronger for donations that are made in the evening; and they are stronger for younger donors.

On the whole, these results are strikingly aligned with our priors in terms of how donors should respond to variation in online salience, particularly in light of the unmediated strategy that we follow to derive a mapping from online searches to char-

[18]Results from pooled specifications are presented in the Appendix. These show that estimated effects are stronger for habitual donors than for occasional donors.

ities, and suggest that evidence on patterns of online activities may be a valuable source of information for researchers seeking to uncover the determinants of giving, and may be a good predictor of donors' responses for charities seeking to devise effective fundraising strategies.

References

Almunia, M., I. Guceri, B. Lockwood, and K. Scharf (2020). More giving or more givers? The effects of tax incentives on charitable donations in the UK. *Journal of Public Economics 183*, 104114.

Baker, S. and A. Fradkin (2017). The impact of unemployment insurance on job search: Evidence from Google search data. *Review of Economics and Statistics 99*(5), 756–768.

Bordalo, P., N. Gennaioli, and A. Shleifer (2013). Salience and consumer choice. *Journal of Political Economy 121*(5), 803–843.

Bordalo, P., N. Gennaioli, and A. Shleifer (2016). Competition for attention. *The Review of Economic Studies 83*(2), 481–513.

Bordalo, P., N. Gennaioli, and A. Shleifer (2020). Memory, attention, and choice. *The Quarterly Journal of Economics 135*(3), 1399–1442.

Brown, S., M. Harris, and K. Taylor (2012). Modelling charitable donations to an unexpected natural disaster: Evidence from the US Panel Study of Income Dynamics. *Journal of Economic Behavior & Organization 84*(1), 97–110.

Cairns, J. and R. Slonim (2011). Substitution effects across charitable donations. *Economics Letters 111*(2), 173–175.

Choi, H. and H. Varian (2012). Predicting the present with Google Trends. *Economic Record 88*, 2–9.

Clotfelter, C. (1990). The impact of tax reform on charitable giving: A 1989 perspective. NBER Working Paper No. 3273.

Connolly-Ahern, C. and L. Ahern (2015). Agenda-tapping: Conceptualizing the relationship between news coverage, fundraising, and the First Amendment. *Journal of Nonprofit & Public Sector Marketing 27*, 1–22.

Da, Z., J. Engelberg, and P. Gao (2011a). In search of attention. *Journal of Finance 66*(5), 1461–1499.

Da, Z., J. Engelberg, and P. Gao (2011b). In search of attention. *The Journal of Finance 66*(5), 1461–1499.

Deryugina, T. and B. Marx (2020). Is the supply of charitable donations fixed? Evidence from deadly tornadoes. National Bureau of Economic Research Working Paper No. w27078.

Dilmaghani, M. (2019). Workopolis or The Pirate Bay: What does Google Trends say about the unemployment rate? *Journal of Economic Studies 46*(2), 422–445.

D'Amuri, F. and J. Marcucci (2017). The predictive power of Google searches in forecasting us unemployment. *International Journal of Forecasting 33*(4), 801–816.

Edwards, J. and J. List (2014). Toward an understanding of why suggestions work in charitable fundraising: Theory and evidence from a natural field experiment. *Journal of Public Economics 114*, 1–13.

Eisensee, T. and D. Strömberg (2007). News droughts, news floods, and US disaster relief. *The Quarterly Journal of Economics 122*(2), 693–728.

Filiz-Ozbay, E. and N. Uler (2019). Demand for giving to multiple charities: An experimental study. *Journal of the European Economic Association 17*(3), 725–753.

Fondeur, Y. and F. Karamé (2013). Can Google data help predict French youth unemployment? *Economic Modelling 30*, 117–125.

Gossner, O., J. Steiner, and C. Stewart (2018). Attention please! University of Zurich Economics Working Paper No. 308.

Guzman, G. (2011). Internet search behavior as an economic forecasting tool: The case of inflation expectations. *Journal of Economic and Social Measurement 36*(3), 119–167.

Hand, C. and G. Judge (2012). Searching for the picture: Forecasting UK cinema admissions using Google Trends data. *Applied Economics Letters 19*(11), 1051–1055.

Karlan, D. and J. List (2007). Does price matter in charitable giving? Evidence from a large-scale natural field experiment. *American Economic Review 97*(5), 1774–1793.

Klar, S. and S. Piston (2015). The influence of competing organisational appeals on individual donations. *Journal of Public Policy 35*(2), 171–191.

Korolov, R., J. Peabody, A. Lavoie, S. Das, M. Magdon-Ismail, and W. Wallace (2016). Predicting charitable donations using social media. *Social Network Analysis* *and Mining 6*, 1–10.

Kőszegi, B. and A. Szeidl (2013). A model of focusing in economic choice. *The Quarterly Journal of Economics 128*(1), 53–104.

Krieg, J. and A. Samek (2017). When charities compete: A laboratory experiment with simultaneous public goods. *Journal of Behavioral and Experimental Economics 66*, 40–57.

Meer, J. (2014). Effects of the price of charitable giving: Evidence from an online crowdfunding platform. *Journal of Economic Behavior & Organization, Elsevier 103(C)*, 113–124.

Meer, J. (2017). Does fundraising create new giving? *Journal of Public Economics 145*, 82–93.

Nasir, M. A., T. L. D. Huynh, S. P. Nguyen, and D. Duong (2019). Forecasting cryptocurrency returns and volume using search engines. *Financial Innovation 5*(1), 1–13.

Ottoni-Wilhelm, M., K. Scharf, and S. Smith (2022). Lift and shift: The effect of fundraising interventions in charity space and time. *American Economic Journal: Economic Policy*, forthcoming.

Reinstein, D. (2011). Does one charitable contribution come at the expense of another? *The BE Journal of Economic Analysis & Policy 11*(1).

Rose-Ackerman, S. (1982). Charitable giving and "excessive" fundraising. *The Quarterly Journal of Economics 97*(2), 193–212.

Scharf, K. (2014). Private provision of public goods and information diffusion in social groups. *International Economic Review 55*, 1019–1042.

Scharf, K. and S. Smith (2016). Relational altruism and giving in social groups. *Journal of Public Economics 141*, 1–10.

Sheremeta, R. and N. Uler (2021). The impact of taxes and wasteful government spending on charitable donations. *Experimental Economics 24*(2), 355–386.

Simon, A. (1997). Television news and international earthquake relief. *Journal of Communication 47*, 82–93.

Smith, G. P. (2012). Google internet search activity and volatility prediction in the market for foreign currency. *Finance Research Letters 9*(2), 103–110.

Stephens-Davidowitz, S. (2014). The cost of racial animus on a black candidate: Evidence using Google search data. *Journal of Public Economics 118*, 26–40.

Swamy, V., M. Dharani, and F. Takeda (2019). Investor attention and google search volume index: Evidence from an emerging market using quantile regression analysis. *Research in International Business and Finance 50*, 1–17.

Tobin, J. (1958). Estimation of relationships for limited dependent variables. *Econometrica 26*, 24–36.

Uler, N. (2011). Public goods provision, inequality and taxes. *Experimental Economics 14*(3), 287–306.

Vlastakis, N. and R. N. Markellos (2012). Information demand and stock market volatility. *Journal of Banking & Finance 36*(6), 1808–1821.

Wu, L. and E. Brynjolfsson (2015). The future of prediction: How Google searches foreshadow housing prices and sales. In *Economic analysis of the digital economy*, pp. 89–118. University of Chicago Press.

A Appendix

A.1 Results for sub-samples from pooled specifications

We also explore effects for sub-samples using the following a pooled specification:

$$\ln V^{A}_{Ist} = \beta_0 + \beta_1\, \Delta GT^{Ak}_{Ist} + \beta_2\, D^{s}\, \Delta GT^{Ak}_{Ist} + \tau_{st} + \gamma_{Is} + \epsilon_{Ist}, \quad s \in \{S1,\, S2\}, \tag{8}$$

with $D^s = 1$ if $s \in S$ and $D^s = 0$ otherwise; where S is a sub-sample of observation alternatively defined in relation to donor age, whether donors are occasional or habitual donors, whether donations are made on weekends or on weekdays, or whether they are made during the daytime or in the evening.

Results for own-salience effects are presented in Tables 15 and 16. The only statistically significant (positive) differential effect in this case is that of habitual vs. non-habitual donors.

A.2 Keyword selection by LASSO

The Least Absolute Shrinkage and Selection Operator (LASSO) estimator is a $\ell 1$-norm penalized least squares estimator that solves the following optimization problem:

$$\hat{\beta} = \arg\min_{\beta} \left\{ \left(y - X'\beta\right)' \left(y - X'\beta\right) - \lambda|\beta| \right\},$$

Table 15: Results from pooled specification with interactions with timing of donation

	log Frequency			log Amount		
	ΔGT^{10}	ΔGT^{5}	ΔGT^{3}	ΔGT^{10}	ΔGT^{5}	ΔGT^{3}
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Weekend vs. weekday donations						
ΔGT	0.229**	0.095	0.103	0.646***	0.420**	0.352**
	(0.114)	(0.091)	(0.079)	(0.222)	(0.213)	(0.178)
Weekend $\times$ ΔGT	-0.010	0.022	-0.006	-0.196	-0.187	-0.123
	(0.090)	(0.092)	(0.079)	(0.231)	(0.237)	(0.185)
Obs	18,155	18,155	18,155	18,155	18,155	18,155
Panel B: Morning vs. evening donations						
ΔGT	0.244**	0.129	0.124	0.761***	0.571***	0.468***
	(0.119)	(0.088)	(0.080)	(0.258)	(0.216)	(0.181)
Morning $\times$ ΔGT	-0.008	-0.031	-0.053	-0.238	-0.419**	-0.316*
	(0.072)	(0.065)	(0.065)	(0.217)	(0.187)	(0.169)
Obs	19,056	19,056	19,056	19,056	19,056	19,056

Notes: The table presents results for regressions of combined sub-samples split by donation timing. The dependent variable is the natural logarithm of the number of donations in columns (1) to (3), and the natural logarithm of the amount donated in columns (4) to (6). Constant and time dummies are included but not reported. Robust standard errors are shown in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

Table 16: Results from pooled specification with interactions with donor characteristics

	log Frequency			log Amount		
	ΔGT^{10}	ΔGT^{5}	ΔGT^{3}	ΔGT^{10}	ΔGT^{5}	ΔGT^{3}
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Younger vs. older donors						
ΔGT	0.464**	0.325**	0.247**	1.110*	0.846**	0.630**
	(0.194)	(0.131)	(0.107)	(0.591)	(0.374)	(0.292)
Older $\times$ ΔGT	-0.068	-0.077	-0.050	-0.104	-0.053	-0.007
	(0.065)	(0.064)	(0.056)	(0.285)	(0.287)	(0.251)
Obs	5,282	5,282	5,282	5,282	5,282	5,282
Panel B: Habitual vs. non-habitual donors						
ΔGT	0.176	0.026	0.045	0.262	0.037	0.105
	(0.111)	(0.088)	(0.075)	(0.178)	(0.148)	(0.122)
Habitual $\times$ ΔGT	0.107	0.069	-0.009	0.314*	0.186	0.028
	(0.082)	(0.067)	(0.053)	(0.173)	(0.139)	(0.107)
Obs	13,895	13,895	13,895	13,895	13,895	13,895

Notes: The table presents results for regressions of combined sub-samples split by donor characteristics. The dependent variable is the natural logarithm of the number of donations in columns (1) to (3), and the natural logarithm of the amount donated in columns (4) to (6). Constant and time dummies are included, but not reported. Robust standard errors are shown in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

where λ is a fixed non-negative regularization parameter (or so-called tuning parameter), y is the dependent variable, X is a matrix of independent variables and β is the vector of the corresponding parameters. This is similar to the traditional regression approach of minimizing the sum of squares, but with an additional penalty term of the form $\lambda|\beta|$.

The higher the value of λ, the further the model's estimated parameters, $\hat{\beta}$, are shrunk towards zero, with more of them taking on a value of zero (i.e., more regressors are removed from the model). The accuracy of the model can be evaluated by the Mean Squared Error (MSE) as follows:

$$MSE = \frac{1}{n} \left(y - \hat{y}\right)' \left(y - \hat{y}\right),$$

where $\hat{y}$ are the predicted values and y the observed values. The lower the MSE is, the more accurate the model is. Our regularization parameter, λ, is chosen based on a ten-fold cross validation criterion and on MSE minimization.

A.3 Aggregation criteria for weekly donations

Table 17 reports results from our baseline specification for different aggregation conventions with respect to weekly donations. Estimated effects are most significant when we allow for a lag of four days (i.e., weekly donations starting on a Thursday) and five days (i.e., weekly donations starting on a Friday, the convention that we adopt).

Table 17: Regression results for different aggregation criteria for weekly donations

Shift (days)	0	1	2	3	4	5	6	7
ΔGT^{10}	0.130	0.170	0.204	0.231	0.272**	0.338***	0.152	0.185
	(0.145)	(0.145)	(0.158)	(0.142)	(0.124)	(0.128)	(0.147)	(0.141)
Obs	10,884	10,883	10,877	10,875	10,879	10,869	10,860	10,854
R^2	0.086	0.089	0.090	0.088	0.087	0.087	0.086	0.087

Notes: The table reports regression results for different time shifts. Columns (1) to (8) represent zero to seven days of delay in donation, respectively. The dependent variable is the natural logarithm of the number of donations. Constant and time dummies are included but not reported. Robust standard errors are shown in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

A.4 Mission keywords for three individual charities

Table 18: Keywords extracted from charities' mission statements: three examples

Charity	Keywords
Abacus Belsize Primary School	school, Belsize, trust, abacus, support, work, play, academy, deliver, primary
Aberdeen Performing Arts	Aberdeen, art, perform, diversity, heart, individuality, everyone, respect, engage, mission
ABF The Soldiers' Charity	soldier, veteran, support, family, help, army, charity, need, past, british owner