Online Salience and Charitable Giving: Evidence from SMS Donations*

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Abstract

We explore the link between online attention 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 online searches for words that appear in those charities' mission statements. The results suggest that an increase in the online 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. We uncover evidence of positive own salience effects and negative cross salience effects on donations.

KEY WORDS: Charitable Donations, Online Search, News Shocks
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1 Introduction

The jury is still out on why people make charitable donations. Irrespective of what the motives for giving might be, useful insights about giving responses can be gained by looking at 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 about 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, 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).[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 donors "buy" when they make a donation to charities that pursue activities related to that issue or goal—can attract donations towards those charities (an *own salience effect*) while driving away 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 gives 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]

The charities in the dataset are grouped into categories on the basis of their mis-

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

[2]Theoretical microfoundations for the role of salience in consumer demand are presented in Gossner et al. (2018).

[3]Texting is among the top three channels of donations in the UK (fast.MAP and the Institute of Fundraising, 2016, *Fundraising Media DNA*), and so evidence on donors' responses with respect to text donations can be taken as fairly indicative of donation responses in the wider population.

sion statements, 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, searches are not themselves a source of exogenous variation but are a close proxy for exogenous events that would affect donation behavior (as well as online search behavior). 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 might 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 might raise donations towards those charities *and* reduce donations towards other charities—a *crowding out* or "cannibalization" effect.[4] But if we interpret salience effects as being equivalent to changes in the salience-adjusted quality (or in salience/quality-adjusted prices), demand theory gives us a less clear-cut answer: if donations as a whole are sufficiently more substitutable for private consumption than they are with one another, then, in principle, cross-effects could even be positive. These predictions are in line with our findings on cross salience effects. The results 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—how donors respond to unanticipated events such as nat-

[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 (Edwards and List 2014; Meer 2017; Reinstein 2011; Cairns and Slonim 2011).

ural disasters (Simon 1997; Eisensee and Strömberg 2007; Brown et al. 2012; Ottoni-Wilhelm et al. 2017; Deryugina and Marx 2020).[5] Our paper is closely related to those studies but departs from them by focusing on online salience, as proxied by variation in online search intensity, rather than on charities' disaster appeals, and by studying effects on general donations rather than just on crisis fundraising.

Donation responses to changes in the intensity of online searches for relevant keywords exhibit a significant degree of persistence beyond the period in which the change occurred. Responses are heterogeneous across different areas of activity, but there is little indication that, within given areas of activity, responses are different for charities that have different organizational characteristics—whether charities are large or small, whether or not 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. Responses 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 about online search behavior have been widely used in several areas of economics research. Some studies have used indicators of online job search 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 measure of investor attention, which can predict future stock price (Da et al. 2011), or a measure of 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 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.[6]

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

[6] 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) focuses on the relationship between donations

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 comes from two main sources. For donations, we employ a unique dataset of daily SMS text giving over the period between 2013 and 2019 from National Funding Scheme (NFS), the largest fundraising platform in the UK. NFS is a charity that operates as an intermediary to facilitate the fundraising activities of UK-based charitable organisations, offering subscribers a facility for making cash donations via SMS to a fundraising campaign of their choice. 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 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 donations 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 donor ID.

Descriptive statistics for our donations data are summarized in Table 1. On average, we observe higher volume of donations on weekdays than on weekends. The average daily amount of donations 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 noticeable differences in the amounts donated by donors of different

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and social media activity (rather than online salience more generally), describing a model of information diffusion via Twitter chats, and testing it using data on donations towards disaster relief. A related theoretical analysis of how information diffusion in social groups is reflected in charitable donations is Scharf (2014).

Table 1: Descriptive statistics for donations data

	Mean Donation (£)	Std. Dev.	Number of Donations
All	26.19	214.39	37,071
Weekend	17.17	121.21	12,596
Weekday	30.83	248.99	24,475
Morning	34.10	273.90	8,254
Evening	23.93	193.96	28,817
Younger donors	23.80	55.36	715
Older donors	100.29	537.68	661
Habitual donors	5.99	3.40	1,983
Non-habitual donors	5.98	3.85	25,402

characteristics. More specifically, older donors (those who belong to the 45-54 and 55+ age ranges) on average give four times more than do young donors (those who belong to under 25, 25-34, 35-44 age ranges), £100.29 vs. £23.80, respectively. The average donation size by non-habitual givers (those for which 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. After removing stop words, we extract from each of these the unstructured text statements the ten most frequent keywords using *Python NLTK* library. These keywords are then sorted by frequency and by order of occurrence. As our analysis focuses on donation aggregates by charity type, we manually categorize organisations into groups based on these charitable missions at two different levels. The more narrowly-defined categorization includes 134 separate groups of charities, while the more broadly-defined categorization includes four groups of charities. 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.[7] This allows us to categorize charities by size (revenues) and location (based on their headquarters' address). We also categorize charities on the basis of their geographical areas of operations (local vs. national) on the basis of 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 donations 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 donations outcomes: number of donations and total amount donated—i.e. $v \in \{Frequency, Amount\}$. Donations data are aggregated to 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 bulk of donations in our data are reported during the week-

[7] `https://www.gov.uk/government/organisations/charity-commission` and `https://www.oscr.org.uk/`.

Table 2: Categorization of charities

Arts/Culture/Education	architecture, education, library, research, science education, science museum, children education, art, arts and culture, art education, art gallery and museums, art museums, ballet, black history and culture, children and arts, cinema, circus, contemporary art, contemporary art festivals, crafts, cricket, cultural education, culture, dance, film, galleries, gymnastics, heritage, medical museums, modern music, museums, music, musical organisations, music festivals, opera, orchestra, painting, performing arts, photography, printmaking, puppets, regimental museum, sport, theatre, windmill museum
Family/Women/Health	women, women breastfeeding, women childbirth injuries, women's mental health, abortion, children in violence, disabled children, elderly, family, youth, carer, adrenoleukodystrophy, children health, attention deficit hyperactivity disorder, autism, birth trauma, blood cancer, brain injury, breastcancer, cancer, charcot-marie tooth disease, chronic illness, cleft palate, dyslexia, healthcare, health care coastal, heart disease, HIV, hyperigm, idiopathic intracranial hypertension, learning disability, drugs & alcohol addiction
Religious/Professional Orgs.	evangelical church, baptist church group, cathedrals, catholic church, catholic youth, charity assistance, christian refugee, church, church community, church group, armed forces, civil servants, police, farmers, pharmacists
Others	drugs, earning an income, foodbanks, homeless, hunger, rescue service, LBGT, Kenyan community, community, disabled, animals, botanical gardens, bulldogs, conservation, dogs, environment, forest, natural disaster, park, plants and fungi

end, when donors are off work and have more time to give 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 start on the following Friday. A systematic comparison of different time aggregation criteria (shown in Table 16 in the appendix) lends support to this choice.[8]

We draw on the Google Trends platform to measure the variation in online search activity by topic. The Google Trends website reports the weekly frequency of Google engine searches for a given keyword originating from a specific geographical region. Using a Python script, we scrape data on weekly search in the UK for the most important keywords appearing in the mission statements the charities in our donations dataset. Since Google Trends data is not available before the end of 2014, we only keep donations data covering from week 49 of 2014 to week 41 of 2019, obtaining a final sample of 10,869 unique observations.

Using this information, we construct an aggregate measure of variation in online salience for each category. This "search shock" 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:

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

where ΔGT^{Ak}_{It} denotes the search shock of 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 methodologically parsimonious; more importantly, it is methodologically conservative, in that it minimizes the role played

[8]Table 16 shows that results from our main specification are qualitatively similar when we use different weekly donations windows, but, as should be expected, responses are most clear-cut when the donation window starts on a Friday.

by the researcher in defining semantic connections.

To study cross-salience effects, we also construct a measure of cross-category search shock. This measure 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 search shock 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 search shock 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 main variables in our sample. As a result of the normalization method used by Google Trends in reporting of information, the sample mean values of the search shock variables, ΔGT^{Ak} and ΔOGT^{Ak}, are all close but not exactly equal to zero. As for donations, typically each charitable category receives around two text donations with the total amount of £67 at weekly frequency. On average, during a week, more than one fourth of the charitable groups receive funds via text giving.

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

3 Empirical strategy

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

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

Table 3: Descriptive statistics for Google Trends-based indicators

	Mean	Std. Dev.	Percentile 25%	50%	75%	Obs
ΔGT^3	0.000	0.081	-0.031	-0.001	0.030	10,869
ΔGT^5	0.000	0.066	-0.029	-0.002	0.027	10,869
ΔGT^{10}	0.000	0.059	-0.027	-0.002	0.023	10,869
ΔOGT^3	0.000	0.040	-0.019	-0.002	0.016	10,869
ΔOGT^5	0.000	0.040	-0.018	-0.002	0.014	10,869
ΔOGT^{10}	0.000	0.044	-0.020	-0.003	0.015	10,869

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.

where $\ln V_{It}^{A}$ is the natural logarithm of aggregate donation outcome for category I at level of aggregation A in week t; ΔGT_{It}^{Ak}, the key variable of interest, is the search shock 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 charities missions change much more slowly (and are time-invariant in our sample), and that charity-related motive represents a relatively small subset of the all the motives that drive variation in online word searches as measured by Google Trends, any reverse causation from charities' missions to variation in online searches for the words they include can be clearly ruled out. And although the keywords that we observe in charities' missions may be the endogenous result of competitive selection amongst charities, our empirical strategy does not hinge on variation in keywords across charities being exogenous: all of our empirical specifications includes charity sector fixed effects and so 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 problem of zero donations in several weeks, we re-estimate the equation (5) by using standard Tobit model (Tobin 1958) and compute its unconditional marginal effects.

Using an alternative specification, we select keywords by 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 a number of augmented specifications. To account for possible persistence effects, we add lagged dependent variables into the equation (5). To study 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 search shock 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 interaction terms between shock variables and charitable categories.

Other dimensions of heterogeneity are explored by splitting the sample by donor age (older vs. younger donors), by whether or not 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).

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 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 most prominent keywords used to construct our mapping). According to the estimates, a one-unit increase in search trend shock for all 10 keywords can lead to 33.8% rise in the number of donations. For a one-unit increase in search shock for the first 3 keywords, the number of donations can increase by about 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 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 trend shock for all ten keywords might result in 113.5% increase in the amount of donations. For a one-unit increase in search shock 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 effect of online search activity on donation demand in all observed weeks, we report the Tobit models' marginal effects on the

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.

unconditional log Frequency in column (3) and log Amount in column (4). The results indicate that increasing search shock for all ten keywords by 1 unit leads to a 76.1% increase in the number of donations and 249.6% in the volume of donation. A one-unit increase in search shock for the first three keywords is associated with a 41.3% rise in donation frequency and 148.8% rise in donated amount. 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 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 lowering the "salience-adjusted price" of giving to donors—which, if the price elasticity of giving is large enough in absolute value, raises the level of giving (Meer 2014; Karlan and List 2007; Almunia et al. 2020). This result is robust to using different measures of online search shocks and estimation methods.

Online salience effects on donations are also 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 keyword from specification (6) are presented in Table 6. They suggest that out of all keywords of each category, only the first keyword selected by LASSO has positive and significant effect on text donation. 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 donation in the regression with three keywords.

Table 7 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 shocks are 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. Effects of search shocks 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 8 reports results of estimates of cross-salience effects on frequency (in column

Table 6: 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 shock variables of most important keywords 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 7: 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.

(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-type search shock 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 9).

Table 10 presents estimates of heterogeneous salience effects on giving to different causes obtained obtained from a specification where the search shock variables are interacted with indicators for charity categories. According to the estimates, Arts, Culture & Education is the most salience-sensitive category, followed by Religious & Other Professional Organizations. The least salience-sensitive category is Women, Family & Health. Giving to Other Social Issues and to Animal & Nature causes do not seem to respond to changes in the intensity of relevant online searches (at least, in the way we measure them). There are several possible reasons for this heterogeneity in responses. It may be a refection of genuine substitution patterns in donors' preferences. But it might 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. Then, a comparatively higher concentration of larger charities in certain areas could account for the heterogeneous responses we see.

To investigate whether heterogeneity in responses reflects heterogeneity in charity organizational characteristics, we 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 and below median income. We then run a regression on a pooled specification that includes interactions with a category-specific indicator

Table 8: 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 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 9: 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 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 10: 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.

variable that takes a 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 obtain 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.

Each donation in our data has a timestamp that can be used for splitting sample by timing of donations. Estimates in Panel A of Table 12 show that donors' responses are stronger during weekdays than on weekends. More specifically, for a one-unit increase in search shock would raise donation frequency by 28.4% during weekdays, compared with 14.9% during weekends. In the same vein, changes in amounts donates in response to changes in online search intensity during weekdays are roughly double those during weekends. Moreover, results in Panel B indicates that responses 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 (at least of three donations records). Table 13 reports results for sub-samples split by these characteristics. With regards to donors' age (Panel A), young donors are more likely to be salience-sensitive than older givers, in line with a prior that younger donor should be heavier users of online search—the coefficient on the main variable of interest (search shock) 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.[9]

5 Conclusions

We study the effects of online salience on charitable giving. We employ a unique dataset on SMS donations from 2013 to 2019, which includes information on the time

[9] Results from pooled specifications are presented in the Appendix. These show that habitual donors are more responsive to changes in online salience than occasional donors are.

Table 11: Heterogeneous responses 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 results for the heterogeneous responses regressions for search shock of ten keywords variable. 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: Results for sub-samples by timing of donations

Panel A: Weekends and weekdays 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 and 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 search shock of ten keywords variable. Panels A and B show results for 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 13: Results for sub-samples by donors 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 donors characteristics for search shock of ten keywords variable. Panels A and B show results for 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.

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 on the basis of their mission statements, and donations to charities in any given category are then linked to Google Trends search scores based on key words extracted from those charities' mission statements.

Our findings are as follows. First, donors respond to changes in salience of the activities pursued by different 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, timing 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. Salience effects are stronger for donations that are made during weekdays rather 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 about how donors should respond to variation in online salience—especially in light of the unmediated strategy that we follow to derive a mapping from online searches to charities—and suggest that evidence about patterns of online activities may be a valuable source of information for researchers seeking to uncover the determinants of giving, as well as for charities seeking to devise effective fundraising strategies.

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A Appendix

A.1 Results for sub-samples from pooled specifications

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

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

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 daytime or in the evening.

Results for own-salience effects are presented in Tables 14 and 15. The only statistically significant (positive) differential effect in this case is that for habitual vs. non-habitual donors.

Table 14: 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 donors						
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 donors						
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 15: 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. occasional 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 donors 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.

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:

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

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 more 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 value 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 16 reports results from our baseline specification for different aggregation conventions with respect to weekly donations. Salience 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 16: 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) represents 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.