Giving By the Numbers:
Peer Effects with Online Crowdfunding

A Thesis
Presented to
The Established Interdisciplinary Committee for Mathematics and Economics
Reed College

In Partial Fulfillment
of the Requirements for the Degree
Bachelor of Arts

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May 2020

Approved for the Division
(Mathematics and Economics)

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Acknowledgements

I want to thank a few people.

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Abstract

This thesis investigates the size and nature of peer effects using data collected from the online crowdfunding platform GoFundMe. On a campaign page, the previous five or ten donations are visible to potential donors. This allows for investigation into how the knowledge of these previous donations affects one's own decision to give as well as the size of the donation. I find that people are strongly influenced by the donations that are displayed to them prior to their own donation but the size of the effect is significantly different for men and women. Moreover, the distribution of the displayed donations is important in influencing how people decide to act.

Introduction

In microeconomics the decision of how much to buy is relatively straightforward. A person chooses how much to consume of each good by maximizing their utility, or overall satisfaction, subject to their budget constraint. Their utility, in turn, stems from a set of underlying preferences. These preferences are well-defined, transitive, and constant with respect to time. Holding preferences constant and allowing relative prices to vary is how decision making is generally modeled. However, we know that people are not endowed with a set of immutable exogenous preferences and decisions are rarely made in such vacuum-like conditions.

Oftentimes consumption is visible which allows for social elements to enter into our decision calculations. With highly visible goods such as clothing, it's clear that people do not act independently; rather, we often mimic one another, observing others and mirroring their decisions. We are constantly receiving cues about how people are spending their money, and it can influence how we choose to spend our own money.

Not only do the choices of others matter to us, but what they would think of our own choices matters. One of the most well known sociological phenomena is conspicuous consumption. According to this theory, people spend disproportionately more money on goods that are more visible, like Rolex watches. That is because these goods convey status (Bagwell & Bernheim, 1996). Buying certain goods can help us craft an identity or at least shape the way that we want to be perceived. These social aspects ultimately affect how we make decisions and they are highly malleable, contingent on our knowledge of others' actions or perceptions. This contradicts the idea of immutable predetermined individual preferences, encouraging us to better understand how preferences are shaped by those around us.

This thesis examines how information about the actions of others drives our decisions within the context of charitable giving through analyzing data from the leader in online crowdfunding, GoFundMe (GFM). On the website the previous five donations are visible at the time of donation, creating a natural field experiment where a potential donor is presented with a clear set of information points before making their own donation. This generates a two-fold effect, people are prompted with the responses of others and they have the knowledge that their own donation will be visible unless they choose to make it anonymously. If future donations are largely explained by the displayed donations, this would indicate more mutable preferences whereas a small effect of displayed donations would be evidence that the size of the effect is limited. Furthermore, if anonymous donations adhere to the same pattern then we might presume that the effect is unrelated to social perception of one's donation. However, there is not a strong consensus in the economics literature about how and to what extent an individual's donation decision is impacted by the knowledge of other's donations. Therefore, this thesis attempts to not only confirm the existence and size of peer effects, but also understand in a more general sense how people's donation sizes are shaped by the values they know others have donated.

How much people decide to donate is closely linked to willingness to pay for a public good that is not traded in a market. Economic valuation studies have employed a variety of methods to understand a person's willingness to pay for a public good. These efforts can take the form of stated willingness to pay surveys or choice experiments. The former relies on people correctly expressing their true preferences and the later tries to decipher one's underlying preferences based on their answers to a series of hypothetical questions. Significant peer effects may signal that people's willingness to pay is not absolute; rather, their willingness to pay depends, in part, on their knowledge of what others are contributing.

In the first chapter, I review a heuristic generally referred to as anchoring or anchoring bias that feeds into decision making and is closely tied to this study. I also review two distinct models of giving that carry divergent implications for how people might respond to the donations of others. The second chapter details information about the choice of platform, method of data collection, and various attributes of the data. Finally, in the third chapter, I construct a variety of models ranging from linear regressions to algorithmic approaches to understand how people respond to the donations of others.

Chapter 1

Literature Review

1.1 Models of Giving

A majority of US citizens give to charitable causes each year, with charitable donations now constituting more than 2% of GDP. Moreover, since 1968, the growth in charitable donations has greatly outpaced the growth of the S&P500. Individual donors account for over three quarters of the total number of gifts each year (List, 2011). This means that charitable donations are a non-negligible and increasingly substantial piece of the economy. Yet, beyond the magnitude of the charitable donation sector, the widespread nature of giving makes it worthy of attention especially within economics, a field dedicated to understanding the allocation of scarce resources. The challenge lies in reconciling voluntary wealth transfers with the self-interested utility-maximizing agents that govern microeconomics. The basic question is what makes people compelled to give?

Models used to answer this question generally fall into two categories, one where the benefit from donating is primarily public and the other where it is private. In the case of a public benefit both the donor and other individuals may benefit. For example, when donating to public radio both the donor and others get to listen to the radio station as a result. In contrast, a private benefit is exclusively enjoyed by the donor. This encompasses all the good feelings or abatement of negative feelings the donor might experience from giving. This distinction in the nature of the benefit proves important as it generates divergent implications for how people respond to changes in income or in the price of giving. Vesterlund (2006) notes that if we consider the benefit to be primarily private, then individuals will donate according to how much they value the product of a nonprofit or charity. Conversely, if the benefit is primarily public then someone else's donation provides the same benefits as one's own donation. Given that one can receive the same utility without incurring any cost, people are strongly incentivized to free-ride off of the donations of others. Consequently, when the donations of others increase in size, we would expect an individual's donations to decrease in response. Alternatively, if the benefit obtained by donating is primarily private then changes in the size of others' donations should have no effect on one's own donations. (Vesterlund, 2006).

1.1.1 Classical Model of Giving

The classical model focuses on the public benefit and assumes that the individuals derive utility from the nonprofit's output and their private consumption of the output, treating the contributions of others as given. In this model, each individual has little incentive to give and would be inclined to free-ride off of others' spending. This, in turn, leads to the possibility of complete crowding out (Vesterlund, 2006). In this situation, if the the government increases spending or funding to a certain service it could trigger a reduction of equal magnitude of private sector funding to support the same service. This is because the desired level of output can now be achieved without the contribution of the individual. Both of these implications, complete crowding out and extensive free riding, seem overly pessimistic and offer a poor depiction of what occurs in practice. Indeed, the classical model appears irreconcilable with the empirical evidence on charitable giving (Glazer & Konrad, 2008). Alternative models, which incorporate various private benefits, have been proposed and include avenues to reduce the propensity to free-ride without leading to the extreme outcome of complete crowding out.

1.1.2 Private Models of Giving

Private models of giving allow donors to receive a personal benefit that stems from the act of donating. That is, part of the benefit derived from charitable giving comes from making the donation rather than from the good that it buys. The private model no longer leads us to anticipate dollar-for-dollar crowding out when others donate to a cause that we are interested in; there is an added benefit to making the donation yourself that can't be experienced from another's donation. Further, these models provide a framework in which the incentive to free-ride is substantially weakened for the same reason.

The nature of the personal benefit that a donor obtains has received considerable attention within the charitable donation literature resulting in a large swath of theories designed to account for this donor-specific benefit. Harbaugh suggests that giving may enter the donor's utility function through two distinct mechanisms, the "intrinsic benefit", the donor's own knowledge of what they have given, and the "prestige benefit", which comes from other people witnessing the donor's generosity (Harbaugh, 1998). In an empirical study of lawyers' donations to their law school, he finds evidence that the prestige benefits accounts for a significant portion of donations. However, Harbaugh notes that the prestige benefit and the intrinsic benefit may not enter directly into the donor's utility function but rather as an amount relative to the gifts made by others. Glazer and Konrad (2008) construct a model where donors contribute in order to signal their wealth as with the theory of conspicuous consumption. They note that charitable donations may have some advantages over private goods, because unlike some forms of conspicuous consumption they may be less prohibited by social norms and can be visible to peers that a person does not directly come into contact with.

At the more extreme end of the private models of giving, Tullock suggests that the donor is not directly interested in the well-being of others. Rather, charitable giving allows one to purchase a feeling of satisfaction derived from one's financial sacrifice. This satisfaction in part stems from the benefit to the donor's reputation. He notes that the benefit to reputation is rooted in others' perceptions of the charity's image rather than its true effectiveness. This means that the gift enhances one's reputation when the people who matter to the donor consider the cause to be a worthy one (Tullock, 1966).

The "intrinsic benefit" that Harbaugh comments on is commonly referred to as the "warm glow" in the literature. Models including the so-called "warm glow" have proven to be more consistent with empirical observations and can also help explain diminished free riding and incomplete crowding out (Andreoni, 1989). Furthermore, if donors only care about the provision of a public good, then a charity has no incentive to announce donations sequentially. On the other hand, with donor utility functions that allow for effects like "warm glow" and "snob appeal", then the charity may benefit through sequentially announcing donations (Romano & Yildirim, 2001). Essentially, the announcement of donations converts the simultaneous game into a sequential game. If agents had standard utility functions, as in the classical framework, seeing others donations would likely reduce the size of their own, but with utility functions that are modified to include a private benefit the announcement can be advantageous to the fundraiser. Through allowing individual's donations to be less responsive to the donations of others, these models ease the extreme implications of the classical model.

1.1.3 Signals of Quality

A common fundraising strategy based on the private benefit model of charitable given involves soliciting “leadership gifts” to help inspire future contributions. These gifts are generally very large and occur at the onset of a fundraiser. Many hypothesize that this type of gift provides a signal to other donors about the quality of the charity that will encourage others to also contribute (Andreoni, 2006). In other words, if someone contributes a large sum of money, other potential donors might assume that person has obtained additional information about the quality of the nonprofit or charity and therefore be more inclined to give. Similarly, it has been shown that the total contributions to a cause tend to increase with the initial amount of seed money available for a campaign (List & Lucking-Reiley, 2002). Note that as a campaign approaches the goal amount, two effects emerge. On one hand, donors may be more compelled to free ride off of the donations of others since the fund is more likely to reach the goal even without their contribution. This effect is aligned with the idea that the benefit is primarily public; a donor is free to enjoy the output of the charity reaching its goal regardless of whether or not they played a part in attaining it. The other effect is the “follow-the-leader” component, where a large anonymous gift sends a signal of quality as in the leadership model of Andreoni. From the discrete amounts of seed money they use in their study, it appears that the “follow-the-leader” effect entirely subsumes the propensity to free ride. However, with a wider range of seed amounts (they use 3 levels 10%, 33%, and 67%), the interaction between the two effects is still unknown. This theory can be test with nearly continuous amounts of seed money using the data collected from GFM.

1.2 Heuristics and Biases

The classical and the private models of giving yielded differing narratives for how we would expect one’s own donations to respond to the donations of others. In the classical model, individuals are likely to decrease their donations if the donations of others increase. In the private model, the situation is slightly complicated, in theory the donations of others should not effect one’s own donation since one is rewarded with “warm glow” or “prestige”.Yet, a key feature in both models of giving is the assumption of a rational actor with well defined underlying preferences. From there, they model decisions through a transactional lens; x units of money for y units of prestige. However, the idea of rational agents preforming calculations based on orderly preferences has been steadily undermined since initial efforts by Kahneman and Tversky (1974), who introduced many of the heuristics, or mental shortcuts, that people systematically make use of to guide their actions.

1.2.1 Anchoring

Among Kahneman and Tversky's heuristics is a mechanism termed anchoring. It captures the idea that people base their own predictions of values off of other known values or statements, especially in circumstances of uncertainty. Essentially, when prompted to act or respond to a given question, people tend to use some initial value, even if it is entirely arbitrary, as a starting point to adjust to their final response. However, different initial "anchors" result in different final estimates which are biased in the direction of the initial value presumably due to insufficient adjustment (Tversky & Kahneman, 1974).

In one of the most well known demonstrations of this effect, Kahneman and Tversky asked subjects to estimate the percentage of African countries in the United Nations. Prior to their estimate, a wheel was spun in their presence with numbers between 0 and 100. After observing the number displayed on the wheel, participants were asked to provide their best estimate of the percent. When 10 was spun the median estimate was 25 percent and when 65 was spun the median estimate was 45 (Tversky & Kahneman, 1974). This shows the strength that arbitrary values have in influencing people's estimates of reality, even when the anchors are unrelated to the question at hand.

While in this example, there is clearly a true value for the statement that people are attempting to estimate, the anchoring effect can also manifest in scenarios that lack a factually true value. In charitable donation scenarios, people are generally free to donate any amount. Here, the uncertainty lies not in the estimation of some true value, but rather in determining a course of action (i.e. whether to donate and, if so, the amount to donate) when it is unclear how one should act.

In one experimental study of charitable giving, undergraduate students were asked to complete a survey indicating how much they would give to a needy child. Groups of students were presented with a no anchor, a low anchor, or a high anchor. Anchors were statements of how many euros the average Italian would donate, with the high anchor condition corresponding to a large sum of euros and the low anchor to relatively few euros. They found that students presented with a high anchor were more likely to donate a higher amount than those who were given a low anchor or no anchor (Rubaltelli, Hysenbelli, & Rumiati, 2013). This study demonstrates how anchoring not only influences estimates of a true value, but can also help one determine the correct, or socially proper, way of acting.

The ambiguity of why people may anchor to a certain value poses some difficulty. Previously, in the wheel of fortune example, we saw how people were prone to latch on to arbitrary unrelated values in reaching their final answer. However, in the charitable donation scenario, another force is at play since the average amount given provides information about the actions of others in an identical situation. Although both anchoring and social influence could result in a similar observed effect, we might expect that the mechanism behind how they influence people's decisions is quite distinct. Therefore, it seems helpful to distinguish between anchoring and peer effects. Anchoring seems to generally involve having one's estimate biased towards any arbitrary initial value, while peer effects can involve basing one's estimate in a way that in biased by one's knowledge of how other people have acted. Peer effects seems to be a distinct form of anchoring, given that anchoring can also occur when the stimulus does not involve the actions of other people.

One highly influential closely related theory is that of "coherent arbitrariness". Through a series of experimental studies, it is shown that initial valuations of goods or experiences can be highly influenced by arbitrary anchors. However, initial valuations are quickly "imprinted" and thereafter subsequent valuations of varying amounts of a good appear orderly and well defined as if crafted from a underlying demand curve. Essentially, subjects remember their previous valuations and will adjust their valuations appropriately in response to changing quantities of a good submerging the arbitrary nature of the first valuation (Ariely, Loewenstein, & Prelec, 2003). Nonetheless, later publications have pulled into question some of these findings. In particular, a similar replication of the experiment yielded a much smaller anchoring effect. The authors also stressed the importance of skepticism toward new empirical results and the need for replication (Maniadis, Tufano, & List, 2014).

1.3 Similar Work

The most closely related paper to my thesis estimates the size of peer effects using a data set from two websites that people used to raise money for charity by running the 2010 London marathon (Smith, Windmeijer, & Wright, 2014). This paper looks at how very large donations, very small donations, the mode of past donations, and the mean of past donations affects subsequent donations. They find strong evidence for the presence of peer effects utilizing indicator variables for high and low donations as well as a linear-in-means model. Ultimately, they believe that donors give what they "think that they personally are expected to give where the distribution of the donations of their peers (along with other factors, such as income and specific cause) feed into the formation of that expectation". The difficulty is that because of the nature of their data, the mean of past donations is not really a consistent entity. As more donations arrive, each donation has less leverage in pulling the mean in either direction. They cite this as a finding — the later donations occur, the less influential they are. The issue is that there is an implicit assumption through using the cumulative mean that the sample size does not matter; the mean is treated the same by people regardless of how many donations there are. The problem then, is that with their platforms, there is no clear indication of which donations people actually see before donating.

This GFM dataset is well suited for studying anchoring and peer effects because the past 5 or 10 donations are always displayed and the user must make an extra effort to see more donations. Furthermore, there are many facets of the site that allow for interesting comparisons. For one, the different categories of campaigns on the site allow one to study, roughly, whether the effect varies in size thematically. Secondly, one can make inferences about anonymity, gender by coding first names, and even potentially familiarity between donors since campaigns range from small scale local efforts to national movements. Thirdly, the immense size of the dataset makes results more reliable and allows for more robustness checks.

A recently published paper (Sisco & Weber, 2019) appears to be the first to analyze a portion of the massive amount of data available on GFM. This study includes internet data from 9,264 campaigns to test several psychological hypotheses regarding the origins of altruism, specifically sexual selection and kin selection. According to the theory of sexual selection, certain traits may be selected for not because they increase one's likelihood of survival but rather because they serve in attracting mates thereby increasing reproductive prospects (Darwin, 1871). Alternatively, with kin selection, traits may be selected for that do not directly increase an individual's likelihood of survival, but that increase another's chance of survival who is likely to have the same genes (Stewart-Williams, 2015). Leveraging donor names to serve as a proxy for gender, Sisco and Weber find that women give with greater frequency while men donate less frequently but in larger sums. They find the larger sums donated by men are not enough to make up for the discrepancy in frequency of donations, as women's donations constitute a larger portion of the total (sum of all donations across all campaigns in their sample). However, they fail to find significant evidence that the campaign recipient gender affects the total amount raised. Furthermore, they find evidence that if the proportion of visible females on screen increases, female donors give less while male donors give more. They attribute this finding to the theory of sexual selection playing a critical role. Alongside gender, the authors also attempt to measure effects stemming from familial ties. They find that the average donation amount is significantly greater when a donor shares the same last name with the donation receiver. This could be attributable in part to the true kin effect they are trying to study but could also could be related to the idea that one empathizes more with someone of the same last name regardless of familial connections. In relation to anchoring, they find that the mean visible donation on screen at the time of giving was a significant and positive indicator of the value of donations of both men and women, with the effect being stronger in men. The empirical data analysis provides support for the presence of anchoring in charitable donation. It also leveraged to support the idea that kin selection and sexual selection play an instrumental role in altruism.

This project builds off of the work of Sisco in some minor ways (analysis of anonymity, seed money, controlling for seasonality, time, and campaign specific features etc), but most notably attempts to contribute to understanding *how* people anchor rather than if they do. By better understanding how people base their donations off of others', we are also better able to estimate the size of the effect, just how much is one's donation swayed their knowledge of what others have given. To tell if some anchoring effect exists the mean of past donations is a suitable candidate, but for understanding the mechanism behind anchoring it is not really sufficient. One disadvantage to using the mean of displayed donations as a hypothetical anchor value is that it assumes that people weigh each of the donations equally regardless of their relative magnitude. Consider three different possible sequences of displayed donations "50,50,50,50,50", "30, 40, 50, 60, 70", and "10,10,10,100,120". Although they all share the same mean, it's difficult to believe that people would respond in the same way to each of the sequences. However, understanding anchoring or peer effects with multiple reference points is not very well understood. Yet, by scraping GFM campaigns, a huge number of potential sequences are displayed allowing for investigation into how people respond to a multitude of reference points.

Chapter 2

Data Collection

2.1 GoFundMe

My main criteria when searching for potential crowdfunding platforms was evidence that they provided a clear anchor people would see before making a donation, there was a timestamp on each donation, and the site allowed scraping. The companies that I considered include GoFundMe, Crowdrise, Kickstarter, Indiegogo, Patreon, Fundly, and Kazoo. Kickstarter, Indiegogo, and Patreon were quickly ruled out because they focus strongly on a tiered donating approach, with several specified levels at which someone may choose to donate. Additionally, the donor may receive products or certain benefits based on their donation level. Therefore, they are out of scope for a project primarily focused on anchoring within the context of charitable giving. On the other hand, GoFundMe, Crowdrise, Fundly, and Kazoo all appeared to be good potential candidates.

GoFundMe provides five lags of previous donations[1] to the viewer that could serve as an anchor as well as a record of all previous donations. Crowdrise, which is owned by GoFundMe, has ten lags of displayed donation as well as a complete donation history. Kazoo displays four lags and has complete donation history. Lastly, Fundly displays the ten highest donations and full donation history is available. All these sites were viable since they provide an anchor through the previously displayed lags and have complete time series data. I chose GoFundMe because it's the largest of all the sites considered and allows spiders to scrape the majority of its website as indicated in the website's robots.txt [2].

[1]While the site now shows the previous five donations, the site used to display the previous ten donations. There is further discussion of this in the data description section.

[2]Visible at https://www.gofundme.com/robots.txt, which specifies to web crawlers what actions

GoFundMe claims to be the largest crowdfunding platform. Since its conception in 2010, the site had amassed over five billion dollars from 50 million people through 2017, when fundraising totals were last announced (Monroe, 2019). It's made headlines on numerous occasions, frequently appearing in the wake of national tragedies or alongside political movements. Initially, GFM charged a five percent commission, but since 2017 has waived that fee for fundraisers in the US, although there is still a payment processing fee (Heller, 2019). There are 18 categories on GoFundMe including medical, memorial, emergency, non-profit, education, animals, business, community, competition, creative, event, faith, family, newlywed, sports, travel, volunteer, and wishes. The category is designated by the campaign organizer. Medical fundraisers are the most common, amounting to about a third of all campaigns (Monroe, 2019).

2.2 Web Scraper

I built the GoFundMe web scraper in python using the scrapy package, an open source web crawling framework designed to move through web pages by following specified links in the html source code and extracting data. Given that GoFundMe designates the order in which to display campaigns by some unknown algorithm, one of the initial questions was how to select data from the website at random. Sampling at random from all possible campaigns would ensure that the data was not biased by the characteristics that the website's algorithm selects for and promotes.

In order to counter the potential bias of the website's internal algorithm for ordering campaigns, I initially built one scraper that crawls through the pages of campaigns in a certain category collecting all the displayed links to each campaign page. However, after 1,000 unique campaigns in a given category, no more would be displayed by the site. Given the size of the website, this was clearly a very small subset of all campaigns. My impression is that campaigns that are selected to appear under the category labels, in general, have lots of donation momentum, high goal amounts, and polished profiles. In contrast, through searching certain keywords rather than just following category links, the disparity is evident; many campaigns are far from funding goals and have received little to no attention. Therefore, sampling from the category pages would be highly subject to the logic underlying the site.

Using the search feature provided a way to bypass the website's campaign ordering logic. The search feature on the website allows a viewer to input certain keywords and then pulls up relevant campaigns that use that word. The issue once again, was

they are allowed to preform on the site

that while a certain term might say that it yielded millions of results, only around 1,000 would actually be displayed out of the full set of results.

The key to resolving this issue was by using zip codes. Within the search feature, it is possible to specify the country as the US and also include a specific zip code. This allowed me to build a scraper that searches a given zip code on the site and then scrapes all the campaign urls for that zip code. This works because every campaign on the site is necessarily tied to a zip code and thus the full list of zip codes partitions all US campaigns.

I downloaded a full list of US zip codes[3]. I randomly partitioned all the zip codes. I passed this list of zip codes from the first partition to the scraper, which traverses the website according to the breadth first search algorithm using three distinct parsing methods. The homepage of the site serves as the root for our graph search. From there, the scraper first completes the search for each zip code from the homepage. These links for each zip code are sent to the first parsing method which pulls all the urls for campaigns attached to that zip code. These links go to the second parsing method which records several campaign specific traits and generate links to the donation history data. These links are sent to the third parsing method which calls itself recursively until all past donations have been recorded. An outline of the scraper can be seen in Figure 2.1 [4].

2.3 Data Description

The campaign zip code table provides the zip code for every campaign scraped and a unique key for identifying each campaign. The time history data for each campaign includes the campaign key, the amount donated, the time of the donation, the donation identification number, whether the donation was anonymous, the self entered name of the donor, as well as the fields "isoffline", "profileurl", and "verified". The campaign attributes data table includes the key for identifying the campaign, the title of the campaign, the category of the campaign, the date that the campaign was created, whether the campaign has been terminated, the campaign organizer, the campaign description if provided, whether the campaign is a registered tax deductible non-profit, the amount raised, and the goal amount.

A total of 15,672 campaigns were collected, with a total of 642,644 individual

[3] https://www.unitedstateszipcodes.org/

[4] Source code for the scraper can be found on my github account, https://github.com/zumiko/thesis

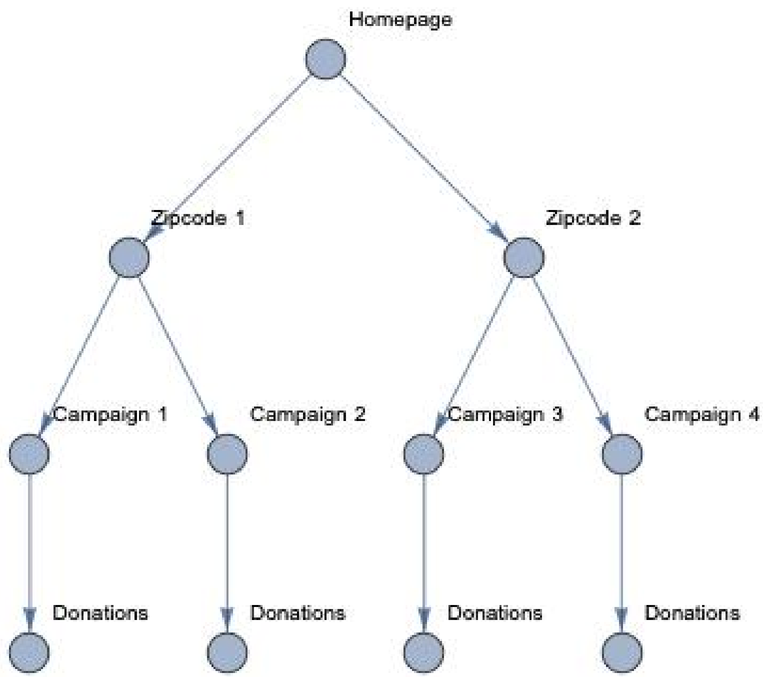

Figure 2.1: Schema of scraper

donations. No more than 1,000 donations could be scraped from a single campaign. The mean donation amount was around \$115 and the median was \$50. For anonymous donors, the mean donation amount is significantly higher at \$127. Approximately, 20 percent of donations were made anonymously. Of all campaigns, around 7.3 percent were tax deductible nonprofits. A quick summary of the data is given below in Table 2.1.

	All donations	Female	Male	Anonymous	Unknown
mean donation	112.36	75.83	110.98	126.78	307.73
total donations	642, 644	286, 658	189, 416	120, 538	46, 032

Table 2.1: Summary of data

In order to gain insights into how gender interacts with charitable giving, first names were assigned a gender, male or female, based on their likelihood of being that gender according to historical data using the gender package in R (Mullen, 2019). Some observations could not be classified and are listed as unknown. These are due to names with ambiguous gender, anonymous donations, couples donating (i.e. "Mr. and Mrs. Potato Head"), donors using their relationship to the recipient (i.e. "Grandma"), or other variants. Obviously, this method is not ideal and thus any interpretation of the results relating to gender should be regarded with mild suspicion.

It is likely that GFM usage may not be uniform across the US and therefore the data may be more representative of certain areas of the country based on where the website is more popular. However, the website is used quite broadly across the US although the demographics of who uses the site is not well known. Additionally the origin of where a donation was made from cannot be determined from the data, which only contains the location of the campaign. Below, we can see the geographical configuration of the data sample in Figure 2.2.

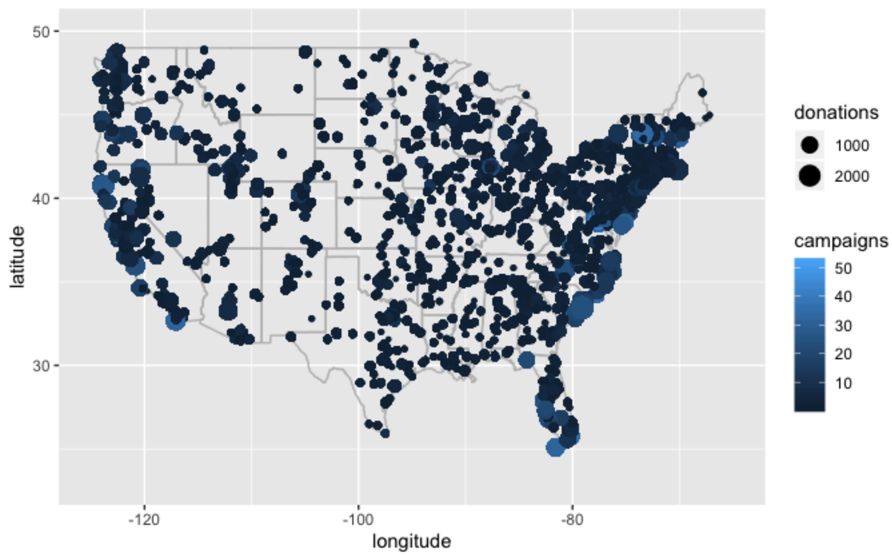

Figure 2.2: Map of data on contiguous states

A significant drawback of the data is that the exact date that the website switched from displaying the previous ten lags to the current layout where the previous five lags are displayed is not precisely known. Given the previous study Sisco and Weber (2019) who collected data in June 2016, the layout change occurred sometime after that month so all donations previous to that month are coded as having ten lags. Similarly, since I began to work on this project, the site has displayed 5 lags so these donations can also be appropriately coded. However, a large portion of the donation data had to be discarded for lag analysis since the exact date is unknown. Checking screenshots of the website posted online could likely narrow the window of donations that cannot be coded.

A natural question to ask is how often campaign goals are met. For all campaigns, a percent of goal met was calculated by dividing the amount raised by the goal amount. This distribution of campaigns' progress towards their goal amounts can be seen in Figure 2.4. This is particularly relevant to the aforementioned work on seed money by List & Lucking-Reiley (2002) who found that increasing the amount of initial seed money resulted in more donations of greater size. Since the amount of seed money is necessarily greater for each subsequent donation, we would expect fewer campaigns to stagnate at levels closer to their goal amounts. Since the probability of donations increases with additional seed money, we would expect that the number of campaigns at each level of percent raised to decrease, which appears to be the case in the figure. This implies that as campaigns approach their goal amounts they either become more likely to receive more donations or the size of donations increases.

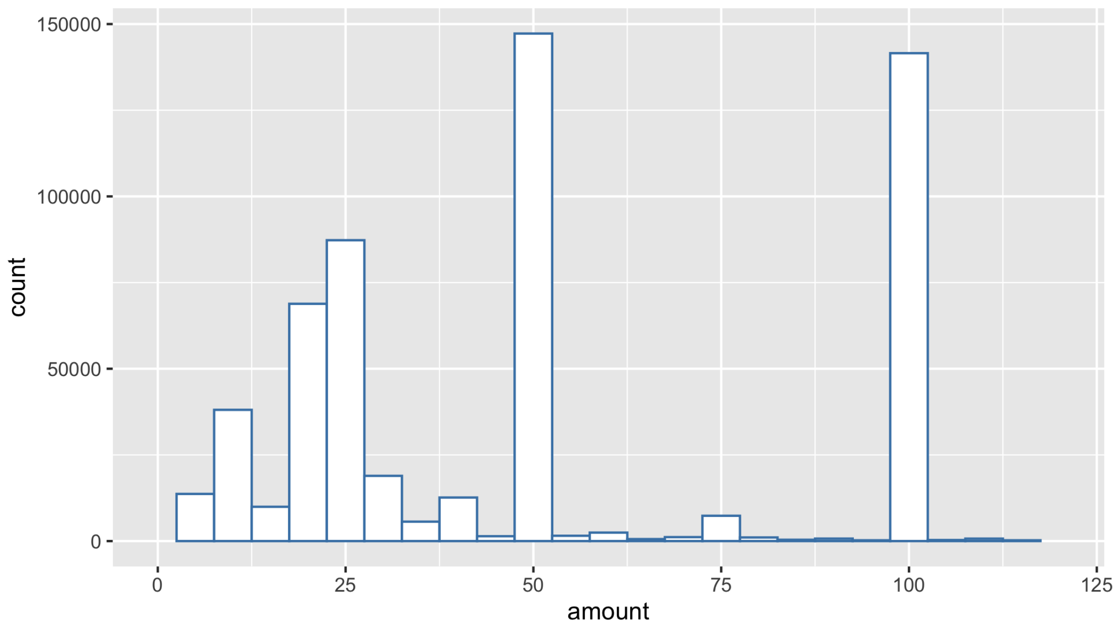

Figure 2.3: Distribution of donation amounts

Another thing, that should be considered is whether, donation amounts are strongly correlated with time of day, day of week or month. If, for example, donations amounts change significantly with the time of day, that could cause nearby donations to appear correlated. Therefore, from the timestamp, the time of day, day of week, month, and year were all extracted. In Figure 2.5, we see that there does appear to be a trend were donations generally fall in a smaller range of values December through April while donations appear to have more of a right skew in the summer months. December also appears to be the only month where the median is pulled downwards. Since December has several holidays, It seems likely that this is due to disposable funds being used for holiday celebrations rather than charitable donations. On the other hand, no obvious pattern was evident for a similar plot with the days of the week on the horizontal axis. Furthermore, in Figure 2.6, we see a scatterplot of donations by their amount and the hour of the day when they were made. Given the volume of

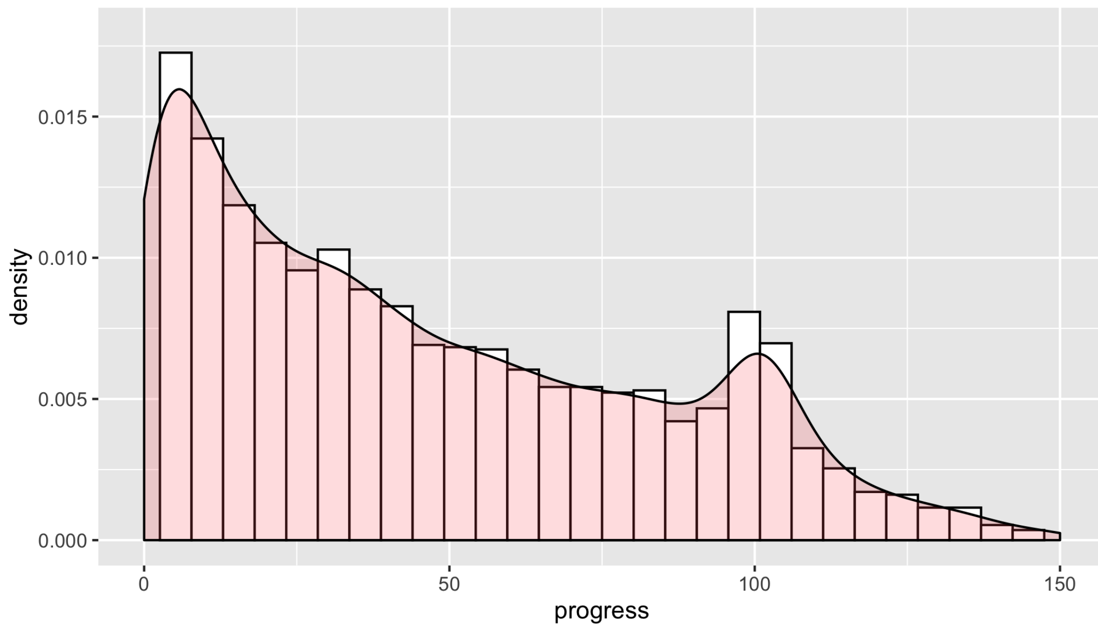

Figure 2.4: Distribution of percent funded

data, points that are located very close together are grouped and colored according to the density of nearby points with lighter points displaying a greater density of donations in that location. Here, there is no discernable evidence that higher donations tend to arrive at a different part of the day than lower donations. Rather it appears that donations, regardless of size, arrive when people are awake.

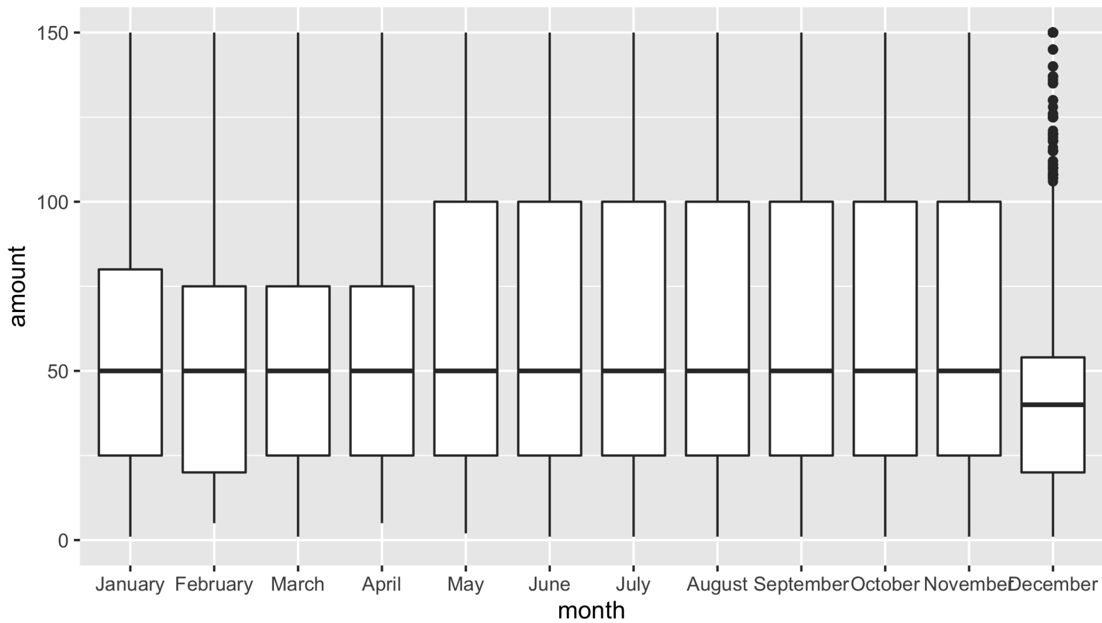

Figure 2.5: Distributions of donation amounts by month

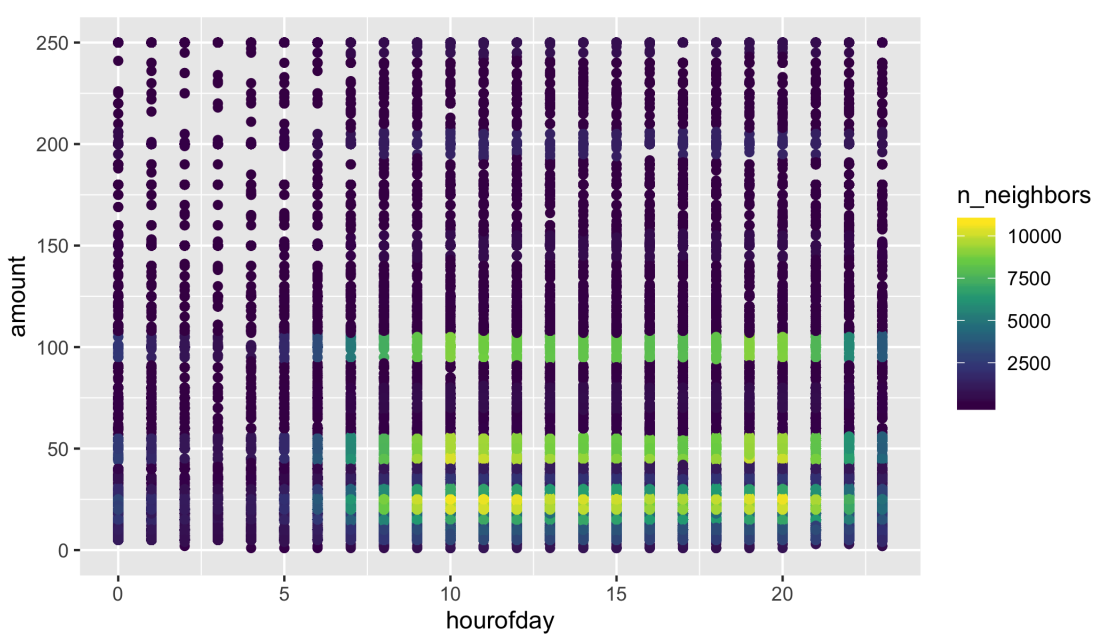

Figure 2.6: Distributions of donation amounts by hour of day

Chapter 3

Regression Models

3.1 OLS Models

Perhaps the most obvious choice for an aggregate value to test for the presence of anchoring is the mean of the displayed donations. Let m be the number of donations displayed on screen (this is necessary because the site initially displayed the previous 10 donations but later modified the layout to only include the previous 5 donations). This means that for y_t, the tth donation, the mean anchor value is calculated as $a_t = \frac{1}{m}\sum_{k=1}^{m} y_{t-k}$ where $t > m$. To test for whether this naive anchor showed any significance as well as determine whether the effect had any interaction with gender and anonymity, the several linear models were estimated [1]. Since it seems plausible that the number of donations displayed on screen might effect the strength of the anchoring effect, we include an interaction term between these variables (written as histavg:lagtype). Similarly, we also include interaction terms between the anchor and whether the donation is made anonymously, the gender of the donor, and whether the campaign is a registered nonprofit.

$$\text{Model 1: } \hat{y}_t = \hat{\beta}_0 + \hat{\beta}_1(a_t) + \hat{\beta}_2(\text{lagtype}) + \hat{\beta}_3(a_t * \text{lagtype})$$

$$\text{Model 2: } \hat{y}_t = \hat{\beta}_0 + \hat{\beta}_1(a_t) + \hat{\beta}_2(\text{lagtype}) + \hat{\beta}_3(a_t * \text{lagtype}) + \hat{\beta}_4(\text{is\_anon}) + \hat{\beta}_5(\text{is\_anon} * a_t)$$

$$\text{Model 3: } \hat{y}_t = \hat{\beta}_0 + \hat{\beta}_1(a_t) + \hat{\beta}_2(\text{lagtype}) + \hat{\beta}_3(a_t * \text{lagtype}) + \hat{\beta}_4(\text{is\_female}) + \hat{\beta}_5(\text{is\_female} * a_t)$$

$$\text{Model 4: } \hat{y}_t = \hat{\beta}_0 + \hat{\beta}_1(a_t) + \hat{\beta}_2(\text{lagtype}) + \hat{\beta}_3(a_t * \text{lagtype}) + \hat{\beta}_4(\text{nonprofit}) + \hat{\beta}_5(\text{nonprofit} * a_t)$$

[1] All R source code for various models can be found on my github account, https://github.com/zumiko/thesis. In these models, lagtype refers to whether five or ten donations were displayed at the time of a donation. Additionally, residual plots and tests for stationarity are included in the R files

	Model 1	Model 2	Model 3	Model 4
(Intercept)	75.59^{***}	73.25^{***}	65.52^{***}	63.40^{***}
	(2.33)	(2.43)	(2.66)	(2.75)
histavg	0.26^{***}	0.26^{***}	0.56^{***}	0.34^{***}
	(0.01)	(0.01)	(0.01)	(0.02)
lagtypeten	-15.89^{***}	-18.13^{***}	2.47	-4.28
	(2.91)	(2.93)	(2.91)	(3.24)
histavg:lagtypeten	0.16^{***}	0.18^{***}	-0.05^{***}	0.08^{***}
	(0.01)	(0.01)	(0.01)	(0.02)
is_anonymous		15.27^{***}		
		(3.31)		
histavg:is_anonymous		-0.05^{***}		
		(0.01)		
is_female			0.87	
			(2.81)	
histavg:is_female			-0.48^{***}	
			(0.01)	
nonprofitTRUE				68.65^{***}
				(7.81)
histavg:nonprofitTRUE				-0.10^{***}
				(0.02)
R^2	0.03	0.03	0.04	0.03
Adj. R^2	0.03	0.03	0.04	0.03
Num. obs.	253019	253019	253019	251621
RMSE	669.87	669.83	665.40	671.36

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table 3.1: OLS regressions for mean of displayed donations

From the Table 3.1, we see that the mean of displayed donations appears highly significant across all of the models. For every one dollar increases the mean we anticipate between around a quarter and fifty cent increase in the subsequent donation with all else equal. From Model 1, we see that having ten displayed donations opposed to five does not appears to increase the size of the effect of the mean of displayed donations. In Model 2, we see that anonymous donations while generally higher, have a signifiant interaction term with the mean anchor value. This interaction term implies that anonymous donations are potentially less responsive to the mean of displayed donations than donations where a person chooses to display their name. In Model 3, we also see that donations coded as female tend to be lower than male donations and more notably have a significant interaction with the anchor, demonstrating that women are far less influenced by the values of the displayed donations. Finally in Model 4, we see that campaigns with nonprofit status receive donations about fifty dollars higher and are generally less correlated with the mean of displayed donations.

The R^2 values range between .03 and .04, meaning that these models have very low explanatory power, accounting for only around 3-4% of the variation in the amount donated. Nevertheless, predictors have extremely low p values indicating that the explanatory variables do have a highly significant discernible effect on the amount donated. Although this may seem somewhat contradictory, it is not a surprising result given that there are a host of omitted variables that would undoubtably exert considerable influence on how much a person might donate such as level of income and relation to the recipient. Unfortunately, it is difficult to compare this model to the similar work because R^2 values are not included in comparable studies.

However, further inspection reveals that the low R^2 values are driven down by the subset of the data when ten lags were displayed. The contrast between the period when ten lags were displayed and when five lags were displayed is evident in Table 3.2. This suggests that the donations on screen may be a stronger predictor when there are fewer present, but with more the effect is diminished though the size is unchanged. Nevertheless, the estimated coefficient of the mean is the same for both subsets of the data.

As discussed in the last chapter, it's possible that donations amounts are correlated with factors such as time of day, that could make it appear as though displayed donations influenced future donations. To account for this effect, additional regressions that included dummy variables for the day of week, hour of day (0-23), month, and year were considered. The inclusion of these variables was not particularly insightful, the R^2 improved very slightly, but the coefficient on past donations remained unchanged. This shows that the effect of displayed donations is probably not attributable to omitted time-based donation patterns. The output of a regression that includes time based dummy variables is included in the first appendix A.2.

	10 displayed	5 displayed
(Intercept)	59.70^{***}	75.59^{***}
	(2.00)	(1.40)
histavg	0.42^{***}	0.26^{***}
	(0.01)	(0.00)
R^2	0.03	0.07
Adj. R^2	0.03	0.07
Num. obs.	165651	87368
RMSE	774.83	401.54

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table 3.2: Explanatory power of 5 vs 10 displayed

An additional concern would be that as donations approach goal amount, donations either increase or decrease in size. If the effect was large, then we would not expect the data to be stationary, however, we will still check if there is a trend apparent. This is related to the work of previously discussed on seed money in Section 2.3 to study the phenomena described by List & Lucking-Reiley (2002) where more seed money leads to both more donations and donations of greater size. To further explore this, we'll calculate the seed money for some donation y_{it}, the tth donation to the ith campaign as $s_{it} = \sum_{k=1}^{t-1} y_{ik}$ (this amount would also be visible to the donor along with the displayed donations). We'll also include a variable called progress that is $\frac{s_{it}}{g_i}$ where g_i is the goal amount for campaign i. Including seed money or progress in the regression equation results in only a very minimal improvement to the model, but there is a significant positive effect indicating that more seed money at the time of the donation results in higher donations, but the size of the effect is very small. Moreover, the the mean of displayed donations remains approximately the same size demonstrating that this increasing seed money is not the reason we observe this effect. These regression results can be seen in the fist appendix A.1.

3.1.1 Size and Order variant models

While the previous models are highly indicative of the existence of anchoring, they do relatively little to explain how an anchor is formed. Rather, basing prediction off the mean implies that all displayed values are weighted evenly, or taken into consideration independent of their size, name, gender, and order. In attempt to increase the explanatory power of our model, we'll now take into consideration the order and the size of the donations. My initial hypothesis was that the order of the five donations would be largely irrelevant. To test this hypothesis, I estimated a model of the form $y_t = \beta_0 + \beta_1 y_{t-1} + \beta_2 y_{t-2} + \beta_3 y_{t-3} + \beta_4 y_{t-4} + \beta_5 y_{t-5}$ on the subset of the training data when five lags were displayed . Then I randomly permuted the lag values and ran the same regression. Then I tried permuting the lags again but with the first lag as a fixed point. The results are shown in Table 3.3.

	Lags	Permutation 1	Permutation 2
(Intercept)	72.08***	77.18***	73.05***
	(1.67)	(1.70)	(1.71)
lag1	0.19***	−0.00	0.10***
	(0.00)	(0.00)	(0.00)
lag2	−0.03***	0.04***	0.02***
	(0.00)	(0.00)	(0.00)
lag3	0.13***	0.17***	0.14***
	(0.00)	(0.00)	(0.00)
lag4	−0.03***	0.02***	0.00
	(0.00)	(0.00)	(0.00)
lag5	0.00	−0.02***	−0.00
	(0.00)	(0.00)	(0.00)
R^2	0.16	0.15	0.16
Adj. R^2	0.16	0.15	0.16
Num. obs.	56959	56959	56959
RMSE	388.38	390.77	389.23

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table 3.3: Permutation of order of lags

The most notable observation is that including all five displayed donations significantly improved the explanatory power of the model. Nevertheless, the gains in explanatory power remain largely unaffected by random permutations. It seems plausible that the most recent donation has some influence due to its position on screen. However, the R^2 values are only very slightly lower for the two randomized permutations. The same procedure was done for the subset of the training data during the period with 10 visible donations. In this case, the original R^2 was 0.007 and after the first random permutation actually increased to 0.009. This demonstrates while including all visible donations was an effective strategy for increasing the explanatory power of the model when five donations are displayed on screen, the same technique did not yield improvements when 10 donation were shown on screen. Overall, order seems only minimally important if at all for the purpose of explaining future donations.

Given that order seems of minimal importance, we now turn our attention to size. Looking at the donations according to their relative size can help us to gain insight into whether relatively high or low donations exert more control over a future donation. Allow five new variables d_1, d_2, d_3, d_4, d_5 so that for the jth donation, d_1 would correspond to the smallest donation displayed and $d_1 \leq d_2 \leq d_3 \leq d_4 \leq d_5$. This permutation allows us to see which donations, relatively smaller or larger, are most important in determining the size of the subsequent donation. The results for the linear regression with these new variables is displayed in Table 3.4[2]. The size of the coefficients on this model are significantly larger than in the previous order based regressions. In particular, the large coefficient for the smallest donation seems to indicate a tendency to not want to be the lowest donation on screen. A one dollar increase in the lowest donation results in almost a three dollar increase in the prediction for the next donation. Perhaps, the most confusing element is the negative coefficient on the second and third smallest displayed donation [3]. This leads me to believe that it is not only important to consider the relative magnitudes but also their distribution, or the spacing between donations. An interesting result is looking at the models that only include the minimum, median, or max of the displayed donations. In particular, we observe that the size of the coefficients descend from the minimum to the median to the maximum. This carries an interesting implication, by raising the minimum donation displayed on screen we increase the subsequent donation far more than if the highest donation on screen increased by the same amount. Another interesting feature is that the minimum and maximum donation have greater explanatory power than the median donation.

[2]This model is just using the subset of data where five donations were present on screen

[3]Though of course, including any one of the predictors does result in a positive coefficient, with decreasing magnitude for larger displayed donations

	All displayed	Min	Median	Max
(Intercept)	25.02***	12.68***	82.53***	78.22***
	(2.08)	(2.08)	(1.79)	(1.73)
d1	2.94***	3.19***		
	(0.06)	(0.04)		
d2	−0.40***			
	(0.03)			
d3	−0.39***		0.25***	
	(0.02)		(0.01)	
d4	0.16***			
	(0.01)			
d5	0.08***			0.08***
	(0.00)			(0.00)
R^2	0.14	0.08	0.03	0.08
Adj. R^2	0.14	0.08	0.03	0.08
Num. obs.	56959	56959	56959	56959
RMSE	392.67	405.98	417.82	407.09

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table 3.4: Relative size of displayed donations regression

3.2 Fixed Effects Models

An issue with the previous regressions is that we are not accounting for the differences between campaigns. It seems clear that campaigns will differ substantially from one another. Some may have detailed descriptions and many pictures while others may be relatively sparse. Additionally, each campaign will have a different cause, be located in a different place, have a different recipient, and be part of a different community. We might expect that these features will be correlated with our explanatory variables. For example, a campaign from a tight knit community might have greater anchoring effects than a campaign for a well-known nonprofit or certain campaigns might attract larger donations from women than from men. Such campaign specific features could result in the detection of biased coefficients because these features are correlated with the parameters we are trying to estimate. A fixed effects model can help resolve this by tersing out time invariate unobserved characteristics of the different campaigns that are likely to be correlated with other explanatory variables (Wooldridge, 2009).

Let c_i be all the features of the campaign that we do not observe and that are constant across time for some campaign i. Here, the x's are our predictors such as the mean of displayed donations. We expect that c_i may be correlated with many of the explanatory variables that we are using in our model. Therefore, we remove the campaign specific term c_i through time demeaning.

$$y_{it} = \sum_{j=1}^{n} \beta_j x_{itj} + c_i + \mu_{it}$$

Taking the mean across time for each campaign, i,

$$\overline{y}_i = \sum_{j=1}^{n} \beta_j \overline{x}_{ij} + c_i + \overline{\mu_i}$$

Time demeaning the original data,

$$y_{it} - \overline{y}_i = \sum_{j=1}^{n} \beta_j (x_{it} - \overline{x}_i)_j + \mu_{it} - \overline{\mu_i}$$

Relabeling demeaned terms,

$$\ddot{y}_t = \sum_{j=1}^{n} \beta_j \ddot{x}_{tj} + \ddot{\mu}_t$$

As with the OLS models, we see that while the mean of displayed donations appears significant the explanatory power of the model is weak. We can see that when there are ten lags of donations displayed the anchoring effect, as captured by the mean of displayed donations, is essentially nullified across all of the models as seen in Table 3.6 compared to

	Model 1	Model 2	Model 3
histavg	0.22^{***}	0.55^{***}	0.21^{***}
	(0.00)	(0.00)	(0.00)
is_female		12.15^{***}	
		(2.69)	
histavg:is_female		-0.53^{***}	
		(0.01)	
is_anonymous			-9.11^{*}
			(3.79)
histavg:is_anonymous			0.30^{***}
			(0.02)
R^2	0.05	0.13	0.05
Adj. R^2	0.02	0.10	0.02
Num. obs.	87368	87368	87368

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table 3.5: Campaign fixed effects regression (5 displayed)

	Model 1	Model 2	Model 3
histavg	0.09^{***}	0.14^{***}	0.16^{***}
	(0.01)	(0.01)	(0.01)
is_female		-25.35^{***}	
		(4.33)	
histavg:is_female		-0.23^{***}	
		(0.02)	
is_anonymous			28.46^{***}
			(4.82)
histavg:is_anonymous			-0.18^{***}
			(0.01)
R^2	0.00	0.00	0.00
Adj. R^2	-0.02	-0.01	-0.01
Num. obs.	165651	165651	165651

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table 3.6: Campaign fixed effects regression (10 displayed)

Table 3.5. This raises the possibility that the anchoring effect may act quite differently in the scenario when ten donations are displayed as opposed to when five donations are displayed. In Model 2, we see that the effect of the mean of past donations is far smaller for female donors compared to male donors and even has an inverse correlation with ten displayed donations. Model 3 gives perhaps the most perplexing results. In Table 3.5, we see that anonymous donations appear to have stronger anchoring effect, but in Table 3.6 we see that anonymous donations are inversely correlated with the mean of displayed donations.

3.2.1 Arrival Rates

Another potential confounding factor could arise from the endogenous sorting of donors to a given campaign. A news article or someone sharing the campaign could alert a subset of donors to a certain campaign who would be predisposed to contribute similar amounts. Such events would cause donors with shared characteristics that may affect how much they contribute to arrive in clusters. This seems plausible given that the readership of a particular news outlet or the social network of someone who shares the campaign may be likely to have somewhat similar income levels or values. Omitting such similarities, that are likely correlated with how much people contribute, would cause us to estimate an exaggerated effect. However, such a mechanism, prompting select people to a specific campaign, would likely result in donations that arrive closer together in time. Strong evidence that donations clustered together, or arriving in high frequency, display strong dependence on the displayed donations while the effect is far more limited for more spread out donations would point to endogenous sorting as being a problematic component of our analysis. Therefore, we now consider the interarrival times between the donations.

Let s_{ij} be the arrival time of the jth donation to the ith campaign, then we calculate interarrival times by $r_t = s_{t-1} - s_t$. This is the time that passed between the last donation and the current donation. Then, for each campaign, we divide r_t into quartiles, with smaller interarrival times falling into the first quartile and larger into the fourth quartile. The results of this regression are seen in Table 3.7[4]. The most telling aspect of this table is that the coefficients on each of the quartiles are positive indicating that the anchoring effect is greater in size for all quartiles relative to the first quartile where donations are most densely packed[5]. The fact that donations that are more sparsely clustered do not have greater anchoring effects makes a tentative case that the effect we detect cannot be

[4]The number of donations is reduced because I only considered campaigns that had more than 100 donations given that donations are split into quartiles for each campaign.

[5]I'm not sure of a great explanation for why we observe this, but I think it is possible that more densely clustered donations are more likely to arrive earlier in sequence of donations and donations that arrive earlier are more likely to be donors who have greater familiarity with the recipient and are therefore less influenced by previous donations or something along these lines.

	Model 1
histavg	0.20^{***}
	(0.02)
lagtypeten	22.81
	(29.47)
quartile2	-13.15^{**}
	(5.07)
quartile3	3.34
	(4.96)
quartile4	9.36
	(4.90)
histavg:lagtypeten	-0.26^{***}
	(0.02)
histavg:quartile2	0.20^{***}
	(0.03)
histavg:quartile3	0.04
	(0.02)
histavg:quartile4	0.12^{***}
	(0.02)
R^2	0.01
Adj. R^2	-0.00
Num. obs.	148595

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table 3.7: Campaign fixed effects with interarrival quartiles

attributed to exogenous shocks, such as a news article, that drive like minded donors to contribute in clusters. In addition, to this approach, I also looked at only donations that occurred over 24 hours after the previous donation and found a significant coefficient on the mean anchor of 0.689 for the mean of displayed donations.

3.3 Tree Based Models

A disadvantage to the previous models is the explicit assumption of functional form. Using an algorithmic approach, we can avoid making assumptions about the underlying linear relationship between the amount donated and our explanatory variables. Furthermore, some argue that trees may more closely model human decision making (James, Witten, Hastie, & Tibshirani, 2013). In particular, this approach may be useful, if there exist strong cutoff values after which donations are not considered in the same way. For example, an extremely high donation may not inform future donations in the same way as donations that fall into the normal range of values. In this section, we attempt to predict the subsequent donation using regression trees, focusing on the subset of the data where 10 lags were displayed on screen since linear models have particularly struggled in that instance.

To build decision trees [6], the predictor space is algorithmically partitioned into J regions, $R_1, R_2, \ldots, R_J$. For each region R_j the value predicted by the model is the mean of the response variables for the training observations in that region, which we'll denote as $\hat{y}_{R_j}$. Since all observations that fall into the same region get the same prediction, to obtain RSS we just find the squared difference between an observation and the predicted value for all observations in a region and sum over all regions so that RSS is given by $\sum_{j=1}^{J} \sum_{i \in R_j} (y_i - \hat{y}_{R_j})^2$. The key idea behind this model then, is partitioning the predictor space into regions with relatively similar donation values. This is achieved through recursive binary splitting which iteratively decides where to divide the predictor space by finding the cut point, s, along some predictor which results in the greatest reduction of RSS. Given p predictors, $X_1, X_2, \ldots X_p$, for each predictor X_j we seek to find s that divides the predictor space into two regions, one where $X_j < s$ and the other where $X_j \geq s$ and results in the greatest reduction of RSS. Then it divides the predictor X_j at point s that resulted in the greatest reduction. Then the algorithm looks at the two new regions and chooses one region to split resulting in three regions. The algorithm continues until some stopping criterion is reached.

3.3.1 Gradient Boosting

With basic regression trees may have the advantage of interpretability, they generally don't preform at a very high level for prediction and they have very high variance depending on a given sample (James, Witten, Hastie, & Tibshirani, 2013). Therefore, we now take the approach of a boosted regression model. The key to boosted tree models is that they are grown sequentially, slowly improving on the previous trees. Every tree after the first, is grown on the residuals of the current model to find the partitions that most improve the overall model. Allow B decision trees, $\hat{f}^1, \ldots, \hat{f}^B$. Then, for the bth tree, we would calculate the current residuals for each observation, $r_i = y_i - \sum_{b=1}^{b-1} \lambda \hat{f}^b$, where y_i is the

[6] The majority of this section follows notation from James, Witten, Hastie, Tibshirani (2013)

donation amount and $\sum_{b=1}^{b-1} \lambda \hat{f}^b$ is the current prediction. Then $\hat{f}^b$ is grown to predict these residuals, r_i, rather than the original donation amounts and we add it to the overall model. To control the rate at which our model "learns" we assign some weight, λ, to how we update the model so that $\hat{f} = \hat{f} + \lambda \hat{f}^b$. Therefore, the final model can be expressed as, $\hat{f} = \sum_{b=1}^{B} \lambda \hat{f}^b$.

We have number of tuning parameters at our disposal for building a boosted tree model. We can control how many splits each successive tree makes by setting the number of terminal nodes, call d, the total number of trees, B, and the shrinkage parameter, λ. When B is too large we are likely to overfit the training data. A low λ is more cautious and responsive in a sense, but will generally require more trees to build a good model. The number of splits, d is generally kept small in a boosted model and can be thought of as controlling the interaction depth.

In order to find the best parameters, we create a search grid of possible values that the parameters can be and then build models for all the possible combinations. In order to speed this process, we use a fraction of the training observations to build each model and the predict on the remaining observations and calculate the MSE. Then, we build the final model using the parameters that resulted in the lowest MSE.

To construct a boosted tree model that accounts for some feature of the displayed donations distribution, several additional sample summary statistics were included in addition to the mean, such as the variance, skewness, and kurtosis of the displayed donations alongside is_female and the minimum and maximum displayed donation values. Below in 3.1, is a relative importance plot of the different variables that the model used. In this R package, this is calculated as the reduction in squared error attributable to each variable.

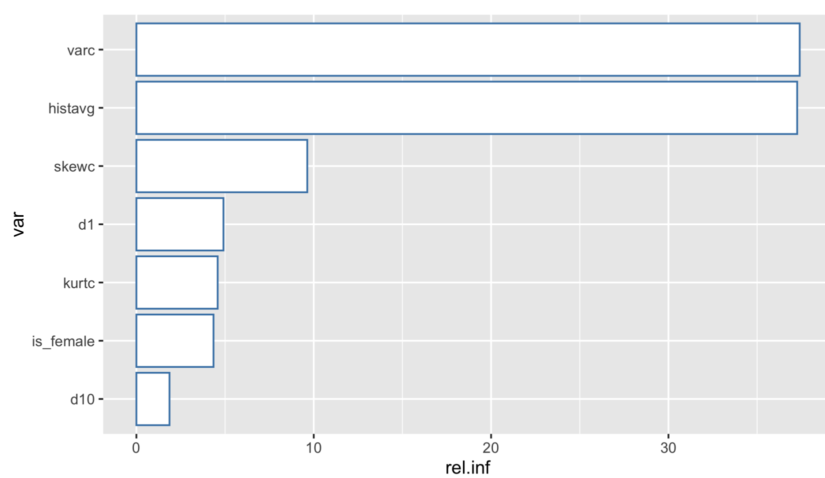

Figure 3.1: Relative importance of predictors with boosted tree

Another way, aside from variable importance plots, to understand the results of the boosted tree model is through looking at the marginal effects of the variables and integrating

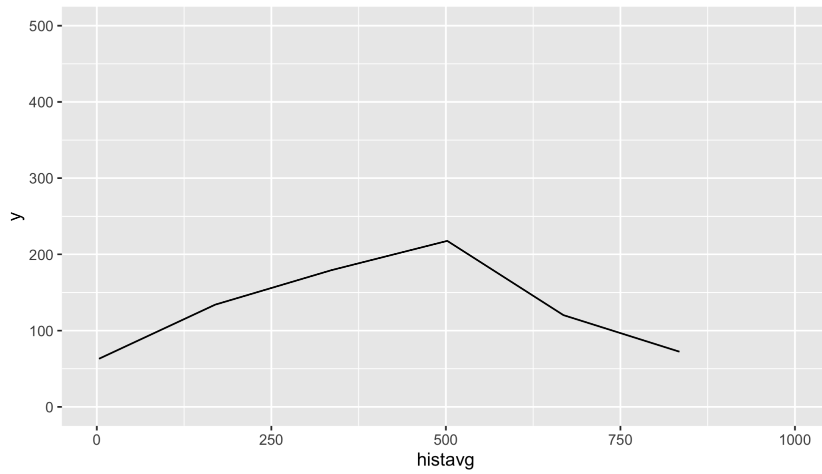

Figure 3.2: Marginal effect of mean of displayed donations

out other variables as seen in 3.2 for the boosted tree. Here, we see how the average of displayed donations is not conforming to a linear relationship and appears more concave down. The issue, however, is that the splits are few and far between especially in the range of frequently donated amounts. It seems likely that the issue is that the boosted model focused on reducing the RSS and trying to fit the outliers of the training data.

3.3.2 Random Forest

We next construct another model derived from another variation of basic decision trees. Random forests employ a technique called bootstrapping to generate B training data sets by drawing from the original data set with replacement. Then we construct B trees on each of the new data sets with one additional modification. Instead of using all p predictors, we only use $m = \frac{p}{3}$ predictors. This serves to "decorrelate" the trees and reduce the variance. This can be particularly helpful when all the predictors are highly correlated as with the predictors we are using. Here, we grow a random forest with 25 trees. Then, to predict, we average the predictions from each of the trees. In Table 3.3, we can see the relative importance of the predictors. The first column represents the decrease in accuracy of predictions when that variable is excluded from the model. The second column shows the average decrease in node impurity (or RSS) from splits along that variable. In particular, we see that while the average of displayed donations is important, other descriptive statistics of the distribution exert considerable influence.

3.3.3 Model Comparison

Since trees are prone to overfitting data, we use the random forest, the boosted tree, and a linear regression with the same predictors to predict responses on a test set of data that was

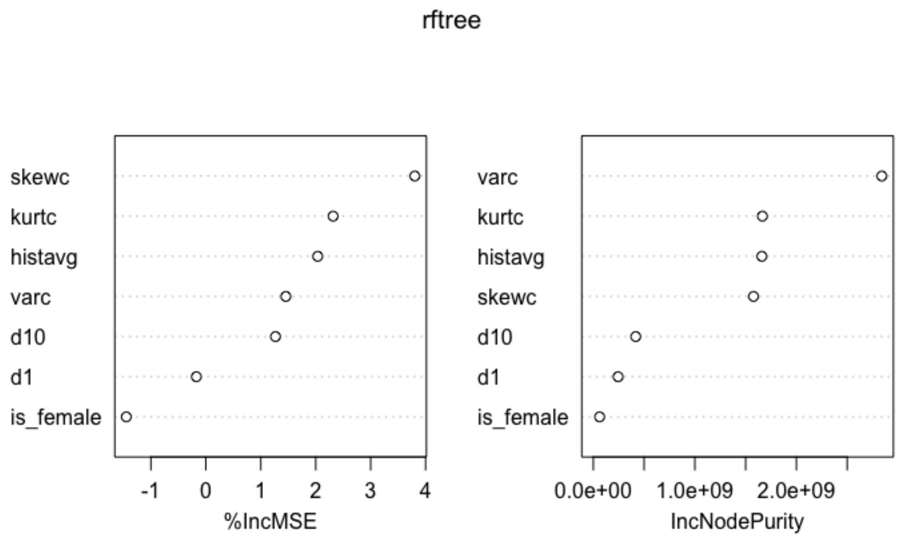

Figure 3.3: Variable Importance with Random Forest

not used to construction of the models. The we take each model's predictions and compare them to the true values of the test data by finding each model's mean squared error, where $\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$ and $\hat{y}_i$ is the predicted value of the model and y_i is the true value for observation i. We also calculate the R^2, given by $R^2 = 1 - \frac{\sum_i (y_i - \hat{y}_i)^2}{\sum_i (y_i - \overline{y})^2}$ where $\overline{y}$ is the mean of amounts donated. The results can be seen in Table 3.8. We see that the boosted model preforms at a similar level to the linear model. However, the random forest model is far better than both the linear model and the boosted model and can explain nearly a third of the variation in amounts donated. This means that the donations displayed on screen are highly influential in determining how people decide to act.

	Linear	Boosted	Random Forest
MSE	54893.56	54913	36014.32
R^2	0.021	0.021	0.357

Table 3.8: Model test MSE comparisons

Conclusion

This thesis has employed a variety of modeling techniques in attempt to understand how knowing the donations of others affects a subsequent donations. Using both OLS and campaign fixed effects regressions, it appears that the mean of displayed donations is a significant predictor but lacks strong explanatory power in a linear model. I also find a positive effect of the mean of displayed donations that in the fixed effects linear in means model unlike Smith, Windmeijer, & Wright (2014) [7]. In agreement with Sisco & Weber (2019), we find evidence that the mean of displayed donations has a larger effect on make donations than on female donations in both standard and fixed models. Our standard models also suggest that anonymous donations may be less responsive to the mean of displayed donations however this is not confirmed by the fixed effects models. The insignificance of an interaction between anonymity and the mean of displayed donations indicates anonymous donor are equally likely to follow suite. Furthermore, by controlling for time of day, day of week, and month, we rule out that this effect is caused by time dependent donation size patterns. Despite the apparent significance in the mean of displayed donations, we find that predictive power of the linear in means model is quite weak, accounting for only $3-4\%$ of the variation in the donated amounts. This does not appear to be widely addressed in previous empirical studies.

We find that including all visible donations greatly improved the explanatory power of the regression based models. This points to the idea that peer effects cannot be well understood as acting average based on the actions of others. While including all the lagged values improves the model significantly for the case of five displayed lags, with ten displayed lags the model continued to preform poorly. This indicates that peer effects may be stronger when the number of reference points are fewer. Furthermore, size based models seem to indicate that smaller donations present on screen are more influential than larger donations in the determination of a subsequent donation. This could potentially indicate an unwillingness to donate less than the lowest donations present on screen. Raising the

[7] This is not a perfect comparison since the are using the mean of past donations so that for y_{it} the tth donation to campaign i, the mean of past donations is $\frac{1}{t-1}\sum_{k=1}^{t-1} y_{ik}$ while the mean of displayed for this thesis only considers the last five or ten values. They attribute this to the mean differenced error term being negatively correlated with the the mean differenced lagged dependent variable.

lowest displayed donation results in a much higher subsequent donations that raising the highest displayed donation by the same amount. The poor explanatory power of the linear models, especially in the case of ten displayed donations, indicates that peer effects may not be well modeled as a linear relationship between variables. If peer effects exhibit strong cutoff values, such as a donation lying outside of the range of frequently given values, an algorithmic approach may be better suited. Using boosted regression trees, proved ineffective likely due to overfitting. However, a random forest model preformed far better than its linear and boosted counterparts, likely due to how its design strives to reduce the variance of the model especially in the case of correlated predictors. Overall, while it appears evident that peer effects can influence donations, the mechanism by which they do seems somewhat complex when multiple reference points are present.

Appendix A

Model Output

	Model 1	Model 2
(Intercept)	75.95^{***}	51.54^{***}
	(2.43)	(2.48)
histavg	0.26^{***}	0.46^{***}
	(0.01)	(0.01)
lagtypeten	-15.42^{***}	-11.62^{***}
	(3.03)	(2.91)
progress	-0.00	
	(0.00)	
histavg:lagtypeten	0.16^{***}	0.14^{***}
	(0.01)	(0.01)
histavg:progress	0.00	
	(0.00)	
seedmoney		0.00^{***}
		(0.00)
histavg:seedmoney		-0.00^{***}
		(0.00)
R^2	0.03	0.03
Adj. R^2	0.03	0.03
Num. obs.	242228	253019
RMSE	683.26	668.82

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table A.1: Seed Money

	Model 1
(Intercept)	-288.52
	(3387.59)
histavg	0.56^{***}
	(0.01)
lagtypeten	7.71
	(8.55)
dowMonday	10.56^{*}
	(4.80)
dowSaturday	3.93
	(5.22)
dowSunday	0.33
	(5.25)
dowThursday	3.46
	(4.73)
dowTuesday	11.25^{*}
	(4.72)
dowWednesday	2.72
	(4.69)
monthFebruary	-6.44
	(6.27)
monthMarch	-1.54
	(6.70)
monthApril	-8.00
	(6.36)
monthMay	0.37
	(6.80)
monthJune	19.58^{**}
	(6.40)
monthJuly	14.52^{*}
	(6.60)
monthAugust	2.86
	(6.49)
monthSeptember	11.90
	(6.62)
monthOctober	1.12
	(6.59)
monthNovember	3.78
	(6.45)
monthDecember	-1.74
	(5.93)
hourofday	0.15
	(0.24)
year	0.17
	(1.68)
is_female	0.77
	(2.82)
histavg:lagtypeten	-0.05^{***}
	(0.01)
histavg:is_female	-0.48^{***}
	(0.01)
R^2	0.04
Adj. R^2	0.04
Num. obs.	253019
RMSE	665.37

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table A.2: Time fixed effects

Appendix B

GFM Layout

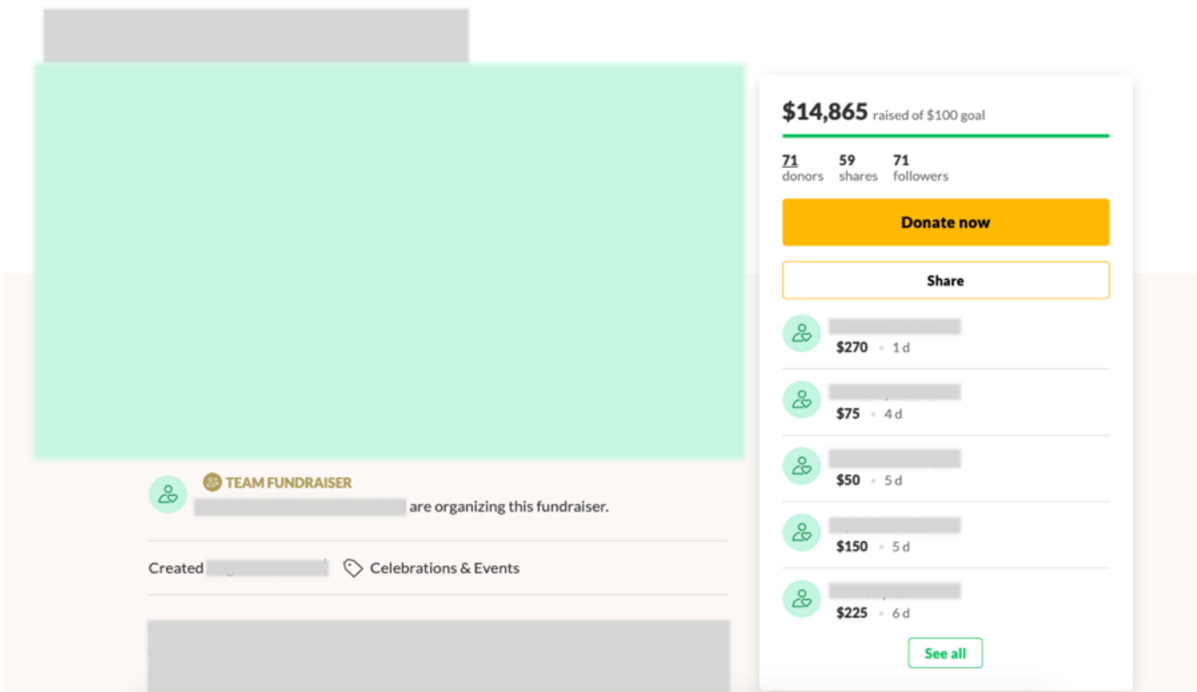

Figure B.1: GFM campaign page layout

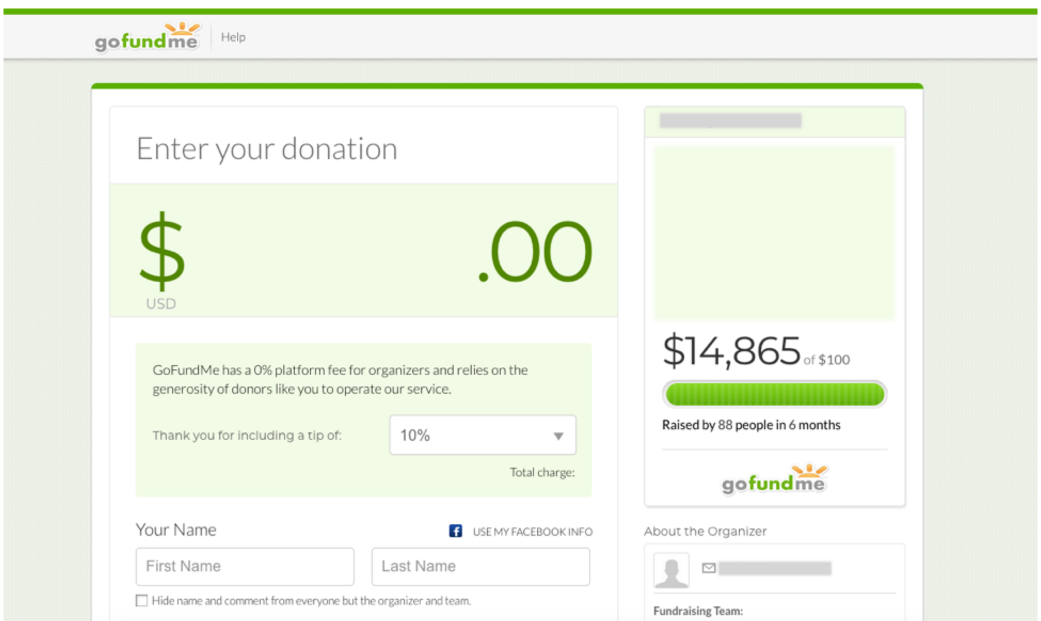

Figure B.2: GFM donation page layout

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