Toward an understanding of why suggestions work in charitable fundraising: theory and evidence from a natural field experiment

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Abstract

People respond to those who ask. Within the charitable fundraising community, the power of the ask represents the backbone of most fundraising strategies. Despite this, the optimal design of communication strategies has received less formal attention. For their part, economists have recently explored how communication affects empathy, altruism, and giving rates to charities. Our study takes a step back from this literature to examine how suggestions–a direct ask for a certain amount of money–affect giving rates. We find that our suggestion amounts affect both the intensive and extensive margins: more people give and they tend to give the suggested amount. Resulting insights help us understand why people give, why messages work, and deepen practitioners' understanding of how to use messages to leverage more giving.

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1 Introduction

With private donations to charitable organizations at roughly 2% of GDP, a growing economic literature has begun to analyze the mechanisms of individual charitable giving. Naturally-occurring data and field experimentation has shown that giving can be substantially affected by changing the effective price of giving (Randolph, 1985; Karlan and List, 2007), the method of solicitation (Landry et.al, 2008), various signaling devices (List and Lucking-Reilly, 2002; Spencer et.al, 2009; Potters et.al, 2007; Bracha et.al, 2011), the revealing of donor's identities (Soetevent, 2005), and the communication of social information (Frey and Meier, 2004; Croson and Shang, 2008; Shang and Croson, 2009).

This study contributes to the literature by exploring how giving is affected by simply suggesting a specific donation during solicitation. Importantly, and in contrast to previous work, we run a natural field experiment that offers a direct comparison between a suggestion treatment and a no suggestion control, and allows the effect on giving to be measured both on the intensive and extensive margins. The experiment is accompanied by a theoretical framework that augments the seminal impure altruism model of Andreoni (1988; 1989; 1990) to offer several channels through which direct amount suggestions have the potential to affect giving patterns. In addition, this framework develops a general formal structure to gain insights on recent empirical results on information in the ask (e.g., Frey and Meier, 2004; Croson and Shang, 2008; Shang and Croson, 2009) and optimal communication strategies in general.

With our theory as a backdrop, we designed a natural field experiment in partnership with the University of Wisconsin-Stevens Point's (UWSP) development office. As part of an alumni fundraising phonathon for UWSP, potential donors were contacted using a script that was standard for the university. We randomly varied the message content to either include a direct suggestion for a donation amount ($20), or no such prompting. The suggestion amount was also varied to analyze if a more "personalized" amount had greater power to affect donation patterns (for example, those who graduated in 2003 were asked to donate $20.03). Finally, a factorial design was used to observe whether the treatment effect was influenced by offering a 1-to-1 match.

We find some interesting insights. On the extensive margin, we document a large and economically significant increase in the number of subjects donating in response to the direct suggestion. Beyond a test of theory, this result is particularly important in a practical sense since it aids fundraisers on one of their most important tasks: finding new individuals to build a donor pyramid which can be tapped on for years to come. On the intensive margin, we find a strong treatment effect of moving observed donations towards the suggestion amount. Most notably, the percentage of donations above the suggestion amount is substantially reduced relative to the control. The observed effect on donation amounts is in the same direction, though larger, than those reported in Shang and Croson (2009).

The overall pattern of the treatment effects implies that the marginal utility of donating the suggested amount is increased, but also that there is decreased marginal utility associated with exceeding this amount. Because our ask amount was below the mean of the no-suggestion control, we observe only marginally significant changes in average revenue per contacted donor. The specific changes in donation patterns we find imply, however, that an optimal suggestion amount can be used to increase revenues in any environment. This method can be particularly fruitful in terms of revenue enhancement should the fundraiser have an ability to characterize individuals by predicted pre-suggestion contributions and provide different suggestions as a function of this amount.

Second, while there is evidence that the personalized ask raised giving rates compared to the generic ask, the effects are not significant at conventional levels. When taking into account those who reneged on their initial pledges, however, the personalized ask outperforms a numerically similar generic ask. This result highlights that personalized messages can increase actual giving rates, but the channel in which they work is noteworthy: the personalized ask does not work immediately, but it causes people to stick to their pledge promises. Finally, we find that the match works to enhance giving, but the data are too noisy to make strong inference.

The remainder of our study is constructed as follows. The next section discusses how our work fits within the broader literature. Section 3 presents our theoretical framework. Section 4 summarizes the experimental design. Section 5 discusses the empirical results. Section 6 interprets our results through the lens of our theoretical model. Section 7 concludes.

2 Relationship to Existing Literature

While asking for specific donation amounts is a tactic employed by many charitable fundraisers, there is scant empirical research on the effect of suggestions on contributions. Warwick (2003) reported the results of a number of direct-mail experiments which varied the donation amount suggested in the request letter. Although presented without comment, in their totality they intimate that lower suggestion amounts increase donation rates compared to higher amounts, but insignificantly affect the level of donations. Importantly, none of his experiments compare suggestions to a no suggestion control. Weyant and Smith (1987), also in a direct mail setting, vary the donation options listed on their request letters ($5-$10-$25 vs. $50-$100-$250) and also include a no option control. Low response rates, however, greatly decreased the power of their experiment. While they found a significant increase in donation incidence for the low suggestions compared to high suggestions, their results were unable to provide conclusive inference in comparison of giving rates between these treatments and the no suggestion control. In terms of donation amounts, no conclusions could be drawn, again from a lack of power. Another set of papers related to our analysis is on the "every penny helps" effect (Cialdini and Schroeder, 1976; Reingen, 1978; Weyant, 1984). By telling potential donors that "every penny helps", these experiments were able to increase donation rates by around 20%.[1]

In the more recent field experimental literature on the effect of information on giving, our study is closely related to the research of Shang and Croson (2009) and Frey and Meier (2004). The Shang and Croson field experiment announced the donation of another donor to individuals who had contacted a local radio station for the purpose of contributing. They were able to increase mean donation amounts with high announced donations, and also decrease mean donation amounts with low announced donations (in the companion paper Croson and Shang 2008). The results were significant both statistically and economically, particularly in their most successful treatment levels (contribution level means were increased 12% relative to the control for announcements in the 90% percentile of observed contributions). Frey and Meier announced to contributors the percentage of a population that had donated (46% or 64%), and found a some-

[1]Relatedly, Dale and Morgan (2010) present results from a laboratory experiment that shows moderate suggested donations produce some positive effects.

what smaller effect on the percentage of individuals donating (positive but non-significant for the population, and significant for a subpopulation of individuals deemed most likely affected by the treatment).

Both pairs of researchers interpreted their results as suggesting that the announcement affected individuals' donation behavior by changing their perception of what constituted a "normal" behavior from the population as a whole. The fact that donation patterns moved in the direction of the signaled societal norm indicated that the individuals had a strong desire to conform to that norm. The basis behind this oft-observed pattern of individual conformity to group behavior was formalized by Bernheim (1994), who argued that agents will conform to a single behavior despite heterogeneous preferences if social status makes up a sufficient portion of intrinsic utility. When these behaviors are visible to other agents, this effect is related to the prestige donation model of Harbaugh (1998), which has been used to explain increases in giving when donor's identities are revealed (Soetevent 2005) or when amount categories of donors are published (Li and Riyanto 2009). While such an effect would seem to be dulled when behavior is apparently not visible to other agents, movement of donations to a perceived norm may still occur if the norm is a signal of the charity's quality (Vesterlund 2003), an indication of the marginal effect on the public good, or if the agent receives intrinsic utility from conforming to a norm behavior.[2] A companion paper to Shang and Croson (2009), Shang et. al (2008), supports the conclusion that there is a social effect occurring by finding a stronger effect when the announced donor was the same gender as the individual compared to when they were the opposite gender.

If potential donors' decisions are indeed affected by information on other agents norms, then an important market agent (and one to which the individual's decision is by definition visible) is the fundraiser themselves. The fundraiser's information set in regards to the public good also greatly exceeds that of other agents. She presumably has a knowledge of all agent's donation decisions, as well as information on the production function of the public good (with the corresponding knowledge of how much marginal effect or "difference" a specific donation amount would make on that good). Since the fundraiser obviously does not face the same donation decision as other agents, her "norms" are not a behavior, but the underlying attitudes that were

[2]This could result from some psychic cost such as the idea of paying one's fair share (Vesterlund 2003), or if conforming to the norm is a learned action as part of a larger behavioral strategy.

expressed in other agent's decisions and, as discussed above, made information on other agent's norms valuable to each donor.

Whether potential donors are concerned about the fundraiser's own norms, or at least treat information received from the fundraiser as a credible signal of societal norms, is an inherently empirical question. The studies above imply that the fundraiser has at least some ability to credibly convey information to the donor. The exact mechanism through which this information transfer occurs, however, has not been definitively shown in the literature. For example, the treatment effect in Shang and Croson was interpreted as the fundraiser credibly conveying a societal norm to the donor, which the donor used in their own decision. A large part of the effect, however, could be that by singling out a specific donation, the fundraiser conveyed their own norm on what was appropriate to give, and the donor was affected by a wish to appear appropriate to the fundraiser.

Our study seeks to contribute to the literature primarily in a practical sense: by examining the effect of suggestion amounts on giving patterns, and determining if their use can be exploited to increase fundraising returns. The theoretical framework we build seeks to explore the possible mechanisms through which an effect on giving could take place. Although we do not claim that our experimental design offers clean inference between these competing explanations, we see both the framework and our experiment as part of the broader literature on the effect of social information on giving, and how this information potentially affects giving patterns.

3 Theoretical Framework

To more formally examine the possible avenues through which the suggestion of a donation amount could have an effect on the donation distribution, let there be $n = 1, ..., N$ non-symmetric potential contributors to the public good being produced by the charity. Let the donation amount of each individual be given by G_n, the amount of consumption of a numeraire outside good be given by Y_n, and the total income of the individual be I_n. Let each individual have a utility function:

$$U_n(Y_n, G_n, \sum_n G_n, A_n, \theta_n)$$

where $A_n \in \mathbf{A}$ is a quality perception variable that affects the individual's marginal utility of the provision of the public good, and $\theta_n \in \theta$ is a vector of generic parameters that affect utility. We include some uncertainty on behalf of the agent regarding the provision of the public good by other agents, making the agent's utility based on the expectation $E_n[\sum\limits_{n' \neq n} G_{n'}]$. Furthermore, we assume that the utility function has three additively separable components:

$$U_n(Y_n, G_n, E_n[\sum_{n' \neq n} G_{n'}], A_n, \theta_n) = \widetilde{U}_n(Y_n, G_n, E_n[\sum_{n' \neq n} G_{n'}], , A_n) + f_n^{WG}(G_n) + f_n^{NORM}(G_n, E_n[\overline{G}], \theta_n)$$

where $E_n[\overline{G}] = \frac{E_n[\sum\limits_{n' \neq n} G_{n'}]}{N}$ is the expected mean of other individual's donations. The first function $\widetilde{U_n}$ corresponds to the "altruistic" component of giving: the individual gains utility from greater provision of the public good, and the provision of the good $\sum\limits_n G_n$ is treated as a consumption good that is weighed against consumption of the numeraire good Y_n. We assume $\widetilde{U}_n$ is increasing and concave in Y_n , and that the cross partial $\frac{\partial^2 \widetilde{U_n}}{\partial \sum\limits_n G_n \partial A_n} \geq 0, \forall n$, meaning that the higher the quality perception variable, the weakly higher the marginal utility of provision of the public good. It is usually assumed that altruistic utility $\widetilde{U}_n$ is also increasing and concave in $\sum\limits_n G_n$. More recent work on coordination in giving has suggested that in some cases a fixed amount of donations must be reached for the public good to have a altruistic return, implying a fixed cost in production and non-concavity of $\widetilde{U}_n$ in $\sum\limits_n G_n$. Since this could be important in some scenarios, we initially only assume that $\widetilde{U}_n$ is weakly increasing in $\sum\limits_n G_n$.

The function f_n^{WG} denotes utility gained from the act of donation itself rather than the increase in provision of the public good. This is traditionally denoted as the "warm-glow effect", and connotates satisfaction gained merely from the benevolent action of giving. We assume f_n^{WG} is increasing and concave in G_n.

The combination of functions $\widetilde{U}$ and f_n^{WG} to model contributor behavior have been commonly employed in the literature as an impure altruism model, dating to Andreoni (1989,1990). The third function, f_n^{NORM}, we label a "social norms utility". This connotates utility gained (or lost) in correspondence to the attitude or actions of other agents in the society regarding the contribution.[3] This could include other contributors, the general public, or the fundraiser themselves. As discussed above, the idea that social norms can directly affect contributions has been discussed and implicated often in the theoretical and experimental literature. It has to the best of our knowledge, however, never been formalized as above.

The above specification can also be seen as a generalization of the prestige model of Harbaugh (1998). In our notation Harbaugh modeled donor utility as $U_n(Y_n, G_n, P(G_n))$, where the function P is the prestige associated with a donation, and U_n is increasing and concave in all arguments. While in Harbaugh's model the prestige function P was a fixed societal return based on the size of the gift, the f_n^{NORM} utility in our model allows for the more general mechanisms behind the utility gained from other individual's attitudes or actions, discussed further below. The function thus becomes explicitly affected by equilibrium agent behavior, or at least the expectation of it. Additionally, any justification of an assumption that f_n^{NORM} is strictly increasing and concave in giving, as Harbaugh rightly assumes for prestige utility, seems unconvincing. This leads to some different results and implications for optimal fundraising design in our model.

We initially only assume the function f_n^{NORM} is weakly increasing in G_n: $\frac{\partial f_n^{NORM}}{\partial G_n} \geq 0, \forall n$. This merely states that a higher donation is never less valuable in the eyes of other agents, meaning it can never lower an individual's social norm utility to donate a higher amount. What this excludes is the idea that a donation can be ostentatiously too high and thus frowned upon. The average donation of other potential donors, $\overline{G}$, indicates societal norms and thus may potentially affect the utility of giving. The θ in this function are additional parameters denoting the perceptions of the potential contributor regarding these norms.

In the Nash equilibrium for this game each potential contributor $n = 1, ..., N$ will, taking other agents expected contributions $E_n[G_{n'}]$ as given, solve:

$$\max_{Y_n, G_n} U_n(Y_n, G_n, E_n[\sum_{n' \neq n} G_{n'}], A_n, \theta_n)$$

$$s.t. \;\; Y_n + G_n \leq I_n$$

[3]In fact, the warm-glow function f_{WG} could be considered part of this function. We keep them separate here to follow the standard in the prevailing literature.

The optimality condition is given as:

$$\frac{\partial \widetilde{U_n}}{\partial G_n} + \frac{\partial f_n^{WG}}{\partial G_n} + \frac{\partial f_n^{NORM}}{\partial G_n} = \frac{\partial \widetilde{U_n}}{\partial Y_n}$$

Under basic assumptions of continuity and differentiability, this serves as a necessary but not sufficient condition for all agents n, given that no assumptions have been made above the partial derivatives of f_n^{NORM} or $\widetilde{U}_n$. For the suggestion of a donation amount to shift the observed equilibrium, the suggestion must affect one of these terms. In this setup, $\frac{\partial \widetilde{U_n}}{\partial G_n}$ and $\frac{\partial \widetilde{U_n}}{\partial Y_n}$ are potentially a function of A_n and $E_n[\sum\limits_{n' \neq n} G_{n'}]$, and $\frac{\partial f_n^{NORM}}{\partial G_n}$ is potentially a function of θ_n and $E_n[\overline{G}]$, or:

$$\frac{\partial \widetilde{U_n}}{\partial G_n}(A_n, E_n[\sum_{n' \neq n} G_{n'}]) + \frac{\partial f_n^{WG}}{\partial G_n} + \frac{\partial f_n^{NORM}}{\partial G_n}(\theta_n, E_n[\overline{G}]) = \frac{\partial \widetilde{U_n}}{\partial Y_n}(A_n, E_n[\sum_{n' \neq n} G_{n'}])$$

What can therefore explain a shift in personal contribution utility caused by a donation suggestion $S \in \mathbf{S}$? First, as is common in such settings, purely psychological concepts such as anchoring and framing (for discussion, see Tversky and Kahneman 1974,1981) cannot be completely ruled out. Next, a suggestion amount could directly affect an individual's quality perceptions A_n, or $\mathbf{S} \times \mathbf{A} \rightarrow \Delta(\mathbf{A})$, affecting the marginal altruistic utility of donation $\frac{\partial \widetilde{U_n}}{\partial \sum\limits_n G_n}$. Although it is unclear why such a shift in quality perception would occur from a generic suggestion amount, it is conceivable that merely the fact that suggestion has been used in solicitation, regardless of what amount it is, changes the individual's view of the charity quality. This would cause all donations to weakly shift up or down based on the shift in A_n. In our experiment, we consider this even more unlikely since, as recent alumni from the fundraising school, subjects should have good knowledge of the quality of the good.

The suggestion may also affect giving by directly altering the individual's expectation of other agent's donations $E_n[\sum\limits_{n' \neq n} G_{n'}]$. This could be the case if agents infer the suggestion as coming from a moment of other's giving, or derived from the marginal effect of donation on the public good due to the current level of $\sum\limits_{n' \neq n} G_{n'}$ (that is, fundraisers ask for an amount that would be "valuable" in an absolute sense). As discussed above and in further detail in Shang and Croson, shifts in giving based on perceptions of other's giving may occur through several pathways. First, even if the utility component f_n^{NORM} does not exist, for $\widetilde{U_n}$ concave in G_n an increase (decrease) of expected giving of others $E_n[\sum_{n' \neq n} G_{n'}]$ will decrease (increase) the marginal altruistic utility of giving $\frac{\partial \widetilde{U_n}}{\partial G_n}$. If this was the only effect, then fundraising would be maximized by convincing donors that others were giving the lowest possible amount.[4] If, however, there is a fixed cost or some other convexity in the provision of the public good, then the assumption that $\widetilde{U_n}$ is concave in G_n does not hold, and $\frac{\partial \widetilde{U_n}}{\partial G_n}$ could increase for higher $E_n[\sum_{n' \neq n} G_{n'}]$. This would be an example where a suggestion amount might secure coordination in the public good by convincing donors that others are donating a sufficient amount to make the public good valuable. If this was the only effect, then the optimal suggestion S depends on the shape of the function $\frac{\partial \widetilde{U_n}}{\partial G_n}$ and is likely finite. It should be noted that in our experiment we do not expect donors to worry about such a coordination problem existing for a university they recently graduated from, and it can be safely assumed that $\widetilde{U_n}$ is concave in G_n.

Beyond the direct effect, a high expectation $E_n[\sum_{n' \neq n} G_{n'}]$ may also increase the perception of quality A_n, if donors feel other's donation indicate their better knowledge of the public good. This would offer a competing effect to the above two that may cause donations to be maximized by convincing donors others were giving the highest possible amount.

Of course, a shift $E_n[\sum_{n' \neq n} G_{n'}]$ also affects $E_n[\overline{G}]$, and thus may affect giving utility as a function of social norms, embodied by f_n^{NORM}. For the remainder of the analysis, we will treat $E_n[\overline{G}]$ as one of the parameters of the perception of social norms in the eyes of the potential contributor θ_n. This allows us to analyze all possible shocks on social norms in the same framework. It should be noted that any shift in $\mathbf{S} \times \theta \rightarrow \Delta(\theta)$, even those not directly instigated by $E_n[\sum_{n' \neq n} G_{n'}]$, may affect $E_n[\sum_{n' \neq n} G_{n'}]$ if donors assume other agents will receive the same suggestion and thus change their giving patterns. This interrelation of giving may increase or decrease the strength of a shifting effect, but will not reverse any of the effects originating in the function f_n^{NORM}

[4] If there is a fixed cost or some other convexity in the provision of the public good, then the assumption that $\frac{\partial \widetilde{U_n}}{\partial G_n}$ is concave does not hold, and $\frac{\partial \widetilde{U_n}}{\partial G_n}$ could increase for higher $E_n[\sum_{n' \neq n} G_{n'}]$. This would be an example where coordination of giving is important (see, e.g., Van Huyck et al. (1992) on how suggestion amounts can be viewed as a coordination game).

discussed below. Indeed, given the critical mass element of any shift to a new equilibrium, a proportionally large "first mover" shift in agent's θ_n must occur to precipitate any observed shift in contributions.

As mentioned above, the social norms can indicate the values of other contributors, the general public, or the fundraiser themselves. It is conceivable that the suggested amount merely acts as a signal of a societal norm. Although we find it more plausible that the suggestion amount results in a change in the individual's perception regarding the fundraiser's personal norms, our experimental design can not cleanly infer that this is indeed what is taking place.

It might at first seem odd that a potential donor should be motivated by the norms of the fundraiser soliciting a contribution. In truth, we already take one ability of the fundraiser to affect behavior for granted: as noted by Andreoni (1998), the only rationale for a non-profit to fundraise at all is if there is a "power of the ask", i.e. an increase in contribution revenues resulting from specifically asking donors to give. While the reason behind this effect is not as clean as our treatment and can be explained in many ways, the fact fundraising is extant and in truth commonplace serves to show that fundraiser actions clearly have some scope to affect behavior.[5] Though donors receiving utility directly by placating the norms of the fundraiser would be an interesting and practically important result in many scenarios, the analysis below is unchanged whether the effect is based on the perception of fundraiser norms or societal norms.

Consider the following scenarios to explain an effect of norms on behavior. Let a potential contributor n have an original utility $U_n(G_n)$ over all possible contributions. Subsequently, a fundraiser suggests a donation of, for example, \$20. The utility associated with donating \$100 may now be greatly increased, being as it now seems immensely generous and benevolent to give an amount so far exceeding what was suggested. The utility associated with \$10 may be similarly reduced, as it now appears cheap to give less than what was suggested by the fundraiser. This would indicate that the suggestion acts to rotate the function f_n^{NORM} around the suggestion point, increasing the utility of donating above the suggestion, and decreasing it below.

Alternatively, the suggestion could be considered a signal of the fundraiser's (or society's)

[5] List and Price (2010) and Meer (2011), for example, found that characteristic similarity between solicitor and potential donor increased donations, while Landry, et. al (2006) found a large increase based on the physical attractiveness of the fundraiser. These studies, along with Meer and Rosen (2011), who found the act of personal solicitation increased giving, suggest that individual donations can be affected by the fundraiser themselves.

subjective valuation of the marginal effect of a donation amount on the public good. In this scenario, the potential donor has an initial expectation of this valuation embodied in the function f_n^{NORM}. The signal affects this expectation, shifting the amount of satisfaction or utility gained from each prospective donation. This would suggest a horizontal shift in the function f_n^{NORM} due to the suggestion, with the shape of the function remaining constant.

A third scenario is the idea that contributors receive a fixed negative utility if the amount they donate is inappropriately low in relation to the norms of the fundraiser or society, thus appearing stingy in front of the solicitor (or symmetrically, a positive fixed utility for reaching an appropriate amount). If the agent is uncertain of the exact range of inappropriate amounts (or alternatively, the degree of inappropriateness of each amount), they will attach an expected disutility to each prospective donation amount. By suggesting a donation amount, the solicitor is in effect announcing the complete appropriateness of the suggestion, thus setting the expected disutility to zero and creating a step function that jumps at the suggestion amount by the disutility amount of being inappropriately low.[6] This would fall in line with the explanation of of the "every penny helps" argued by Cialdini and Schroeder (1976): that the comment helped legitimize smaller contributions.

Though it is interesting to parse these alternatives in a behavioral sense, of greater practical importance is the implication of the effect of suggestion on revenue maximizing fundraising design. If $\frac{\partial^2 f_n^{NORM}}{\partial G \partial S} < 0, \forall n$ and the effect of S originates in f_n^{NORM}, then revenue would be maximized by suggesting the lowest possible amount. This would be justified by the first scenario above. If $\frac{\partial^2 f_n^{NORM}}{\partial G \partial S} > 0, \forall n$, then revenue would be maximized by suggesting the highest possible amount. This would be justified by the second scenario for some functional forms of f_n^{NORM} (namely if $\frac{\partial^2 f_n^{NORM}}{\partial G^2} < 0$). Lastly, revenue could also be maximized by some finite suggestion amount relative to the prior state of the individual. This will mainly occur when there is some convexity in the function f_n^{NORM}: this obviously occurs based on the fixed utility achieved by reaching a threshold in the third scenario, and also in the second scenario for some non-concave forms of f_n^{NORM}.

Our theory can also lend insights into how a 'personal' ask can influence contributions. To see

[6] This is in many ways similar to the choice under regret explanation given by Irons and Hepburn (2005) to explain the phenomenon of choice overload (eg. Bertand et.al (2005), Iyengar and Lepper (2000)).

how relaying the idea that a suggestion is personal to the individual can increase the size of the above effect, let there be M types of individuals. Suppose the fundraiser has different attitudes on what constitutes an appropriate donation amount for each of the M types, based perhaps on observables such as income, social status, age, etc. If the fundraiser has no information on the type of each individual, they are forced to only offer a single suggestion S to all potential donors. If, in the eyes of a contributor, there is a positive possibility that this has occurred, the relation that a suggestion is personal to them should increase the strength of any effect. This is because it contains more information on the fundraiser's attitude of what is appropriate for the specific individual than a generic suggestion. If this mechanism does exist, one would find subjects further from group mean characteristics more affected by a personalized request that singled them out. Our treatment, unfortunately, does not allow the variation to test this conjecture. Note that it is again impossible to rule out that increased effects of personalization could also be explained through purely psychological effects. This includes increased salience of the suggestion when personalization is included, or a greater connection to the fundraiser once it is relayed that the solicitor knows personal information about the potential donor.

4 Experimental Design

In September 2009, recent graduates were contacted as part of the UW Steven's Point's Annual Campaign for the Point. Our sample consists of 9,487 alumni who had all graduated between the years 2000 and 2008. Importantly, potential donors should therefore have little uncertainty about the quality of the public good being provided. Potential donors were contacted by paid current students, who were given a standard script with which to ask for donations. This solicitation script, shown in Figure 1, differed only in regards to the language specific to each treatment.

As shown in Table 1, the experimental design is a 4x2 factorial design with a roughly equal percentage of subjects assigned in each cell. The treatment groups were assigned by randomized blocking on observables, and each variable passed the propensity score balancing test of Rosenbaum and Rubin (1985) for each treatment. In the control group, subjects were given no suggestion of the donation amount. In the first treatment group, subjects were given a generic suggestion of $20. In the second treatment group, subjects were given a more "personalized" suggested donation, equivalent to their graduation year in dollars and cents. For instance, if a subject graduated in 2003, the solicitor suggested a donation of \$20.03. Subjects in this group were explicitly told that the donation amount that had been suggested was directly linked to their graduation year.

There is a concern that because personalized suggestions ranging from \$20.00 to \$20.08 changed two potentially important features from the control (personalization and the fact such numbers represented "weird" or "odd" ask levels), they might not yield the true treatment effect of this particular personalization. Therefore, in the third treatment group subjects were randomly suggested values of \$20.01, \$20.04, \$20.07, and \$20.08. The "Unusual Ask" treatment group's suggestions may or may not have corresponded to their year of graduation, and they were given no explanation why such an atypical amount was being suggested.

In the four groups above, half the subjects were randomly offered a 1-to-1 match for each dollar that they donated, pledged by a local business. The other half of the subjects were not offered any match. As the script in Figure 1 shows, the solicitor asked for a specific donation amount, and then subsequently added that for every dollar of that donation a local business would match a dollar. We feel that this makes it fairly clear when we ask (for example) for \$20, we are suggesting a donation of \$20 (and thus a total value of \$40), and not \$10 (and thus a total value of \$20). Our results support the fact that subjects also interpreted the suggestion in this manner. If one feels that this wasn't clearly induced by the script, then it is of interest that subjects interpreted the suggestion as being for the donation and not the total value of the gift.

Recall that in the literature, the theoretical rationale for an effect of matching donations is twofold: there is clearly a price effect resulting from the fact that the marginal effect of donation on the quantity of the public good $\partial \sum_n G_n$ has doubled, but also a possible shift in quality perception A_n associated with the presence of a backer to match donations (see Karlan and List (2007) for a more patient discussion). The price effect in this case positively shifts the distribution of pre-suggestion donations. As noted above, given our sampled population, we expect that the quality channel will be muted since these solicitees know a great deal about the public good (UWSP).

Including the match is useful on several levels. First, it offers an experimental comparison of the size of the suggestion effect with that of an effect already documented in the literature. Second, it allows some ability to check the robustness of our results: the presence of a large interaction effect between matching and suggestion may indicate a large role of either the specific suggestion amount or the quality perception of the charity on the ability of a fundraiser to affect donation.

5 Experimental Results

Summary statistics for each treatment group, as well as pooled statistics for all suggestion treatments and for match and no match subjects, are given in Table 2 ("No Ask" in this and all subsequent tables denotes the control treatment where we did not use a suggestion). In the analysis that follows, we are interested in three major dimensions of the results: the percentage of potential donors contributing, the average donation of the contributors, and the revenue per potential donor (a combination of the previous two). Also of note is the absolute difference between the suggestion amounts and the donation amounts, in comparison to the non-suggestion control. In all regressions, we control for the age of the subjects, whether they reside in state or out of state, and include dummies for graduation years and the matching treatment. We also report specifications that remove outlier donations, defined as being more than three standard deviations from the mean of the total sample of donations (for all summary statistics and regression results with outliers removed, see the appendix).

One might be concerned that for 6,163 (or 64.9%) of our subjects the solicitor was not able to completely read the script, and therefore never received a direct pledge or refusal from the potential donor. The reasons for this range from the obviously exogenous (no answer on the line, a busy signal), to the potentially endogenous (claiming a wrong number, disconnecting half way through the script). As Table 2 shows, the positive correlation between the percentage of "contacted" subjects and the percentage of those contacted subjects who donated supports the idea of some endogeneity. As such, in our analysis of the percentage of potential donors contributing we offer statistics for both extremes: the entire sample (Intent to Treat) and those actually fully contacted (Treatment on the Treated). This turns out to have little effect on the conclusions.

5.1 Generic Suggestion Results

The first important comparison is between the no suggestion control group and our baseline generic treatment: the \$20 suggestion treatment group. For policy reasons, we consider this the most applicable to an average fundraising campaign, and thus analyze it separately from the other two suggestion treatments (although as Table 2 shows, the results are still strong with all the ask treatments pooled into one group). Table 2 shows that of all solicitees, a considerably greater number in the \$20 ask give compared to the control (4.47% vs. 3.01%). Further, of those actually contacted, 12.6% gave in the \$20 ask compared to 9.55% in the control. On the intensive margin, the ask reduces the average donation amount (\$19.35 versus \$23.92), and as Table 3 shows, the distribution of gifts is more centered on \$20.

To provide a sense of the average treatment effects, we provide Tables 4 and 5, which report results of regression specifications concerning giving rates. Column 1 in Table 4 shows how the average pledge amount changes with introduction of the \$20 ask: the \$20 suggestion treatment shows significantly lower mean donation amounts at the $p < .05$ level (t-stat). To complement this result, Column 1 in Table 5 models the probability of giving a positive amount. What we learn from this model is that a significantly higher percentage (nearly 50% more, t-stat, $p < .05$) of potential donors contribute in the \$20 ask.[7] Column 3 of Table 4 shows that the ask treatment collapsed the donation distribution around the suggestion amount: the absolute difference between the donation amount and \$20 is reduced by an estimate of \$6.08 (t-stat, $p < .01$). This result remains strongly significant (t-stat, $p < .01$), though smaller (\$5.45), when outliers are omitted.[8] The overall results of the \$20 treatment indicate a strong and economically significant effect of the direct amount solicitation.

Changes in the average donation could result solely from an effect of causing counterfactual non-donors to donate, with no effect on counterfactual donors. There is strong evidence that this was the not the case. As noted earlier, the number of donations at each amount reported in Table 3 gives some idea of how the donation distribution was affected by the \$20 suggestion.

[7]The estimated average marginal effect of the ask treatment on the probability of donation was an increase of 0.0148 over a baseline of 0.0301 for ITT (Table 5, Column 1) and an increase of 0.0324 over a baseline of 0.0949 for TOT (Table 5, Column 2).

[8]For all summary statistics and regression specifications with outliers removed, see the appendix.

As Table 6 shows by range, the percentage of donors donating \$20 is significantly higher in the \$20 suggestion group, while the percentage of donors donating above \$20 is significantly higher in the no suggestion group (Fisher's exact test, $p < .01$ for both ranges, whether as a percentage of donors, contacted subjects, or all subjects). The percentage donating less than \$20 is similar across groups. The expected heterogeneous treatment effects limit what can be said about how suggestion affected original non-donors, low donors, and high donors. Certainly, the total effect of suggestion appears to occur from a combination of increasing the percentage of subjects contributing, moving many subjects to the suggestion amount, and sharply decreasing the amount of subjects donating above the suggestion amount.

The donation revenue per subject for each treatment is given in Table 2. Revenues under both population specifications were directionally larger in the \$20 suggestion group compared to the no suggestion control. The difference is insignificant for the entire population, but is marginally significantly higher (on a 10% level) than the no suggestion treatment with outliers removed. Given that the effects of suggestion were to increase participation and move contributions towards the suggestion amount (which was lower than the average gift in the baseline), our finding that revenues across treatments are comparable is to be expected. It is notable, however, that the increased participation overcame the decreased contribution mean in our results.

The individual results of the match treatment are in line directionally with the results in Karlan and List (2007): more subjects give and revenues are increased when a match is in place. None of these effects, however, is significant at conventional levels. Furthermore, Table 2 shows that the effect of the ask treatment was directionally but insignificantly larger than that of the match treatment when compared to the no ask, no match control. The effect of the ask treatment is also very similar whether a match was offered or not. Tables 4 and 5 report regressions with an added interaction term for the match treatment. In terms of donation amounts and the amount of donors contributing, the fact a match was or was not offered did not significantly change the size of the suggestion effect. Our preferred interpretation of this set of match results is that since our experimental population fully understood the quality of the public good (UWSP), there was not as large of a scope to increase quality perception, and therefore donations, as in Karlan and List. This would be an important result in terms of understanding the basis behind the effect of matching on giving patterns.

Further insights on the effect of suggestion can be gleaned from the fact that subjects had the option to pay their pledge immediately by credit card, or later by mailing in a check. As Table 9 shows, this option to delay led to a significant portion of pledges not actually being paid by would-be donors. The $20 ask had lower percentages of non-payment than the no ask control, although this difference was insignificant by a Fisher's exact test. This difference was a combination of more people in the control pledging by check, and more check-payers reneging on their pledge (both insignificantly). As a percentage of the total subject population, the amount of individuals giving an unfulfilled pledge is very similar between the top treatment groups. The percentages of pledges rescinded by pledge amount are given in Table 10. The most noteworthy difference between the groups in this regard was the fact that not a single person donating above the suggestion amount in the $20 ask treatment failed to pay, as opposed to 28.6% of the same range of pledges in the no ask group. This difference is significantly different (Fisher's exact test, $p < .05$).

5.2 Personalized Suggestion Results

The effect of a "personalized" suggestion compared to a generic suggestion can be thought of in several different ways, depending on assumptions. The most basic is to compare the results of the $20 suggestion treatment and the class year treatment. As Table 2 shows, the percentage of subjects donating is nearly identical in each treatment, and the average donation amounts are not significantly different (and nearly identical when outliers are removed). The absolute difference between the ask amount and the donation amount is insignificantly different with outliers (see Table 7), but donation amounts are significantly closer to the suggestion amount in the class year treatment when outliers are removed (t-stat, $p < .05$).

Using this comparison as a measure of the effect of personalization assumes that an ask amount of $20 is numerically and psychologically similar to an ask amount of $20.XX. If this is not the case, a better comparison is between the class year treatment and the unusual suggestion treatment. Figure 2 provides a graphical summary of our results based on the fraction of givers.

What is evident is that across every dollar bucket, the personalized ask outperforms the unusual ask. This suggests that personalization matters in terms of whether the person gives. As seen in Table 8, however, when pooling across these buckets the percentage of subjects donating in the unusual suggestion treatment is only marginally significant at conventional levels (t-stat, $p < .10$ for ITT, $p < .05$ for TOT). Further, there is no significant difference in the average donation with or without controls. Since some of the class year subjects graduated in the year 2000, they were given an ask amount of $20, allowing a test of whether a $20 versus $20.XX effect exists. The year 2000 graduates had very similar giving patterns as the rest of the years, consistent with there being a small effect of this kind.

One could also claim that the unusual suggestion treatment differed from the other two in that, by asking for an amount that was "strange" compared to $20 or an explained class year amount, the effect of suggestion was psychologically different. Other possibly confounding effects include individuals who happened to receive a suggestion corresponding to their graduation year inferring that such a personalization had taken place, or those that received slightly different amounts than their grad year thinking that the fundraiser had wrong information about them, which might have reduced their willingness to give.

Since 255 (or 11.0%) of our subjects in the unusual ask randomly received their graduation year amount, we can check this conjecture. The giving percentages were very similar between the groups (3.40% of those who got their class year, 3.52% of those who did not), and none of the other statistics on gift amounts approach significance at conventional levels (although this is to be expected with only 9 gifts from those who got their class year). If any one of these confounding effects exist and the numerical effect does not, the comparison of the $20 suggestion to the class year suggestion is preferred. If both effects exist, then the personalization results are in general confounded.

The donation revenue per subject in Table 2 shows revenues under both population specifications were similar in the class year suggestion group and the $20 suggestion group. The Class Year suggestion group revenues are directionally larger than both the no suggestion control and unusual suggestion groups. Again, the differences are insignificant for the entire population, but the class year treatment is marginally higher (t-test, $p < .10$) compared to the no suggestion treatment with outliers removed. The difference between the class year treatment and the unusual suggestion treatment is marginally significant (t-test, $p < .10$). The difference between the class year treatment and the no ask control was insignificant for the entire population, but the class year is marginally higher (t-test, $p < .10$) with outliers removed.

In terms of reneged pledges, the class year treatment has very similar percentages of non-payment compared to the $20 ask. Non-payment in the class year treatment is lower than the no ask and unusual ask treatments, although this difference is insignificant by a Fisher's exact test. Again, this results from a combination of more pledgers by check and more reneging check pledgers. As a percentage of the total subject population, the amount of individuals giving an unfulfilled pledge is virtually identical across all treatments. As Table 10 shows, the class year treatment also did not have a single person pledge above the suggestion amount and subsequently fail to pay. This is only significantly different from the no ask control, however, if it is pooled with the $20 treatment (Fisher's exact test, $p < .05$).

Interestingly, we do observe larger effects on the class year ask versus the unusual ask. For instance, whereas only 29 of 107 pledges (27.1%) went unfulfilled in the class year ask, 29 of 84 (34.1%) went unfulfilled in the unusual ask. In Table 10, directionally lower rescinding rates are observed at all donation levels in the class year ask, with the largest differences being found in the small donations bin. Much of this difference can be explained by more subjects pledging by check in the unusual suggestion treatment. While these differences are insignificant in themselves, this level of reneging leads to the true revenues per contact to be considerably higher in the class year ask compared to the unusual ask ($0.755 versus $0.491), a difference that is significant at conventional levels (t-test, $p < .05$). The remainder of the above analysis obtains similar results when received donations are considered instead of pledged donations. In addition, since once donors give they are more likely to give in the future, this finding on personalization is likely a lower bound on the total effect of the personalization.

6 Discussion of Results

One major result of our experiment is a practical one: we found a large response to the treatment of a direct amount suggestion to potential donors. This occurred both on the extensive margin, with an economically significant increase in the percentage of subjects who donated, and on the intensive margin, with the donation distribution moving sharply to the suggestion amount. These sizable observed effects show the promise of suggestion amounts, and highlight the import of the ask amount when designing an optimal fundraising strategy. In our case, our suggestion turned out to be below the mean of donations in the control, but the increased donation rate overcame lower average donations to (insignificantly) increase revenue. If the same effects occurred for higher suggestion amounts, revenue increases based on suggestion could be particularly lucrative. An important question, therefore, is not only if our results generalize to other fundraising organizations, but also to higher ask levels.

The results on the extensive margin are surprisingly large. The increase in donation rates (31.9% TOT, 48.5% ITT) also exceeds that of the "every penny helps" effect. The stronger effect of smaller suggestion amounts on donation incidence may well be related to the "every penny helps" effect, in that it increases the valuation of smaller gifts, thus inciting more overall donation (discussed further below). Taking this into account, along with the results of Warwick (2003) and Weyant and Smith (1987) that participation rates were reduced with higher suggestion amounts, there is some reason to believe that the increase in donor participation may be tempered by higher suggestion amounts.

On the intensive margin, the ability of the treatment to affect the donation distribution is more pronounced than the announcement of another individual's donation by Shang and Croson (2009).[9] We expect our subject population to be more responsive to treatment than theirs, being as our subjects were cold-called, and theirs were contacting a fundraiser with a donation amount presumably already in mind. Our subject pool also contained counterfactual non-donors while theirs did not. Nonetheless, if one wishes to interpret our treatment as a shift in the perception of fundraiser norms and theirs of fellow donor's norms, it is interesting that our results are at least as strong or stronger than theirs. In terms of the extrapolation of our results to higher suggestion amounts, Shang and Croson also found their treatment to become less effective as announced donations became very high (although their most successful treatment in terms of increase revenue

[9] Our most successful treatment increased the percent of donations at the suggestion amount from 28.5% to 70.4%, compared to an increase of 12.3% to 24.0% in their most successful treatment. The effect on donation amount was 19.1% of the control mean donation in our most successful treatment, compared to 12.2%.

was above the control mean, at the 90 percentile of the observed control distribution).

What can our theory inform us about extrapolation to different suggestion amounts, and in light of the above results, what forces may be at play? Again, the main results of the treatment were to sharply increase the amount of donors donating at the suggestion amount (including many donors who would have counterfactually not donated), and sharply decrease the amount of individuals donating above the suggestion amount. This implies several things about the marginal utility $\frac{\partial U_n}{\partial G_n}$ after the suggestion. First, for such a large concentration of individuals to be moved to the suggestion amount, it must be that $\frac{\partial U_n}{\partial G_n}$ at the suggestion amount is very high in relation to the marginal utility above or below the suggestion amount. Considering the fact that there is individual heterogeneity in income and utility function parameters that should cause variance in donations, there is a necessity for an even greater proportionate rise in marginal utility at this suggestion point to account for so much movement to the suggestion.

Second, the fact that we see a large reduction in donations above the suggestion amount indicates that the marginal utility $\frac{\partial U_n}{\partial G_n}$ above the suggestion amount is small. This causes individuals to sharply substitute away from donations to personal consumption until their donation amounts are reduced to the suggestion amount.

Both these facts are consistent with the idea that the function U after the suggestion is not only strongly convex in G_n, but at least resembles a step function, with the step or steep portion centered on the suggestion amount S. Individuals gain utility from complying with the suggestion S, but little more utility from going beyond that amount. From an optimal suggestion standpoint, this rules out the idea of offering very low suggestions to individuals, as it would be likely to move their donations down to that low point. Likewise, it would also rule out offering very high suggestions. To see this, note that reaching the step of the function f_n^{NORM} is very valuable utility-wise for an individual, but it obviously comes at a cost in personal consumption Y. If the step is reached only at a very high donation level, it is not worth increasing donations enough to reach the step, and thus the suggestion is unsuccessful at moving a potential donor to that point.

The results instead suggest that revenue will be optimized through a suggestion that is a certain amount greater than the counterfactual donation, but not too far away from that amount. This makes information that offers predictive power on the counterfactual no-suggestion contribution very valuable for the prospective fundraiser. Without this information, only a single suggestion can be made to all potential donors. This risks the result that occurred in our experiment: many people chose to donate when they otherwise would not have, but many counterfactually high donors reduced their donations to be more in line with the suggestion amount. The result was an only marginal increase in overall revenue. Suggestions may also fail to increase revenue, it appears, if they are too high to incite a change in behavior.

Reconciling these results in the framework above without the function f_n^{NORM} is difficult. The possible effects occurring without this function (resulting from a change in $E_n[\sum_{n' \neq n} G_{n'}]$ and/or A_n) would seem to predict the distribution of giving shifting up or down rather than collapsing on the suggestion point. With asymmetric individuals and treatment effects one could surely find a distribution of $E_n[\sum_{n' \neq n} G_{n'}]$ and A_n over the subjects to render the results we see in our experiment, but such a distribution would seem purely coincidental.

Furthermore, because the function f_n^{WG} is assumed to be concave, if U_n is indeed convex after the suggestion it would require strong convexity in the function $\widetilde{U_n}$ or f_n^{NORM} . As discussed, $\widetilde{U_n}$ only is plausibly convex if there is a large fixed cost to the public good, rendering coordination an important issue. This would not seem to be the case for a large university where the prospective donors had recently graduated.

If, therefore, the source of the convexity is purely in f_n^{NORM}, the results are consistent with there being a fixed "norm" utility of reaching the suggestion amount that would cause a discontinuity in f_n^{NORM}. Several of our behavioral justifications we discussed in Section 2 fit such a result. The first is the idea that the individual has an original function f_n^{NORM} based on their perceptions of social norms and the signal of the fundraiser's (or society's) norms simply shifts the function f_n^{NORM} horizontally in G_n. If this were the case, the function f_n^{NORM} would obviously have the same form before and after the suggestion treatment. Assume that θ consists of only a single scalar parameter and $f_n^{NORM} = \{0 \text{ for } G_n < \theta_n; \lambda_n \text{ for } G_n > \theta_n\}$, where $\lambda_n > 0$ is large enough relative to $\frac{\partial U_n}{\partial G_n}$ at other points than θ_n such that the majority of individuals donate at θ_n. Without a suggestion amount being made, θ_n is a random draw from some unknown distribution $F(\theta)$. When a suggestion is made, θ_n becomes S. This would also explain why so many individuals chose to donate \$20 when they counterfactually would not have donated: their θ_n was too high, making it too expensive in terms of lost personal consumption to reach the fixed utility λ_n, but when it was reduced to \$20, it became viable.

Another justification is that of uncertain disutility from donating an inappropriately low amount or uncertain positive utility for reaching an appropriately high amount. In either case, the original function f_n^{NORM} would have a form that accounts for the expected disutility/utility at each donation point, conditional on the individual's information set. Once the suggestion is made, the "appropriate" threshold is known with certainty, and f_n^{NORM} becomes a step function, with lower utility below the suggestion point and higher above. It should be noted that if this were the case, we would expect to see fewer positive donations below the suggestion amount in the treatment than the control, which was not observed. Both the above explanations would be consistent with the "every penny helps" effect, as small donations becoming more valuable would increase the percentage of subjects donating.

A major difference in our results to Warwick (and to a lesser extent, Weyant and Smith) is that we found suggestions greatly affecting the intensive margin of giving, whereas they did not. Part of this may lie in the fact that our experimental solicitation was in the form of a phone call, whereas their solicitation was by direct mail. This would fit into the social pressure of fundraisers on givers argued by Meer (2011) and Meer and Rosen (2011). The pattern of non-payment of pledges offers further insight into the utility function associated with giving. The non-trivial percentage of individuals which ended up not following through with their pledges (29.8% of the total sample) is suggestive that there was disutility associated with turning down the solicitor on the phone, even if one did not plan to actually donate (see Della Vigna et al., 2012, for face-to face social pressure of this sort). Directional differences in reneging between treatments seemingly included immediate plans to renege. This could be seen by more people promising to later mail a check instead of paying immediately, as opposed to differences simply confined to differences in the reneging of check pledgers. Importantly, even though there was no evidence that suggesting a donation amount caused the disutility of reneging to increase, or led to greater amounts of spurious pledging, it was the case that fewer people in the personalized ask reneged on their pledge (compared to the numerically similar unusual ask). This might indicate that the disutility of actually reneging on a pledge was enhanced by making the ask personal.

This type of effect deserves more careful scrutiny because we view it as novel to the literature, but only suggestive here due to our sample size limitations.

What is also true is that spurious pledgers seemed more readily moved to the suggestion amount than those who followed through with their gift. It is intuitive that individuals who were pledging solely to appease the fundraiser would be more likely to respond to a signal of the desires or the norms of the solicitor. The resulting significant difference between followed-up pledging of individuals donating above \$20 in the no ask and the two successful ask treatments fits nicely into the shifting f_n^{NORM} step-function interpretation above: heterogeneous subjects had differing expectations of the norms of the fundraiser, thus causing some spurious pledgers to pledge a high amount in the no-ask treatment. This group was moved to the suggestion amount by the solicitor's signal, thus leaving only those with utility of donation not driven by societal or fundraiser norms remaining at amounts above the suggestion.

Our personalization treatment was somewhat better at moving individuals to the mean than the generic \$20 treatment, although the amount of individuals donating was nearly identical. It was better than the "unusual" identical suggestion amounts in inciting donation, but similar in moving to the suggestion amount, resulting in increased revenues that became more strongly significant when spurious pledges were removed. Considering that there was a great deal of homogeneity in the group in general (all young alumni from the same school), in the theoretical framework above personalization should not be expected to have a great effect.

7 Conclusion

Understanding the demand side of fundraising has become an emerging literature. In this study we combine theory with a natural field experiment to explore the effect of suggestion amounts. Our results show a surprisingly large and economically significant effect of suggesting a donation amount to potential donors. On the extensive margin, we find a nearly 50% increase in the percentage of individuals donating after receiving a generic suggestion. In light of the fact that perhaps the most important job of the fundraiser is building a donor pyramid for future contributions, this result has immediate practical significance. On the intensive margin, we find observed donations collapse strongly to the suggestion amount.

One interpretation of our results viewed through the lens of our model is that after a suggestion amount is made, individuals receive a fixed amount of utility from donating at least as much as the suggestion, but little utility from exceeding it. This result suggests that even though altruism is often claimed to be an important driver of donor behavior, in this case our data are more consistent with a model of impure altruism. In terms of optimal fundraising design, this implies that optimal suggestions should be made at an amount greater than the counterfactual donation, but not at an infinitely high amount. The optimal spread is not a question that can be answered by this study and requires more research.

Our empirical results also corroborate an idea that the previous literature has hinted: an individual's utility resulting from donation, far from being set in stone, is highly malleable and responsive to even seemingly simple techniques. For fundraising practitioners, this necessitates a greater understanding of the nature of contribution utility functions in order to take advantage of this malleability to increase fundraising revenues. Treatments such as ours are able to offer greater insight on the nature of these utility functions. We trust the literature will continue to use the scientific method to shed light on important philanthropic issues.

8 References

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9 Tables and Figures

TABLE 1: Experimental Design and Treatment Subject Totals

	Match	No Match
No Ask: Subjects were asked to donate but not suggested a specific donation amount.	1,178	1,140
$20 Ask: Subjects were suggested a donation amount of $20	1,217	1,196
Class Year Ask: Subjects were suggested an amount corresponding to their grad year (ex: $20.03 if they graduated in 2003, years 2000-2008). The caller explained the relation between the amount and the grad year.	1,160	1,201
Unusual Ask: Subjects were suggested one of the amounts $20.01, $20.04, $20.07, or $20.08. They were given no explanation why this amount was being suggested.	1,179	1,216

Note: Match subjects were offered a match of 1:1 by a local business for every dollar they donated.

TABLE 2: Summary Statistics

Treatment Group	Subjects	Contacted	% of total donating	% of contacts donating	Mean Positive Donation (SD)	Revenue/Contact (SD) Total	Revenue/Contact (SD) Contacted
No Ask	2,318	733	0.0301	0.0955	23.92 (16.28)	0.722 (4.96)	2.285 (8.63)
Pooled Ask	7,169	2,591	0.0417	0.1154	19.99 (9.06)	0.836 (4.41)	2.315 (7.10)
$20 Ask	2,413	857	0.0447	0.1260	19.35 (7.36)	0.866 (4.29)	2.439 (6.93)
Class Yr Ask	2,361	852	0.0453	0.1256	20.17 (9.04)	0.914 (4.61)	2.534 (7.41)
Unusual Ask	2,395	882	0.0351	0.0952	20.82 (10.74)	0.730 (4.32)	1.983 (6.95)
No Match	4,753	1,627	0.0368	0.0543	21.55 (11.92)	0.798 (4.66)	2.331 (7.75)
No Ask	1,140	364	0.0271	0.0421	24.06 (13.10)	0.675 (4.53)	2.115 (7.82)
Ask	3,614	1,263	0.0398	0.0580	20.99 (11.61)	0.837 (4.71)	2.394 (7.74)
Match	4,734	1,697	0.0409	0.0596	19.89 (9.90)	0.819 (4.43)	2.286 (7.17)
No Ask	1,178	369	0.0331	0.0530	23.21 (18.87)	0.768 (5.36)	2.452 (9.37)
Ask	3,556	1,328	0.0436	0.0615	19.07 (5.66)	0.836 (4.08)	2.240 (6.44)

Note: Contacted subjects are characterized as those who were read the entire script, followed by a direct pledge or refusal by the subject. The Pooled Ask is the combination of all treatments where a suggestion was made.

FIGURE 1: Script Read by Callers to Subjects

Hello, this is ______ calling from UW Steven's Point for The Annual Campaign for Point.

FOR NO ASK TREATMENT:

This year we're again hoping to raise a half million dollars to support UWSP students and programs and increasing the number of donors is a major goal of this year's campaign. To reach our goal, we're asking for a gift from you today.

FOR $20 ASK TREATMENT:

This year we're again hoping to raise a half million dollars to support UWSP students and programs and increasing the number of donors is a major goal of this year's campaign. To reach our goal, we're asking for a gift of $20.00 from you today.

FOR CLASS YEAR TREATMENT:

This year we're again hoping to raise a half million dollars to support UWSP students and programs and increasing the number of donors is a major goal of this year's campaign. To reach our goal, we're asking for a gift of <u>class year in dollars and cents</u> from you today, since you graduated in the year <u>class year</u>.

FOR UNUSUAL ASK TREATMENT:

This year we're again hoping to raise a half million dollars to support UWSP students and programs and increasing the number of donors is a major goal of this year's campaign. To reach our goal, we're asking for a gift of <u>[$20.01, OR $20.04, OR $20.07, OR $20.08]</u> from you today.

IN ADDITION, FOR ALL MATCHING TREATMENTS:

In addition, for each $1 you donate this year, [*the matching local business*] will match your donation with funds going directly to support student scholarships!

For your convenience, we take all major credit cards.

[After they decide whether or not to give, and how much, continue below]

If I can just quickly verify your address [*verify address*]

And you are currently at [*verify employer, title*]?

And we don't seem to have an email address listed for you, do you have an email address? [*ask for email address if they simply answer 'yes'*].

[*Confirm amount and where it will go*]

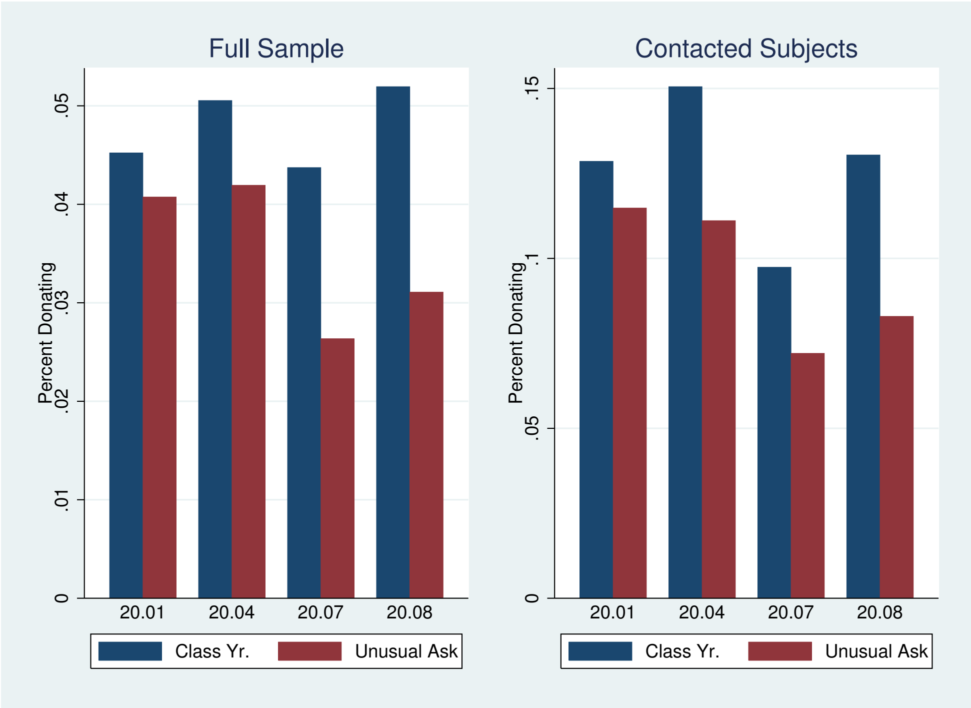
Thank you so much, we are extremely grateful for your support. Have a good evening!

TABLE 3: Pledges by Amount and Treatment

Pledge Amount ($)	No Ask	$20 Ask	Class Year	Unusual Ask	Total
5	1	0	1	0	2
10	18	21	10	11	60
15	2	1	0	0	3
20	20	76	14	3	113
20.01	0	0	7	17	24
20.02	0	0	9	0	9
20.03	1	0	5	0	6
20.04	0	0	12	16	28
20.05	0	1	12	0	13
20.06	0	0	10	0	10
20.07	0	0	11	13	24
20.08	0	0	11	14	25
20.09	0	0	0	1	1
21	0	0	0	1	1
25	15	5	2	4	26
30	3	0	1	0	4
35	0	0	0	1	1
50	8	4	1	2	15
75	1	0	0	0	1
100	1	0	1	1	3
All	70	108	107	84	369

Note: Both Match and Non-Match Subjects included.

FIGURE 2: Percent Pledging by Amount for Class Year Treatments



Note: Both Match and Non-Match Subjects included.

TABLE 4: $20 Ask and No Ask Subjects Donation Amounts

	(1) Pledge Amount (OLS)	(2) Absolute Diff. from $20 (OLS)	(3) Absolute Diff. from $20 (OLS)
Ask Dummy	-4.215**	-6.080***	-3.904*
	(2.065)	(1.671)	(2.346)
Match Dummy	-1.841	-0.916	1.682
	(1.902)	(1.539)	(2.498)
Lives Instate	-1.046	0.389	0.0707
	(2.684)	(2.172)	(2.180)
Age	0.189*	0.203**	0.207**
	(0.110)	(0.0891)	(0.0890)
Ask * Match			-4.331
			(3.286)
Constant	20.49*	-0.927	-2.883
	(10.79)	(8.727)	(8.830)
Observations	178	178	178
R^2	0.222	0.333	0.342

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Graduation Year Dummies and Caller Dummies included in each specification.

TABLE 5: $20 Ask and No Ask Subjects Donation Probability

	(1)		(2)		(3)	
	Pledged		Pledged		Pledged	
	(Probit, ITT)		(Probit, TOT)		(Probit, TOT)	
	β	Mfx	β	Mfx	β	Mfx
Ask Dummy	0.193***	0.014***	0.183**	0.032**	0.183**	0.032**
	(0.072)		(0.090)		(0.090)	
Match Dummy	0.048	0.003	0.031	0.005	0.031	0.005
	(0.071)		(0.088)		(0.088)	
Lives Instate	0.020	0.001	-0.107	-0.019	-0.107	-0.019
	(0.095)		(0.122)		(0.122)	
Age	0.030***	0.002***	0.032***	0.005***	0.032***	0.005***
	(0.005)		(0.006)		(0.006)	
Ask * Match					-0.135	-0.024
					(0.177)	
Constant	-2.617***		-2.132***		-2.132***	
	(0.222)		(0.268)		(0.268)	
Observations	4717		1585		1585	
Mean Predicted Probability	0.041		0.117		0.117	

β=estimated coefficient, Mfx=marginal effect at sample mean. Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Note: Graduation Year Dummies and Caller Dummies included in each specification.
ITT includes all subjects, TOT includes only contacted subjects.

TABLE 6: Percentage of Donations by Range

Range and Treatment	Pledges	% of Pledgers	% of Total	% of Contacted
Under 20.00				
No Ask	21	0.3000	0.0091	0.0286
$20 Ask	22	0.2037	0.0091	0.0257
Class Year Ask	11	0.1028	0.0047	0.0129
Unusual Ask	11	0.1310	0.0046	0.0125
20.00-20.08				
No Ask	21	0.3000	0.0091	0.0286
$20 Ask	77	0.7130	0.0319	0.0898
Class Year Ask	98	0.9159	0.0415	0.1150
Unusual Ask	63	0.7500	0.0263	0.0714
Over 20.08				
No Ask	28	0.4000	0.0121	0.0382
$20 Ask	9	0.0833	0.0037	0.0105
Class Year Ask	5	0.0467	0.0021	0.0059
Unusual Ask	10	0.1190	0.0042	0.0113

Note: Percentages are given as those of each treatment group.
Both Match and Non-Match Subjects included.

TABLE 7: $20 Ask and Class Year Subjects

	(1) Absolute Diff. from Ask (OLS)	(2) Pledged (Probit, ITT)		(3) Pledged (Probit, TOT)	
	β	β	Mfx	β	Mfx
\$20 Ask Treatment	-1.513	0.017	0.001	0.010	0.002
	(1.115)	(0.066)		(0.081)	
Match Dummy	-2.093*	0.007	0.001	-0.028	-0.005
	(1.114)	(0.066)		(0.081)	
Lives Instate	-2.125	0.037	0.003	-0.059	-0.011
	(1.689)	(0.092)		(0.117)	
Age	-0.023	0.027***	0.002***	0.026***	0.005***
	(0.061)	(0.004)		(0.005)	
Constant	5.066	-2.251***		-1.636***	
	(5.395)	(0.195)		(0.232)	
Observations	215	4762		1704	
R^2	0.213				
Mean Predicted Probability		0.045		0.124	

β=estimated coefficient, Mfx=marginal effect at sample mean. Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Note: Graduation Year Dummies and Caller Dummies included in each specification.
ITT includes all subjects, TOT includes only contacted subjects.

TABLE 8: Class Year and Unusual Ask Subjects

	(1) Absolute Diff. from Ask (OLS)	(2) Pledged (Probit, ITT)		(3) Pledged (Probit, TOT)	
	β	β	Mfx	β	Mfx
Unexplained Treatment	-0.259	-0.121*	-0.009*	-0.174**	-0.030**
	(1.475)	(0.069)		(0.084)	
Match Dummy	-0.641	0.065	0.005	0.029	0.005
	(1.466)	(0.068)		(0.083)	
Lives Instate	-6.325***	0.121	0.009	-0.002	-0.000
	(2.321)	(0.101)		(0.129)	
Age	-0.030	0.024***	0.002***	0.022***	0.004***
	(0.078)	(0.004)		(0.005)	
Constant	9.093	-2.496***		-1.877***	
	(10.109)	(0.217)		(0.259)	
Observations	190	4746		1731	
R^2	0.227				
Mean Predicted Probability		0.043		0.117	

β=estimated coefficient, Mfx=marginal effect at sample mean. Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Note: Graduation Year Dummies and Caller Dummies included in each specification.
ITT includes all subjects, TOT includes only contacted subjects.

TABLE 9: Rescinded Pledges Summary Statistics

Treatment Group	Pledges	Paid	Unpaid	% Paid by check	% Unpaid (Check)	% Unpaid (Pledges)	% Unpaid (Total)	Mean Positive Donation (SD)	True Rev./Contact (SD) Total	True Rev./Contact (SD) Contacted
No Ask	70	46	24	0.6714	0.5106	0.3429	0.0104	26.08 (17.70)	0.574 (4.62)	1.746 (7.89)
Pooled Ask	299	213	86	0.6656	0.4322	0.2876	0.0119	21.31 (11.32)	0.660 (4.19)	1.757 (6.55)
$20 Ask	108	80	28	0.6389	0.4058	0.2593	0.0116	21.38 (10.60)	0.736 (4.36)	1.931 (6.54)
Class Yr Ask	107	78	29	0.6356	0.4265	0.2710	0.0122	21.22 (11.47)	0.755 (4.48)	2.021 (7.08)
Unusual Ask	84	55	29	0.7380	0.4678	0.3452	0.0121	21.36 (12.32)	0.491 (3.69)	1.332 (6.00)
No Match	175	123	52	0.6686	0.4444	0.2971	0.0109	22.14(12.86)	0.628(4.35)	1.76(7.08)
No Ask	31	17	14	0.7419	0.6087	0.4516	0.0123	24.71(11.25)	0.522(4.22)	1.50(6.89)
Ask	144	106	38	0.6528	0.4043	0.2639	0.0105	21.72(13.11)	0.661(4.39)	1.84(7.13)
Match	194	136	58	0.6650	0.4497	0.2990	0.0123	20.69(10.98)	0.650(4.26)	1.74(6.67)
No Ask	39	29	10	0.6154	0.4167	0.2564	0.0084	23.62(19.95)	0.624(5.00)	1.99(8.78)
Ask	155	107	48	0.6774	0.4571	0.3097	0.0135	19.89(6.75)	0.659(3.99)	1.67(5.95)

Note: Rescinded pledges occured when subjects pledged to mail a check, but such a check was never received.
Both Match and Non-Match Subjects included.

TABLE 10: Rescinded Pledges by Pledge Amount

Treatment Group	Under $20.00		$20.00-$20.08		Over $20.08	
	Pledges	% Rescinded	Pledges	% Rescinded	Pledges	% Rescinded
No Ask	21	0.4286	21	0.3333	28	0.2857
Pooled Ask	44	0.2727	231	0.3060	24	0.1304
$20 Ask	22	0.3182	77	0.2727	9	0
Class Yr Ask	11	0.0909	91	0.3077	5	0
Unusual Ask	11	0.3636	63	0.3437	10	0.3333

Note: Rescinded pledges occured when subjects pledged to mail a check, but such a check was never received. Both Match and Non-Match Subjects included.

10 Appendix

TABLE 2A: Summary Statistics Including Dropped Outliers

					FULL SAMPLE			OUTLIERS (3SD) DROPPED		
Treatment Group	Subjects	Contacted	% of total donating	% of contacts donating	Mean Positive Donation (SD)	Revenue/Contact (SD) Total	Revenue/Contact (SD) Contacted	Mean Positive Donation (SD)	Revenue/Contact (SD) Total	Revenue/Contact (SD) Contacted
No Ask	2,318	733	0.0301	0.0955	23.92 (16.28)	0.722 (4.96)	2.285 (8.63)	22.06 (12.01)	0.647 (4.24)	2.052 (7.37)
Pooled Ask	7,169	2591	0.0417	0.1154	19.99 (9.06)	0.836 (4.41)	2.315 (7.10)	19.52 (6.17)	0.809 (4.09)	2.239 (6.56)
$20 Ask	2,413	857	0.0447	0.1260	19.35 (7.36)	0.866 (4.29)	2.439 (6.93)	19.35 (7.36)	0.866 (4.29)	2.439 (6.93)
Class Yr Ask	2,361	852	0.0453	0.1256	20.17 (9.04)	0.914 (4.61)	2.534 (7.41)	19.42 (4.62	0.872 (4.13)	2.419 (6.62)
Unusual Ask	2,395	882	0.0351	0.0952	20.82 (10.74)	0.730 (4.32)	1.983 (6.95)	19.86 (6.27)	0.689 (3.81)	1.872 (6.11)
No Match	4,753	1627	0.0368	0.0543	21.55 (11.92)	0.798 (4.66)	2.331 (7.75)	20.77 (8.35)	0.756 (4.20)	2.211 (6.96)
No Ask	1,140	364	0.0271	0.0421	24.06 (13.10)	0.675 (4.53)	2.115 (7.82)	24.84 (12.54)	0.675 (4.52)	2.115 (7.82)
Ask	3,614	1263	0.0398	0.0580	20.99 (11.61)	0.837 (4.71)	2.394 (7.74)	19.88 (6.86)	0.782 (4.10)	2.239 (6.69)
Match	4,734	1697	0.0409	0.0596	19.89 (9.90)	0.819 (4.43)	2.286 (7.17)	19.29 (6.90)	0.782 (4.05)	2.185 (6.54)
No Ask	1,178	369	0.0331	0.0530	23.21 (18.87)	0.768 (5.36)	2.452 (9.37)	19.72 (11.2)	0.621 (3.96)	1.989 (6.904)
Ask	3,556	1328	0.0436	0.0615	19.07 (5.66)	0.836 (4.08)	2.240 (6.44)	19.19 (5.46)	0.836 (4.08)	2.240 (6.44)

Note: Contacted subjects are characterized as those who were read the entire script, followed by a direct pledge or refusal by the subject.

TABLE 4A: $20 Ask and No Ask Subjects with Outliers Dropped

	(1) Pledge Amount (OLS)	(2) Absolute Diff. from $20 (OLS)	(3) Absolute Diff. from $20 (OLS)
Ask Dummy	-3.374**	-5.455***	-5.182***
	(1.682)	(1.296)	(1.833)
Match Dummy	-2.582*	-1.510	-1.182
	(1.546)	(1.191)	(1.964)
Lives Instate	0.843	2.425	2.377
	(2.237)	(1.724)	(1.745)
Age	0.101	0.138*	0.139*
	(0.0911)	(0.0702)	(0.0705)
Ask * Match			-0.545
			(2.584)
Constant	24.19***	1.404	1.155
	(8.824)	(6.799)	(6.924)
Observations	176	176	176
R^2	0.201	0.325	0.325

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Note: Graduation Year Dummies and Caller Dummies included in each specification.

TABLE 7A: $20 Ask and Class Year Subjects with Outliers Dropped

	(1)
	Absolute Diff. from Ask (OLS)
$20 Ask Treatment	-1.216**
	(0.573)
Match Dummy	-0.0166
	(0.581)
Lives Instate	0.603
	(0.872)
Age	-0.0411
	(0.0318)
Constant	0.813
	(2.618)
Observations	209
R^2	0.154

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Graduation Year Dummies and Caller Dummies included in each specification.

TABLE 8A: Class Year and Unusual Ask Subjects with Outliers Dropped

	(1)
	Absolute Diff. from Ask (OLS)
Unusual Treatment	0.00585
	(0.577)
Match Dummy	0.804
	(0.573)
Lives Instate	0.284
	(0.933)
Age	-0.0643**
	(0.0303)
Constant	0.483
	(3.933)
Observations	185
R^2	0.220

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Graduation Year and Caller Dummies included in each specification.