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Avoiding Peer Information and Its Effects on Charity Crowdfunding: A Field Experiment

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Abstract. We study the behavior of an individual avoiding peer information from a natural field experiment of charity crowdfunding. The unique experimental design enables us to employ an instrumental variable strategy to identify how the behavior influences individual giving to and promotion of charity campaigns. We find that, even with free access, 89% of individuals chose not to seek peer information. These individuals were less likely, whereas their peers were more likely to give and help promote in the past. The behavior would reduce the total distribution of campaigns by 8.5% and the total donation amount by 7.7%. A stylized model is used to illustrate how the pressure from peer comparison drives the individuals not to seek the information and how this behavior could influence giving and promoting behaviors of a group of marginal individuals.

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1. Introduction

The value of information is well documented. It allows individuals to make choices that yield higher expected payoffs than choices they would make in the absence of information. Rational people therefore should be seeking information if the information is readily available and the acquisition cost is low. Economics and psychology research, however, has documented that people often avoid information for different reasons (see Gino et al. 2016 and Golman et al. 2017 for excellent surveys on the literature). Such information-avoidance behavior could lead to worse decision making, unethical or less prosocial and more selfish behaviors, and confirmation bias (Jonas et al. 2001, Hart et al. 2009, Exley 2020, Exley and Kessler 2021). These consequences can enhance the spread of misinformation, cause political polarization, facilitate media bias (Gentzkow and Shapiro 2010), and lead to the spread of infectious disease, such as Acquired immunodeficiency syndrome (Caplin and Eliaz 2003). Despite a large stream of literature on the prevalence of the information-avoidance behavior and its consequences, studying the behavior in the context of a charity giving setting helps provide new insights. For example, to what extent do individuals choose not to view peer giving information? How does the choice impact the giving behaviors? What is the incentive behind this choice? The goal of this study is to address these questions by empirically examining what drives the behavior of information avoidance and its impacts on charity giving.

Partnering with Waterdrop ("Shuidichou" in Chinese), the largest online crowdfunding platform for charities supporting individuals with a terminal illness in China, we ran a natural field experiment by manipulating the information availability in the messages that solicit charity donations from individuals. Each message contains voluminous important information on the charity campaign. The experiment only focused on a single piece of information—whether and how much friends gave—for the recipient of the message. Recipients could choose whether to see the information. Golman et al. (2017) specify two criteria for active information avoidance. First, individuals should be aware that the information is available; second, individuals choose not to gain the information even if it can be accessed for free or even costly to avoid. Because the link to the information in the experiment was displayed at the top of the message and recipients could click the link to access the information in a quick and easy way, we can classify the choice of not viewing the information as information avoidance.[1]

We define "information avoiders" as individuals who choose not to view the peer donation information and "information seekers" as those who actively seek the information. We then ask the following questions. First, who chooses to avoid and seek information? Second, how and why does peer donation information influence an information avoider's decisions of giving to and promoting (i.e., resending the message to other peers in her network) a charity campaign if the information is revealed to the person? Third, do the decisions of an information seeker change if the information is not available? The answers to these questions will extend our understanding of why people avoid and seek information and the consequences.

Because information avoiders and information seekers can be intrinsically different and they cannot be identified a priori, we cannot randomize the two groups of individuals into different information availability conditions, as field experiments typically would do. Instead, we design the experiment to focus on one treatment condition (G3) that offers the recipients the option to choose whether they see the information. This design allows us to distinguish information avoiders from information seekers. To infer the impacts of information avoidance or seeking on these two groups of individuals, we design two additional treatment conditions in the experiment; the peer donation information is revealed to all recipients in the first condition (G1), and this information is not available for all recipients in the second condition (G2). We then compare the behaviors of the treatment group of focus (G3) with those of G1 and G2, employing an instrumental variable (IV) estimation strategy. Specifically, we estimate the effect of information avoidance on information avoiders by pooling individuals of G1 and G3 and use the assignment into G1 and G3 as the instrumental variable for information avoidance, which is the treatment in focus. The group assignment is a valid instrument because it is random to any unobserved factors that may affect individuals' giving and promoting propensities and correlated with the information avoidance decision. We also conduct regression estimation on G2 and G3 using the same assignment variable as the instrument for information seeking that is the treatment.[2] Estimation results represent the causal effects of avoiding (seeking) information on information avoiders (seekers). By designing our field experiment based on the IV estimation strategy, which is typically used for nonexperimental data, we break away from the standard classification of empirical methods in the literature (e.g., see figure 1 in Al-Ubaydli and List 2016). By adding G1 and G2 to the experimental design, we can also rule out several alternative mechanisms that drive the empirical findings, as we will discuss in Section 5.

We use a stylized model that theoretically describes how a recipient's giving and promoting decisions are influenced by the peer donation information and how avoiding the information can be optimal. The model assumes that peer giving information increases individuals' utility either because such information helps assess the quality of the charity campaign to reduce uncertainty or generates positive joint consumption of prosocial behavior. However, a disutility arises when the recipient decides not to give but the sender does because of the pressure from peer comparison. Such pressure will only exist if the recipient actually sees the peer giving information. The model shows how seeking (avoiding) peer information positively (negatively) influences the charity behaviors of the *marginal* individuals, who will either seek or avoid the information if there is a chance. It also derives several propositions that can be tested from the data.

We find that information avoidance was pervasive in the field experiment, as 89% of participants chose not to see the peer donation information, even though the cost was negligible, and they did not interact physically or verbally with the peers when seeking the information. A key difference between information avoiders and information seekers is that the avoiders gave and helped promote less than the latter in the past; however, the avoiders are more likely to give to and promote the current campaign. We also find that the message senders of information avoiders were more active in charity donation in the past. These results are consistent with our hypothesis that information avoidance is driven by the incentive to evade peer comparison and that the expected probability of peer giving positively affects individuals' charity behavior.

Our IV regressions show that, compared with the scenario in which the information was exposed, information avoidance reduced the (unconditional) giving amount by 0.6%–0.7%, the giving rate by 3.7%–4.7%, and the resending rate by 5.4% among information avoiders. The aggregate effects on the crowdfunding platform are even bigger because the drop in giving and resending rates will further reduce the reach of a campaign in the ˜~donor network and the giving rate of recipients' peers. We find that the drop in the giving and resending rate will translate into an 8.5% reduction in total resending on Waterdrop and a 7.7% reduction in total giving for charities. Note that our experiment only manipulates one piece of information out of the hundreds of pieces of information contained in a campaign message. The prior belief thus is that the effect from the experiment should be negligible. Yet, our results suggest a surprisingly significant economic consequence.

Although a large body of research demonstrates the prevalence of the information-avoidance behavior and its consequences, we have limited evidence in the charity giving setting. The novel insights from our study are threefold. First, we find that information avoidance is pervasive as 89% of participants chose not to see the peer donation information. Second, we show that, for a group of individuals, they will be positively affected by the giving behavior of peers; however, if an option is given, they would rather choose avoiding the peer donation information. Third, we find that this avoidance behavior is driven by the incentive to avoid the comparison pressure from peer giving.

Although the goal of the paper is to study the information-avoidance behavior, the empirical findings can have significant policy implications for charity crowdfunding. Online crowdfunding is a new phenomenon in fundraising and becoming increasingly popular because of lower funders' search costs, feasible funding in small increments, and lower information gathering and monitoring costs (Agrawal et al. 2014). According to Fundly.com, the global amount raised by crowdfunding in 2020 reached U.S. $34 billion. Donations used to pay for life events and causes of individual fundraisers reached U.S. $5.5 billion in 2020 and was the second-largest type of crowdfunding.[3] Therefore, the success of a crowdfunding campaign critically relies on supporters promoting the cause by spreading the word among their peers so that it can reach a large audience. Supporters' giving can also motivate their peers to donate to the cause. Our evidence indicates that information avoiders and information seekers coexist simultaneously. Therefore, understanding the effects of the avoidance behavior on information avoiders and the seeking behavior on information seekers is important for a charity crowdfunding platform to design to what extent the peer donation information should be provided. If, for example, information avoidance is prevalent on a platform and for these individuals, the effects of allowing avoidance of the information is negative on giving, the platform should not offer such a choice to potential donors.

The rest of the paper proceeds as follows. We will discuss the related literature in Section 2, and we present in Section 3 a stylized model and derive propositions that predict giving, promoting, and information avoidance from the model. Section 4 offers details of the design of the field experiment. Section 5 presents analysis results using the field experiment data and discusses the mechanism that drives our empirical findings. Finally, Section 6 concludes.

2. Related Literature

Our work adds to the large body of literature on why people choose not to obtain information. Past research has documented that individuals avoid useful information because they prefer compound lotteries (Kreps and Porteus 1978) or are risk or disappointment averse (Gul 1991). Individuals may also avoid the information that they do not want to think about (Golman et al. 2022) or to maintain optimism (Brunnermeier and Parker 2005). By not being exposed to information, they may avoid bias (Camerer et al. 1989) and resist temptation (Carrillo and Mariotti 2000). Avoidance can also help them exploit the "moral wiggle room" (Dana et al. 2007, Larson and Capra 2009, Matthey and Regner 2011, Bartling et al. 2014, Feiler 2014, Grossman 2015, Grossman and Van Der Weele 2017) and create self-serving biases (Konow 2000, Haisley and Weber 2010). Unlike most of these studies that are either theoretical works or based on laboratory experiments, our study builds on a natural field experiment. It helps avoid potential issues from laboratory experiments that lead to concerns about the external validity (Levitt and List 2007) and selection bias caused by subjects' participation decisions (Al-Ubaydli and List 2015). We therefore consider our work complementary to the previous research. We also add to this body of research by showing the desire to escape peer comparison pressure as another motive for information avoidance.

A stream of research that examines the role of social information in charitable donations and public goods provision in the economics (for reviews, see Andreoni 2006 and Vesterlund 2006) and psychology (for reviews, see Cialdini and Goldstein 2004, Weber and Messick 2004, and Penner et al. 2005) literature is also related to our study. Frey and Meier (2004), for example, studied the role of conditional cooperation in a field experiment of a mail fundraising campaign. They found that people increase contributions when many others also contribute. Shang and Croson (2009) manipulated how much another donor has given in a field experiment of a fundraising campaign for a public radio. They find a positive effect of others' giving amount on individual contributions, but the effect is only significant for new members. In a laboratory experiment, Exley (2016) provides evidence that individuals use risk as an excuse not to give. When they face trade-offs between charity and self-payoff, they are more averse to the risk of the former and less averse to the latter. However, such asymmetry disappears in the absence of the trade-off. Designing an online experiment that manipulates the image concerns, Exley and Kessler (2021) show that image concerns play a lesser important role in driving information avoidance than the common approach used in prior studies. Using both field and online experiment approaches, Exley and Petrie (2018) show that the flexibility that offers individuals the time to think about the impending prosocial ask reduce prosocial behavior. Our work differs from these studies by focusing on the information-avoidance behavior, which is an individual decision (rather than being exogenously manipulated), and its effect on charity giving.

Finally, we highlight two previous works that are closely related to the context of our study. They both ran field experiments to examine avoidance behaviors in the charity giving setting. The first one by DellaVigna et al. (2012) uses door-to-door fundraising to study how households may seek or avoid fundraisers. In the second paper, Andreoni et al. (2017) placed bell ringers at the entrances of a supermarket to solicit donations and focus on how people actively avoid verbal solicitation from bell ringers. Our work departs from these two papers in several ways. First, the behavior we study is distinct. The phenomenon documented in Andreoni et al. (2017) is not about information avoidance. In fact, the authors intentionally ensured that the verbal solicitation did not contain any useful information. One could argue that the fundraisers in DellaVigna et al. (2012) might provide useful information about charities; however, obtaining such information entails physical interaction with fundraisers, which could have significant time and other costs (e.g., having strangers at home) for households. In this sense, shunning the interaction with fundraisers cannot be classified as information avoidance. By contrast, our experiment ensured that the conditions for information avoidance specified in Golman et al. (2017) were satisfied. Second, we dive deeper to investigate who are information avoiders and information seekers and what would have happened if they were not allowed to avoid or seek information. Neither of the two prior studies examined these policy-relevant issues. Finally, we look at not only the giving but also, the promoting behavior, which is one of the most important innovations for the success of crowdfunding campaigns.

3. A Model of Giving, Promoting, and Information Avoidance

We use a stylized model in this section to illustrate the underlying mechanism behind individuals' decision not to seek the peer donation information and the consequences on their giving and promoting decisions because of the information avoidance. The model abstracts away from the various factors that may influence the giving decision that have been documented in the vast literature on charity donation. In particular, the altruistic motive is captured in a reduced-form way in the model.

The model compares three scenarios. After receiving the messages from senders, recipients in the first scenario (G1)[4] are informed of whether and how much senders donate. They do not have the information in the second scenario (G2). In the third scenario (G3), which is the focus of the study, recipients are given an option to choose whether to see senders' donation information ($S_i = 1$) or not ($S_i = 0$). To simplify the analysis, we only focus on recipient i's choice of whether to give, $g_i = \{0, 1\}$, and after making the decision, whether to promote the charity campaign by resending the message to her other friends, $r_i = \{0, 1\}$. We abstract away from the giving amount decision. Instead, we assume that if $g_i = 1$, the donation amount is fixed at d.[5]

We assume that revealing sender j's donation information, g_j, helps the recipient evaluate the "quality" of the charity campaign (Vesterlund 2003), and thus affects her utility of giving. This assumption is reasonable because the quality of charity campaigns is uncertain for most individuals (Rose-Ackerman 1980, 1981; Handy 1995), and an individual's assessment of campaign quality typically goes beyond the information provided from Waterdrop. For example, she does not precisely know how much the need for donations is; she might also care about how much the fundraiser is associated with her community. Such information, however, can be gleaned from peers' giving decisions. An alternative justification is that the recipient obtains more utility of giving if the sender has also given because of the positive joint consumption of prosocial behaviors (for example, see Bruhin et al. 2020 in the blood donation context). Such a social multiplier effect is also found to be present in other contexts (e.g., schooling in Cipollone and Rosolia 2007 and Lalive and Cattaneo 2009 and contribution to public good in Borjas and Doran 2015). The reward function is specified as

$$u_i(g_i) = (\delta \cdot \mu_i \cdot \{g_j = 0\} + \mu_i \cdot \{g_j = 1\}) \cdot \{g_i = 1\}, \tag{1}$$

where {.} is an indicator function that equals one if the condition inside the brackets is true and zero otherwise. The parameter μ_i represents the utility of giving if sender j gives. We assume that μ_i has a continuous distribution function F with positive support in $[\mu^L, \mu^H]$, where μ^L and μ^H are the lower and upper bounds of the distribution, respectively. If the sender does not give, the recipient's utility will be discounted by $\delta \in (0, 1)$. For simplicity, we assume that the matching of senders and recipients is random; that is, the recipient's distribution is independent of the probability that the sender gives, P_j. The recipient does not know g_j for sure, but she holds rational beliefs about g_j; that is, the recipient knows P_j.

We assume that if $g_i = 0$ but the recipient knows $g_j = 1$, she will incur a utility loss $-\theta$. Although the sender is not physically present, we consider that the utility loss arises from the pressure of "peer comparison," similar to the "social pressure" in DellaVigna et al. (2012). Such pressure can be because of "self-signaling" to maintain "self-image" (e.g., Benabou and Tirole 2002, Grossman 2015) because the recipient incurs a psychological loss by receiving a signal indicating she is less altruistic than her peer.[6] Alternatively, the pressure can be because of pure social comparison without involving altruism because the recipient does not want to appear worse than her peer in giving behavior. We do not separate the two reasons in the model. Note that the utility loss is only triggered when the recipient actually knows that the sender gives.

When a recipient i in G1 makes the giving decision, she knows g_j and chooses g_i to maximize her utility function:

$$\begin{aligned} U_i^1(g_i, g_j) = {} & \beta \cdot (W - d \cdot \{g_i = 1\}) \\ & + ((\delta \cdot \mu_i \cdot \{g_j = 0\} + \mu_i \cdot \{g_j = 1\}) \cdot \{g_i = 1\}) \\ & - \theta \cdot \{g_j = 1\} \cdot \{g_i = 0\}, \end{aligned} \tag{2}$$

where W is the total budget for the individual; $(W - d \cdot \{g_i = 1\})$ is the budget left for the recipient's consumption after giving; and $\beta > 0$ represents the marginal utility of consumption, which is assumed to be constant.

For G2, recipient i does not know g_j (except the probability of giving P_j) and chooses g_i to maximize the following expected utility:[7]

$$U_i^0(g_i, P_j) = \beta \cdot (W - d \cdot \{g_i = 1\}) + ((\delta \cdot \mu_i \cdot (1 - P_j) + \mu_i \cdot P_j) \cdot \{g_i = 1\}). \tag{3}$$

We assume that if the sender's information is not revealed, peer comparison will not lead to psychological pressure. Therefore, the utility loss $-\theta$ in Equation (2) does not exist. We believe that this assumption is reasonable. Even if the recipient knows that the sender's P_j is high and thus, experiences pressure when she chooses not to give, the utility loss should be significantly less than knowing that j has given. Equations (2) and (3) capture the key difference between the two treatment groups; seeing the peer donation information can reduce the utility because of the pressure of peer comparison.

Conditional on her giving decision g_i, the recipient decides whether to promote the charity campaign by resending the message r_i. We assume that the extent to which the recipient wants to promote the campaign to another peer k is a proportion α (< 1) of her giving utility. This motive implies a warm glow; that is, the recipient values the donation of others less than her own donation (e.g., Tonin and Vlassopoulos 2010).

For G1, the recipient chooses r_i to maximize the following utility function:

$$U_i^{r1}(g_i, g_j) = (\alpha \cdot (\delta \cdot \mu_i \cdot \{g_j = 0\} + \mu_i \cdot \{g_j = 1\}) \cdot P_k - c) \cdot \{r_i = 1\}. \tag{4}$$

In this specification, the higher the utility the recipient gets from giving to the campaign, the higher is the incentive to resend. $P_k = Pr(g_k = 1)$ is the probability that k will give. Finally, c represents the cost of resending.[8]

For G2, the recipient chooses r_i to maximize the utility function:

$$U_i^{r0}(g_i, P_j) = (\alpha \cdot (\delta \cdot \mu_i \cdot (1 - P_j) + \mu_i \cdot P_j) \cdot P_k - c) \cdot \{r_i = 1\}. \tag{5}$$

For G3, recipients can choose whether to see senders' donation information. The recipient will choose $S_i = 0$ (i.e., not to see the information) or 1 (i.e., see the information) to maximize the following utility function:

$$V(g_i, P_j) = max_{g_i} U_i^0(g_i, P_j) \cdot \{S_i = 0\} + E_{g_j} max_{g_i} U_i^1(g_i, g_j) \cdot \{S_i = 1\}, \tag{6}$$

where $max_{g_i} U_i^0(g_i, P_j)$ represents the utility function in (3) when the recipient chooses the optimal g_i; that is,

$$max_{g_i} U_i^0(g_i, P_j) = max\{\beta \cdot W,\ \beta \cdot (W - d) + (\delta \cdot \mu_i \cdot (1 - P_j) + \mu_i \cdot P_j)\}. \tag{7}$$

Based on the previous setup, the second component in (6) can be derived as

$$E_{g_j} max_{g_i} U_i^1(g_i, g_j) = P_j \cdot max\{\beta \cdot W - \theta,\ \beta \cdot (W - d) + \mu_i\} + (1 - P_j) \cdot max\{\beta \cdot W,\ \beta \cdot (W - d) + \delta \cdot \mu_i\}. \tag{8}$$

The first line on the right side of the equation is the case in which the sender gives, and the second line is the case in which the sender does not.

Removing $\beta \cdot W$ from all terms in (7) and (8), Equation (6) can be rewritten as

$$V(g_i, P_j) = max\{0,\ -\beta \cdot d + (\delta \cdot \mu_i + (1 - \delta) \cdot \mu_i \cdot P_j)\} \cdot \{S_i = 0\} + (P_j \cdot max\{-\theta, -\beta \cdot d + \mu_i\} + (1 - P_j) \cdot max\{0, -\beta \cdot d + \delta \cdot \mu_i\}) \cdot \{S_i = 1\}. \tag{9}$$

3.1. Marginal Individuals Under the Effect of Peer Donation Information

Based on this setup, let $\widehat{\mu}_1(g_j = 1) = \beta \cdot d - \theta$. It can be shown from Equation (2) that, if $\mu_i \le \widehat{\mu}_1(g_j = 1)$, the individual will not donate even if the peer gave. The peer information does not have value for this type of individual. We will show later that these individuals will not seek the information to avoid the utility loss $-\theta$. Let $\widehat{\mu}_1(g_j = 0) = (\beta \cdot d)/\delta$. Equation (2) shows that, if $\mu_i \ge \widehat{\mu}_1(g_j = 0)$, the individual will donate even if the peer did not give. The information again will not have value for this type of individual because it does not affect their decision. The peer effect is only positive for the *marginal* individuals whose utility is in the range

$$\widehat{\mu}_1(g_j = 1) < \mu_i < \widehat{\mu}_1(g_j = 0). \tag{10}$$

Equation (2) shows that the individual will give only if $g_j = 1$; otherwise, he or she will not give. Because peer information is only valuable for *marginal* individuals, the availability of such information will only affect these individuals.

Define $\widehat{\mu}_2(P_j) = (\beta \cdot d)/[\delta + (1 - \delta) \cdot P_j]$. From Equation (3), we can see that an individual with $\mu_i > \widehat{\mu}_2(P_j)$ will give. A positive peer effect also occurs for G2; because $\widehat{\mu}_2$ is a decreasing function of P_j, the recipient is more likely to give if she believes the sender is likely to give. Assuming recipients have rational beliefs, we will observe from the data that the likelihood of recipients giving is positively correlated with senders giving.

3.2. Propositions

Based on the stylized model, we derive several propositions from the model that can be tested from the field experiment data. Proofs of the propositions are in the appendix. The first three propositions predict the giving and promoting behaviors of G1 and G2.

Proposition 1. *Assume for any P_j that the probability mass of choosing $g_i = 1$ is positive in G2; that is, a positive proportion of individuals of G2 will always give to the charity campaign. Then, $Eg_i(G1) > Eg_i(G2)$; that is, the average giving rate across individuals of G1 is higher than G2.*

That is, with the peer donation information, individuals will donate more to charities.

Proposition 2. *If a recipient gives, she is more likely to promote the campaign to friends, holding everything else equal, for either G1 or G2. That is, $Er_i(g_i = 1) > Er_i(g_i = 0)$.*

That is, recipients who give are more likely to resend. As a result, the following proposition states that individuals are more likely to promote charities with the peer donation information:

Proposition 3. *Assume for any P_j that the probability mass of choosing $g_i = 1$ is positive in G2; that is, a positive proportion of individuals of G2 will always give to the charity campaign. Then, $Er_i(C1) > Er_i(C2)$; that is, the average resending rate is higher for G1 than G2.*

The following three propositions predict the giving and promoting decisions of information avoiders and seekers of G3, which is the focus of this study.

Proposition 4. *For G3, the decision of whether to seek peer information depends on the recipient's utility of giving. For those with $\mu_i < \beta \cdot d$, the optimal choice is $S_i = 0$. For those with $\beta \cdot d \le \mu_i < (\beta \cdot d)/\delta$, the optimal choice is $S_i = 1$. For those with $\mu_i \ge (\beta \cdot d)/\delta$, the decision does not affect the utility.*

This proposition suggests that less altruistic individuals (i.e., $\mu_i < \beta \cdot d$) will choose not to seek the information to avoid the utility loss $-\theta$. Note that some of the marginal individuals defined in the previous subsection whose utility is in the range of $\beta \cdot d - \theta < \mu_i < \beta \cdot d$ fall into this information-avoider group. The consequence is that, by avoiding the information, they will not give even though their senders have given. Another group of marginal individuals whose utility is in the range of $\beta \cdot d \le \mu_i < (\beta \cdot d)/\delta$ will seek the peer donation information. Whether they give or not depends on the senders' giving decision. Finally, because individuals with utility higher than $(\beta \cdot d)/\delta$ will give anyway, whether to seek the information does not affect their utility. If we believe that in charity crowdfunding, not seeking information is a default for most individuals, the information-avoider group also consists of individuals who have high μ_i.

Because those with utility in the range of $\beta \cdot d - \theta \le \mu_i < \beta \cdot d$ choose not to see the information and thus, do not give, the average giving rate of G3 will be lower than that of G1, which is formally shown in the next proposition.

Proposition 5. *The following proposition is to compare the behavior of information avoiders of G3 with the scenario in which they see the sender's donation information.*

a. *For information avoiders of G3, $Eg_i(S_i = 0|G3) < Eg_i(S_i = 0|G1)$; that is, the giving rate of individuals of G3 who choose to avoid seeing the peer information (G30) is smaller than if the peer information is revealed in G1 for the same individuals.*

b. *For information avoiders of G3, $Er_i(S_i = 0|G3) < Er_i(S_i = 0|G1)$; that is, the resending rate of G30 is smaller than if the peer information is revealed in G1 for the same individuals.*

The last proposition predicts how information seekers of G3 would give to and promote the charity campaign if they could not see the peer donation information.

Proposition 6. *The following proposition is to compare the behaviors of information seekers of G3 with the scenario in which they see the sender's donation information.*

a. *The giving rate of individuals of G3 who seek to see the peer information (G31) is larger than if the peer information is not revealed in G2 for the same individuals. That is, $Eg_i(S_i = 1|G3) > Eg_i(S_i = 1|G2)$.*

b. *The resending rate of G31 is larger than if the peer information is not revealed in G2 for the same individuals. That is, $Er_i(S_i = 1|G3) > Er_i(S_i = 1|G2)$.*

Note that because the model abstracts away from other factors that may also influence the giving and resending decisions, it will not fully explain all data patterns in the field experiment. As an example, the deterministic model implies that no information avoiders of G3 will give, which is inconsistent with the observation that we discuss in the next section. However, estimating the model from data is not our goal. The exercise in this section aims to illustrate the mechanism driving information avoidance in our framework and derives the implications of such behavior on individual giving and promoting behaviors that can be tested from data.

4. Field Experiment

We conducted the experiment via Waterdrop, the largest charity crowdfunding platform in China. Waterdrop is a nonprofit company focusing on fundraising for low-income patients who are usually seeking medical treatment for a terminal illness. The platform was established in 2016 and has been growing rapidly. Within its first two years, it attracted more than 160 million registered users. According to a report compiled by the Institute of Sociology under the Chinese Academy of Social Sciences, by the end of 2018, it had helped over 300,000 patients and received more than 40 billion donations, and the total donation amount had exceeded Renminbi (RMB) 12 billion (U.S. $1.7 billion), representing over 10% of the total charitable donations in China.

An individual in need of donations can start a fundraising campaign on Waterdrop by providing a short description consisting of the type of illness, the target amount needed for treatment, and the documents required by Waterdrop to verify the campaign. Once verified, Waterdrop will post the campaign on its mobile app to inform registered users of the fundraising. WeChat is the channel Waterdrop uses to solicit donations, collect funds, and expand reach. The fundraiser typically first sends out a message to her network via WeChat. A recipient of the message can give via WeChat Pay, one of the most popular digital payment methods in China. If the recipient wants to promote the campaign, she will resend the message to other friends in her network,[9] typically through Moments or Friends Group, the fundamental social network features of WeChat. Resending messages is important for the success of fundraising because as word spreads among givers' networks, awareness of the campaign can increase exponentially in a short time. Waterdrop estimates that about 80% of donations come from individuals who received the resent messages. To highlight the importance, Waterdrop considers both giving and resending "support" for charities. Notably, individuals can resend messages without giving.[10] In addition, Waterdrop does not inform senders whether their friends give after receiving the messages. To obtain the information, they have to go back to the original fundraising campaign posted on the WeChat mobile app and search for that information at the end of the campaign page. This feature helps minimize the concern that recipients' giving and resending decisions are driven by the social pressure from senders, as in DellaVigna et al. (2012).

4.1. Experimental Design

The experiment was conducted November 9–11, 2019. The main challenge for our experimental design is that information avoiders and information seekers cannot be identified a priori, and as such, we cannot randomize the two groups of individuals into different information availability conditions, as field experiments typically would do. Our strategy is to add a condition under which the information is exposed to every participant and another under which the information is not available. This design enables us to use the IV estimation method to identify the causal effects of information avoidance and information seeking.

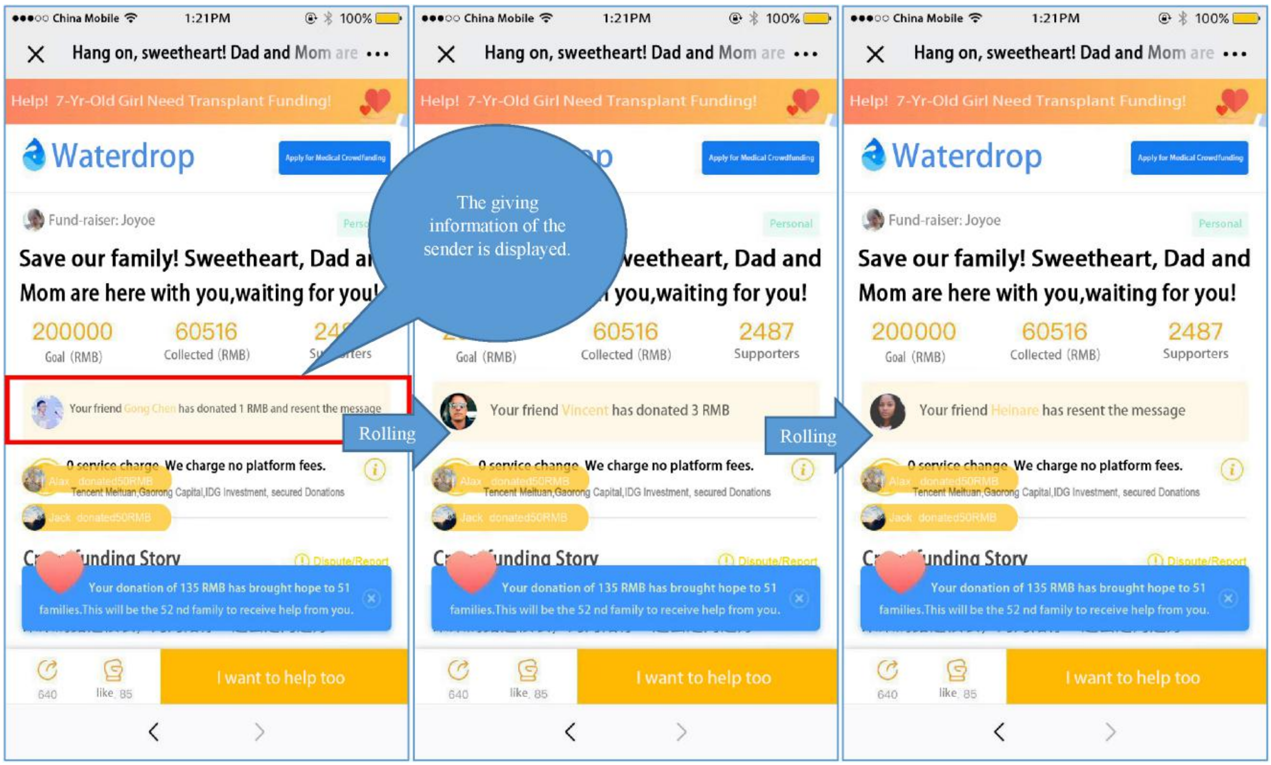
During the experiment, if an individual received a message about a charity campaign[11] sent from a friend through WeChat and read the message, he or she was randomly assigned with equal probability into one of the three treatment groups. The assignment remained the same if the individual subsequently received more messages during these three days, ensuring the consistency of individuals' group assignment. In our analysis, each observation is an event that a recipient received a message. Among those observations, about 6% are directly sent from the fundraiser. Because the relationship between the recipients and fundraisers can be unique and more importantly, because there was no donation information from fundraisers, we excluded those observations and only focused the analysis on the cases in which senders and recipients are potential donors.[12] Our sample consisted of 296,144 observations, involving 25,108 unique charity campaigns and 158,736 unique recipients. Roughly one third of the observations were randomized into each condition.

The messages in G1 contained information that is identical to Waterdrop's current practice. After clicking the message, the recipient saw the peer donation information, including which peers have supported the campaign and how much they have given, close to the top of the message (see Figure 1 for an example of the message). Note that even if no one has given yet, the recipient can still see the names of individuals who resent the message, as they are considered to have helped the campaign. If there are multiple peers supporting the campaign, the photos and donation information of the peer will continuously roll up, one replacing another one. The message also contained other fundraising information, including the name of the fundraiser, a story describing the cause and usually containing several photos, the target amount of money to raise, the current total raised, and the current number of supporters.

For messages in G2, the space displaying the peer donation information was left blank (see Figure 2 for an illustration). Therefore, message recipients in this group could not see the sender's donation information.[13] The implication is that the recipient cannot tell whether the sender helped the campaign without giving (i.e., resent the message only) or gave and if they gave, how much. Note that this no information scenario is different from the no donation cases in G1, as G1 individuals would see the sender who helped the campaign without giving. All other information that a recipient could view was identical to G1.

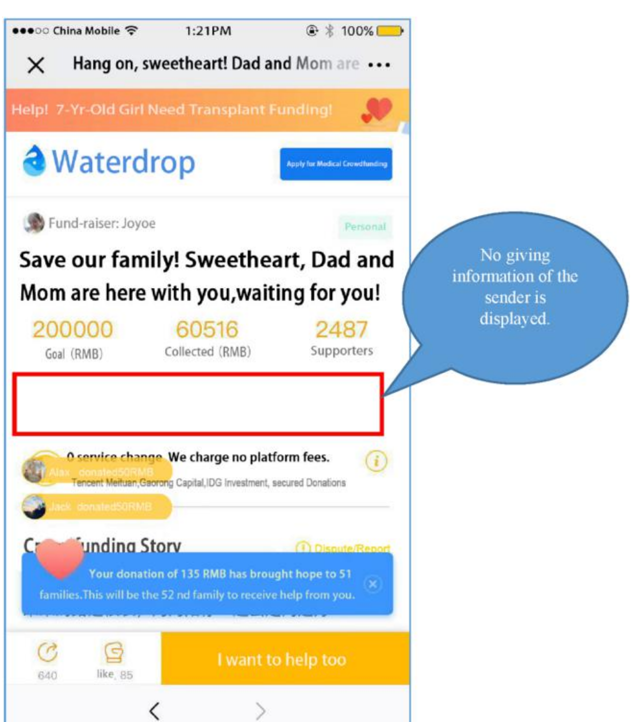
Messages in G3 offer the recipient an option to check the sender's donation information. The space displaying the peer donation information for G1 was replaced by a link showing the option (see the left panel of Figure 3 for an example of the message). If the recipient clicked the link, she saw a pop-up window displaying the information (see the right panel of Figure 3). The third sender in the figure has "helped" the campaign by resending the message without giving. The recipient could choose not to click the link and thus, avoid the information. Note that because the name and the donation information in Figure 1 keep rolling up, the individual who sees the message in the figure receives identical peer information as the individual who sees

Figure 1. (Color online) An Example of Messages Viewed by G1 Participants



the message in Figure 3. All other designs of the message in G3 are identical to the other two groups. Because the sender did not know whether the recipient clicked the link, social pressure to seek or avoid the information is unlikely. Furthermore, because the time to open the pop-up window is less than a second, the time cost of the action should be quite low.

Figure 2. (Color online) An Example of Messages Viewed by G2 Participants

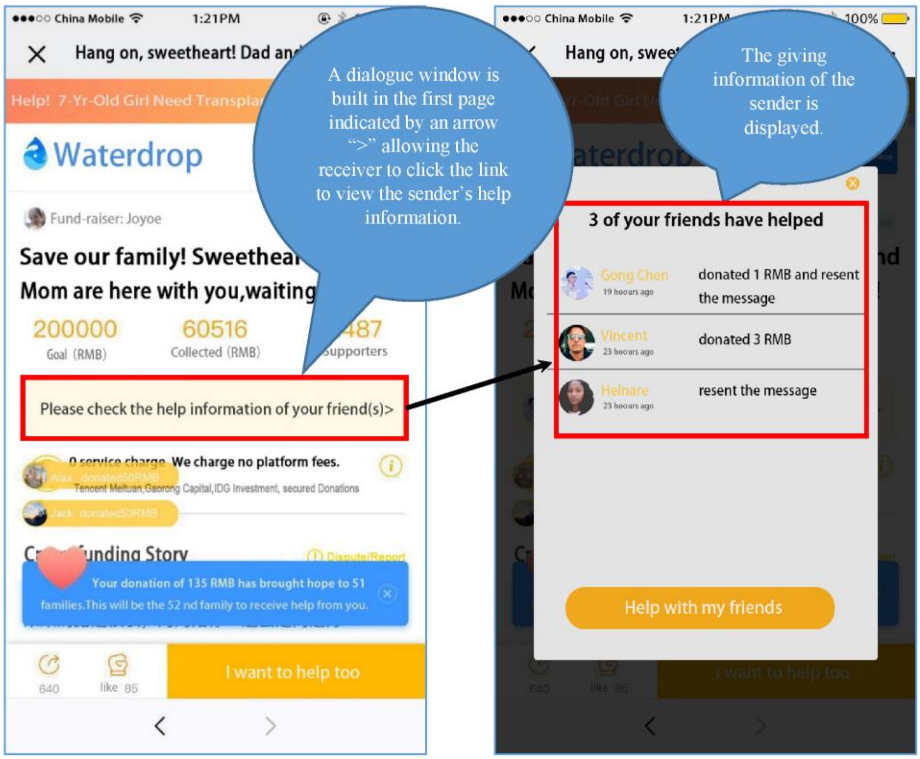


4.2. Data, Randomization Check, and Descriptive Statistics

We collected three sets of variables for each data observation in the experiment. The first set is related to the recipient: whether she gave; the donation amount; the number of minutes between receiving the message and giving to the campaign; whether she resent the message to other friends,; the number of campaigns she has given to; and the number of campaigns she has resent in the previous one, three, and six months. The second set is related to the charity campaign: the target amount of fundraising, the number of words in the campaign description and the number of photos contained in the message, whether the campaign was verified by Waterdrop, and the social distance between the recipient and the fundraiser. Social distance is measured by the number of times the message was resent before it reached the receiver.[14] The third set of variables is related to the sender: the number of campaigns she has given to and resent in the past, whether she gave to the current campaign, and the amount.

Given the random assignment, observables about senders, recipients, and charity campaigns should be similar across the three groups. Table 1 presents the results of the randomization check. We regress the campaign and

Figure 3. (Color online) An Example of Messages Viewed by G3 Participants



the recipient's and sender's characteristics on the indicators of whether an individual belongs to G2 and G3. Therefore, the intercept estimates in the regressions represent the average value of individuals in G1, and the coefficients for the two indicators represent the difference between G2 and G1 and between G3 and G1, respectively.

For G1, the average target amount of a charity campaign was RMB 226,768 (roughly U.S. \$32,395). The average number of words in a campaign description was 495 with five photos. On average, the campaigns attracted 1,394 supporters, and the fraction of the goal met is 18.6%, suggesting that most campaigns failed to reach the target amount. Regarding the recipient characteristics, almost no one (0.4%) had raised funds via Waterdrop before. Individuals, on average, gave 0.338 times in the past month, and the average donation amount was RMB 22. The average social distance between the fundraiser and the recipient was 5.35, with 28.2% missing information among all observations. Senders, on average, gave 4.947 times and RMB 96 in the past. They also resent 2.66 times to promote other charities. For a randomization check, as expected, the estimated coefficients for the two indicators (G2 and G3) are statistically insignificant for all variables except the one indicating that the social distance is missing and the number of campaigns that a sender gave in the past.[15] We also test whether any differences exist between individuals in G2 and G3. The p-values reported in the last column suggest the two groups are indeed similar. Overall, the evidence suggests that the three treatment conditions are well balanced across observable characteristics.

Next, we compare the main outcomes of interest, giving and resending, across the three conditions. The results are reported in Table 2. The giving rate is between 6.2% and 6.5% across the three conditions. Although our experiment was conducted in another country with different charity causes, the giving rate is close to the 6.29% reported by DellaVigna et al. (2012). The giving rate of G1 is significantly higher than that of G2, a result consistent with Proposition 1 in Section 3. It is also significantly higher than the giving rate of G3. The difference between G2 and G3, however, is not significant. The average donation amount is RMB 2.07 in G1, which is higher than the donation amount in G2 but statistically indistinguishable from G3.

The resending rate ranges from 3.4% to 3.7% in the three conditions, suggesting that the motive to help promote charity campaigns is very low. Based on Waterdrop's data, conditional on resending, an individual on average resends messages to 12 friends. Therefore, the chance of the message reaching a friend in the recipient's network is only 41%–44%, which implies that most of the charity campaigns on Waterdrop are unlikely to go

Table 1. Covariate Balance

Variables	G1 (N = 98,322) (1)	G2 (N = 99,055) (2)	G3 (N = 98,737) (3)	p-value of testing G1 = G2 (4)	p-value of testing G1 = G3 (5)	p-value of testing G2 = G3 (6)
Panel A: Campaign characteristics						
Target amount (RMB)	226,768.2	227,758.7	227,414.5	0.5194	0.6822	0.8354
	(127,401.3)	(128,185.6)	(128,198.4)			
# Words	495.1501	501.2314	498.9134	0.1115	0.3016	0.5829
	(280.2088)	(290.3050)	(284.3511)			
# Photos	5.2250	5.1648	5.2063	0.1485	0.6517	0.2971
	(3.3313)	(3.3182)	(3.3423)			
# Supporters	1,394.111	1,353.039	1,367.086	0.1624	0.2907	0.6167
	(2,341.325)	(2,250.857)	(2,283.953)			
Fraction of goal met	0.1855	0.1812	0.1848	0.0922	0.7686	0.1583
	(0.1974)	(0.1929)	(0.1975)			
Panel B: Recipient characteristics						
Recipient raised funds before (yes/no)	0.0042	0.0043	0.0051	0.7951	0.1176	0.1794
	(0.0647)	(0.0656)	(0.0710)			
# Campaign donations in past month	0.3379	0.3447	0.3269	0.5253	0.2734	0.1062
	(0.7534)	(0.8125)	(0.9076)			
Total donation amount in past month (RMB)	21.7674	22.2048	27.7225	0.8181	0.3580	0.3909
	(98.6334)	(81.2814)	(147.0294)			
Social distance from the fundraiser	5.3533	5.3209	5.3417	0.5438	0.8207	0.6932
	(4.5385)	(4.3569)	(4.4891)			
Distance missing	0.2824	0.2729	0.2747	0.0477	0.1091	0.6895
	(0.4502)	(0.4455)	(0.4464)			
Panel C: Sender characteristics						
# Campaign donations in the past	4.9465	5.0682	4.9613	0.0726	0.8186	0.1085
	(9.4892)	(9.7417)	(9.5032)			
# Campaigns resent in past	2.6549	2.6635	2.6156	0.8823	0.3928	0.3272
	(6.4145)	(5.6247)	(5.0193)			
Donation amount to the campaign (RMB)	95.9866	94.0969	101.2257	0.4918	0.3322	0.1907
	(279.5672)	(249.9646)	(280.3080)			

Notes. This table reports the results of checking covariate balance across the three treatment groups (G1, G2, and G3). To test the difference between each of the pair groups, we regress each covariate on two indicator variables, G2 and G3, indicating whether an individual was assigned to G2 and G3, respectively. Group standard deviations are reported in parentheses in the table.

"viral." This is probably the main reason that most of the campaigns on the platform failed to reach the target amount. Conditional on giving, however, the resending rate increases to about 12%, which is three times higher than the corresponding figure conditional on not giving. This result is consistent with Proposition 2 in Section 3.

Table 2. Descriptive Statistics

Variables	G1 (N = 98,322) (1)	G2 (N = 99,055) (2)	G3 (N = 98,737) (3)	p-value of t test G1 = G2 (4)	p-value of t test G1 = G3 (5)	p-value of t test G2 = G3 (6)
(1) *Giving rate*	0.0647	0.0622	0.0623	0.0234	0.0290	0.9348
	(0.2459)	(0.2415)	(0.2416)			
(2) *Donation amount*	2.0714	1.9223	2.0588	0.0745	0.8877	0.0941
	(20.0662)	(16.9379)	(19.2601)			
(3) *Resending rate*	0.0366	0.0362	0.0344	0.5996	0.0083	0.0342
	(0.1878)	(0.1867)	(0.1823)			
(4) *Resending rate* (condition on *Give* = 1)	0.1186	0.1172	0.1104	0.8130	0.1527	0.2361
	(0.3233)	(0.3217)	(0.3135)			
(5) *Resending rate* (condition on *Give* = 0)	0.0310	0.0308	0.0294	0.8530	0.0471	0.0712
	(0.1732)	(0.1728)	(0.1689)			
p-value of t test: Row (4) = row (5)	0.0000	0.0000	0.0000			

Notes. This table reports descriptive statistics of the outcome variables across the three treatment groups (G1, G2, and G3) in columns (1)–(3). Columns (4)–(6) present the p-values of testing the difference between each of the pair groups (G1 vs. G2, G1 vs. G3, and G2 vs. G3). Group standard deviations are reported in parentheses in the table.

The resending rate of G1 is higher than that of G2, consistent with Proposition 3 in Section 3. Conditional on not giving, the resending rate of G3 is significantly lower than that of G1 and G2; conditional on giving, however, the resending rate is not significantly different. Overall, the resending rate of G3 is significantly lower than that of the other two groups.

5. Effects of Information Avoidance and Information Seeking

So far, we have not distinguished information avoiders and information seekers in the comparative statistics. Our empirical analysis in this section focuses on the differences between these two groups.

5.1. Differences Between Information Avoiders and Seekers

We define G30 (G31) as G3 recipients who chose to avoid (seek) the peer donation information. Strikingly, the first row of Table 3 shows that only 11% of recipients are in G31, whereas 89% are in G30. This contrast highlights that, even though the information can be accessed at low cost and there is no physical interaction as in DellaVigna et al. (2012) nor verbal request as in Andreoni et al. (2017), the majority of individuals still chose not to see how much their peers gave when they had the option. Based on the model presented in Section 3, the reason for the prevalence of information avoidance is that there are four types of recipients. The first type consists of people who are certain that they will give to the charitable cause (i.e., $\mu_i \geq (\beta \cdot d)/\delta$ (see Section 3.1); "always givers"), and the second type consists of people who know they would not give for sure (i.e., $\mu_i < \beta \cdot d - \theta$; "never givers"). For the first two types, they do not need peer information for making a decision. Proposition 4 shows that the first type will not seek the information to avoid the utility loss from the peer comparison pressure. If not seeking the information is a default (unless the information is valuable), which seems to be a reasonable assumption, the second type also includes information avoiders.[16] The third type is amenable to peer influence, and avoiding the information is the optimal choice (i.e., $\beta \cdot d - \theta \leq \mu_i < \beta \cdot d$; "conditional avoiders"). Only the last type, whose utility is in the range of $\beta \cdot d \leq \mu_i < (\beta \cdot d)/\delta$, has the incentive to seek the information ("conditional seekers"). This type of information seekers belongs to the minority on the charity crowdfunding platform.

How does information avoidance influence potential givers' decisions regarding whether to support the campaign? As shown in Table 3, information avoiders are more likely to give and resend the campaign to their friends. Their donation amount is also significantly higher. These results seem to suggest that information avoidance promotes charitable behaviors, which contradicts Proposition 5 in Section 3. They are also inconsistent with the results in Table 2; if information avoiders give and resend more by avoiding the information, we should observe higher giving and resending rates in G2 than in G1. However, the evidence suggests that the opposite is true.

The comparison results are misleading because information avoiders and seekers can be systematically different. This point is illustrated in Table 3. The table compares some campaign characteristics. The campaigns in G30 tend to have a lower target amount, fewer words that describe the cases, a lower number of supporters, and a lower fraction of the goal met. The table also compares recipient characteristics across the two groups. G30 individuals gave less frequently and less in dollar amount in the past one, three, and six months. In contrast, Table 3 shows that the senders of information avoiders gave and resent more frequently in the past than the senders of information seekers. They are also more likely to give to the current campaign. Taken together, the evidence suggests that a recipient who was less active in charity donation in the past is more likely to avoid seeing the donation information of a sender who was more active in the past, whereas a more active recipient is more likely to seek the information of a less active peer. Because of the selection, the differences in giving and resending rates between G30 and G31, as observed in Table 3, cannot be interpreted as the causal effects of information avoidance. The presence of such a self-section issue calls for a different identification strategy to estimate the causal effects.

5.2. IV Regressions

We now investigate the causal effects of information avoidance. In other words, we ask what would happen to information avoiders had they not been able to avoid the information. To address the self-selection issue, our strategy is to employ an instrument, which is derived from the experimental design, in the regression analysis. Letting an outcome variable (give or not and resend or not) for recipient i be Y_i, we specify

$$Y_i = \beta_0 + X_i\beta + \gamma \cdot T_i + \varepsilon_i, \tag{11}$$

where X_i is a vector of control variables observed in data, T_i is an indicator of treatment, and ε_i is an error term that captures the unobserved factors that can affect an individual's give and resend decisions. The parameter of interest is γ, which represents the treatment effect on Y_i.

In the experiment, because of self-selection—G3 individuals could choose whether to check the sender's information—T_i can be endogenous. We treat this self-selection as a "noncompliance" issue, as identified in the clinical trial literature, and we use the random group assignment as an instrument for the treatment (Angrist et al. 1996, Little and Rubin 2000, Duflo et al. 2007). A valid instrument would be correlated with the likelihood

Table 3. Comparison Between Information Avoiders and Information Seekers

Variables	Group 31 (N = 10,769) (1)	Group 30 (N = 87,968) (2)	p-value of t test G31 = G30 (3)
Decisions			
(1) *Giving rate*	0.0524	0.0635	0.0000
	(0.2228)	(0.2438)	
(2) *Donation amount*	1.6847	2.1047	0.0327
	(12.2757)	(19.9474)	
(3) *Resending rate*	0.0208	0.0361	0.0000
	(0.1427)	(0.1865)	
Campaign characteristics			
(4) *Target amount* (RMB)	238,189	226,096	0.000
	(131,338)	(127,747)	
(5) # *Words*	507.1051	497.9105	0.0015
	(286.4683)	(284.0762)	
(6) # *Photos*	5.2269	5.2038	0.4993
	(3.3939)	(3.3359)	
(7) # *Supporters*	1,642.136	1,333.414	0.0000
	(2,670.116)	(2,229.782)	
(8) *Fraction of goal met*	0.2059	0.1822	0.0000
	(0.2124)	(0. 1954)	
Recipient characteristics			
(9) *Raised fund before*	0.0056	0.0050	0.4318
	(0.0744)	(0.0705)	
(10) # *Campaign donations last month*	0.4468	0.3122	0.0000
	(0.8517)	(0.9131)	
(11) *Total donation amount last month*	33.3342	27.0355	0.0000
	(122.8448)	(149.7081)	
(12) # *Campaign donations in previous 3 Ms*	0.7556	0.6002	0.0000
	(1.4844)	(1.8407)	
(13) *Total donation amount in previous 3 Ms*	41.9640	34.8105	0.0000
	(130.2496)	(155.5380)	
(14) # *Campaign donations in previous 6 Ms*	1.2681	1.0506	0.0000
	(2.6155)	(3.3026)	
(15) *Total donation amount in previous 6 Ms*	56.2922	46.7566	0.0000
	(153.4072)	(171.4773)	
Sender characteristics			
(16) # *Campaign donations in the past*	4.5000	5.0177	0.0000
	(7.9900)	(9.6708)	
(17) # *Campaigns a sender resent in the past*	2.4264	2.6387	0.0000
	(3.6559)	(5.1611)	
(18) *Donation rate to the campaign*	0.7819	0.8331	0.0000
	(0.4130)	(0.3729)	
(19) *Donation amount to the campaign*	102.0404	101.1260	0.7493
	(334.6373)	(272.9170)	

Notes. This table reports the outcome variables and covariates for G30 and G31 in columns (1) and (2), respectively, and the p-values of testing their statistical difference in column (3). Standard deviations are reported in parentheses in the table. Ms, months.

of receiving T_i (i.e., the *relevance* condition) but exogenous to ε_i (i.e., the *exogeneity* condition).

We first estimate the treatment effects of information avoidance (i.e., T_i is avoiding the sender's information *AI*) based on individuals in G1 and G3 in the regression. The experimental design suggests we can use G1 as the "control" group, in which everyone saw the peer donation information, and G3 as the "treatment" group, in which individuals were not supposed to see the information. G31 individuals, however, are "noncompliers" because they did not comply with the treatment. In Equation (11), $T_i \equiv AI_i = 0$ if the individual saw the information (i.e., the individuals of either G1 or G31) and 1 if not (i.e., the individuals of G30). We use the indicator of being assigned to G3 ($Z_i = 1$ if in G3 and 0 if in G1) as the instrument for AI_i. Because 89% of individuals in G3 chose not to see the sender's information but the chance of a G1 individual not seeing the sender's information is 0%, Z_i is highly correlated with AI_i. Because of the random group assignment, Z_i is independent of ε_i. Therefore, it is a valid instrument for AI_i.

We use the two-stage least squares (2SLS) approach in actual regression analyses. In the first stage, we regress AI_i on each individual in G1 and G3 as

$$AI_i = \begin{cases} 0 & \text{if } i \text{ belongs to G1} \\ \alpha_0 + W_i \cdot \alpha + e_i & \text{if } i \text{ belongs to G3,} \end{cases} \quad (12)$$

where W_i is a vector of observed variables that can affect the propensity of individuals to avoid the sender's information and e_i is an error term. This regression gives us the predicted $\widehat{AI}_i$ for each individual. We then estimate Equation (11) as the second-stage regression, replacing AI_i for everyone with $\widehat{AI}_i$ (note that $\widehat{AI}_i = 0$ for G1). This procedure obtains an unbiased estimate of γ and establishes the causality of information avoidance on the giving and resending outcomes.

To obtain a full picture of the effects of peer donation information, we also investigate the treatment effects of information seeking. We replace T_i with SI_i (i.e., seeking the peer donation information) in Equation (11) and use individuals of G2 and G3 in regressions to estimate the effect. G2 individuals are the control group (i.e., did not see the sender's information), and G3 individuals are the treatment group (i.e., were supposed to see the information). G30 individuals represent noncompliers because they violated the treatment condition. Again, we can use the indicator of being assigned to G3 ($Z_i = 1$ if in G3 and 0 if in G1) as the instrument for SI_i. Because 11% of G3 individuals saw the information but the chance of G2 individuals seeing the information is 0%, Z_i is correlated with SI_i. We use the same 2SLS method to estimate Equation (11). Because $SI_i = 1 - AI_i$, we only need to run the first-stage regression to estimate $\widehat{AI}_i$, and we set $\widehat{SI}_i = 1 - \widehat{AI}_i$ for G3 individuals.

5.3. Results from First-Stage Regressions

The results of first-stage regressions of Equation (12) are reported in Table 4. We use different specifications to test the robustness of the results. In column (1), the regression only includes a constant in the regression, which essentially uses the mean of the information avoidance as $\widehat{AI}$. As expected, the constant is 0.891, indicating that 89% of G3 individuals are information

Table 4. Results for the First-Stage Regression

	First-stage DV = *AI*		
Variables	(1)	(2)	(3)
Target amount		−0.000***	−0.000***
		(−4.413)	(−4.172)
# Words		−0.000	−0.000
		(−0.703)	(−0.587)
# Photos		0.000	0.000
		(0.752)	(0.556)
# Supporters		−0.000	−0.000
		(−0.990)	(−1.309)
Fraction of goal met		−0.043***	−0.036***
		(−3.096)	(−2.669)
Recipient raised funds before		−0.010	−0.016
		(−0.490)	(−0.769)
ln(1 + # *recipient donations last month*)		−0.059***	
		(−12.347)	
ln(1 + *recipient total donations amount last month*)			−0.014***
			(−9.039)
ln(1 + # *sender donations in the past*)		0.012***	
		(7.729)	
ln(1 + # *sender resends in the past*)			0.009***
			(4.600)
Constant	0.891***	0.913***	0.919***
	(530.88)	(159.202)	(151.749)
Campaign-time fixed effects	No	Yes	Yes
Day fixed effects	No	Yes	Yes
Observations	98,737	98,737	98,737

Notes. The *t* statistics of estimates are in parentheses. Standard errors are clustered at the case level. Campaign-time fixed effects refer to the date that a campaign was originated. Day fixed effects refer to the date of the experiment conducted. DV, dependent variable.

***Significant at the 1% level.

avoiders. In columns (2) and (3), we include a list of control variables along with campaign-time and day fixed effects. Because the number of campaigns a recipient gave to in the past is highly correlated with her donation amount in the past, we include one of them at a time in columns (2) and (3) to avoid multicollinearity. We do the same for the sender's giving and resending variables.

The results in columns (2) and (3) show that the target amount of a charity campaign and the fraction of the goal met are both negatively associated with the likelihood of being an information avoider. The former variable may indicate a fundraiser's need for donation, whereas the latter may inform the "quality" of a campaign. Both could enhance the interest of individuals to learn more and thus, reduce the propensity of avoiding information. The coefficients for the number of campaigns a recipient gave to in the past month in column (2) and the total donation amount in column (3) are negative and statistically significant. Finally, the positive and statistically significant coefficients for the number of campaigns a sender gave to in the past in column (2) and the number of campaigns a sender resent in the past in column (3) highlight that the recipient is more likely to avoid information when receiving messages from a peer who was active in the past. This result can be interpreted as the evidence of the effect of the pressure from peer comparison, a key assumption of our conceptual framework; because the recipient believes that the altruistic peer is likely to give, in response, she is more likely to avoid the information sent from such a peer so as to avoid the pressure. The results are consistent with the comparison between G30 and G31 individuals in Table 3.

5.4. Effects of Information Avoidance

Table 5 reports the results for the second-stage regression testing the effect of viewing peers' information on the supporting behavior among information avoiders.[17]

Table 5. Results of Second-Stage Regressions on the Effects of Information Avoidance

	Second stage					
Variables	*Give* (1)	*Resend* (2)	ln(1 + *Donation amount*) (3)	*Give* (4)	*Resend* (5)	ln(1 + *Donation amount*) (6)
$\widehat{AI}$	−0.002*	−0.002*	−0.006	−0.003*	−0.002*	−0.007*
	(−1.699)	(−1.654)	(−1.489)	(−1.958)	(−1.738)	(−1.663)
Target amount	0.000***	0.000	0.000***	0.000***	0.000	0.000***
	(5.341)	(0.414)	(6.539)	(5.599)	(0.202)	(6.688)
# Words	0.000***	0.000*	0.000**	0.000***	0.000	0.000**
	(3.235)	(1.652)	(2.573)	(3.214)	(1.590)	(2.558)
# Photos	−0.000	−0.000	−0.001**	−0.000	−0.000	−0.001*
	(−1.450)	(−1.387)	(−2.195)	(−1.196)	(−1.265)	(−1.946)
# Supporters	−0.000	0.000	−0.000*	−0.000	0.000	−0.000*
	(−0.451)	(0.181)	(−1.755)	(−0.455)	(0.381)	(−1.699)
Fraction of goal met	0.029***	0.003	0.104***	0.034***	−0.000	0.116***
	(4.071)	(0.406)	(4.919)	(4.937)	(−0.006)	(5.630)
Recipient raised funds before	0.031***	−0.001	0.066***	0.033***	0.001	0.072***
	(3.490)	(−0.088)	(2.676)	(3.678)	(0.167)	(2.897)
ln(1 + *# recipient donations last month*)	0.042***	0.023***	0.095***			
	(16.944)	(11.269)	(13.953)			
ln(1 + *recipient total donation amount last month*)				0.002***	0.006***	0.005***
				(3.863)	(12.377)	(3.257)
ln(1 + *# sender donations in the past*)	0.012***	−0.006***	0.029***			
	(16.717)	(−8.551)	(13.603)			
ln(1 + *# sender resends in the past*)				0.006***	−0.001	0.005*
				(5.290)	(−0.557)	(1.692)
Constant	0.025***	0.044***	0.092***	0.039***	0.037***	0.133***
	(8.871)	(16.709)	(10.632)	(13.388)	(13.296)	(15.177)
Campaign-time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Day fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	197,059	197,059	197,059	197,059	197,059	197,059
R^2	0.013	0.005	0.009	0.007	0.005	0.006

Notes. The *t* statistics of estimates are in parentheses. Standard errors are clustered at the campaign level. Campaign-time fixed effects refer to the date that a campaign was originated. Day fixed effects refer to the date of the experiment conducted.

*Significant at the 10% level; **significant at the 5%level; ***significant at the 1% level.

Columns (1)–(3) use $\widehat{AI}_i$ obtained from the results of the first-stage regression in column (2) of Table 4, and columns (4)–(6) are based on results in column (3).[18] Similar to what we did in the first-stage regressions, to avoid multicollinearity, we include the numbers of recipients' and senders' past donations in one set of regressions (columns (1)–(3)) and include the total donation amount of recipients and the total number of resends of senders in the past in another (columns (4)–(6)). Each column in the table reports the regression results for one of the three outcome variables (i.e., give or not, resend or not, and the log of giving amount).

In columns (1) and (4), the coefficient on the variable of interest, the predicted $\widehat{AI}$ obtained from the first stage, is negative (-0.002 and -0.003, respectively) and statistically significant at 10% for the giving decision. As this is a linear probability regression, the estimates suggest that information avoidance reduces the absolute value of giving rate by 0.2%–0.3%, consistent with the prediction in Proposition 5(a). Because the baseline giving rate is 6.47% in G1, avoiding the peer donation information will dampen the giving rate by 3.7%–4.7% relative to the baseline, which is economically meaningful.

The negative and statistically significant coefficients for $\widehat{AI}$ in columns (2) and (5) indicate that avoiding peer donation information reduces the propensity to resend by 0.2%. Because the baseline resending rate is 3.66% in G1, information avoidance will result in a 5.5% reduction in the resending rate relative to the baseline, consistent with the prediction from Proposition 5(b). For completeness of the analysis, we further investigate the effect of information avoidance on the (unconditional) donation amount. Columns (3) and (6) show that it will decrease the amount by 0.6%–0.7%. Thus, allowing information avoiders to avoid the peer donation information adversely affects their supporting behavior at both the extensive and intensive margins.[19]

Regarding other control variables, the target amount of the charity, the number of words describing the campaign, the fraction of the goal met, whether the recipient previously raised funds via Waterdrop, her past donation counts and amounts, and the sender's past giving and resending, in general, are positively associated with the recipient's giving and resending decisions.[20] In our theoretical model, the parameter μ_i has a direct effect on the recipient's giving and resending propensities. The results here indicate that the need and quality of a campaign and more notably, the recipient's and the sender's activeness in charity donation in the past will have a positive impact on μ_i.

We note that other information may be available in messages that could be affected by the different treatment conditions, and this information could also influence information-seeking, giving, and promoting decisions. In this case, the omitted other information will create an issue for our estimation strategy because the group assignment can correlate with the error term ε_i in Equation (11), deeming the IV invalid. However, our experiment was conducted within a tight time period (3 days, relative to the average 7.52 days for a campaign in the data). We do not expect the fraction of the goal met and the number of supporters for a given campaign to vary significantly over the time of the experiment. In addition, we have included in regressions the number of supporters and the fraction of the goal met, both dynamically updating over time when a recipient sees the message, to control for the potential missing variable issue. Therefore, we believe that this concern should not be a major issue.

Furthermore, we highlight that all individuals who participated in our experiment are those who chose to open the charity campaign message. We only manipulated the peer donation information in the message. If these individuals are more altruistic and thus, less elastic to the treatment than those who chose to ignore the message, the findings may underestimate the effects of information avoidance for general potential donors.

5.5. Effects of Information Seeking

Next, we examine the effect of information seeking on information seekers based on the IV regression. Results are reported in Table 6.

Across specifications, we find that seeing the peer donation information increases the giving rate and (unconditional) donation amount of information seekers. This evidence is consistent with the prediction of Proposition 6(a). However, the estimated coefficients are not statistically significant. By contrast, the estimated coefficient for $\widehat{SI}$ on the resending rate is negative, which contradicts the prediction of Proposition 6(b). Although the coefficient is also insignificant, the magnitude is large, ranging from -1.0% to -1.4%, representing roughly a 27%–38% decrease from the baseline resending rate of 3.62% in G2. This result suggests that seeing the peer donation information might have a significant dampening impact on information seekers' propensity to spread the word about the charity.

We speculate that the statistically insignificant result could be because of the lack of test power given that only 11% of recipients of G3 chose to see the information and that the giving rate and resending rate range between only 3% and 6%. Furthermore, other complicated factors that our theoretical model has not considered may make our empirical results inconsistent with the predictions from Proposition 6. In particular, the model does not account for the possibility that the identity of the sender may influence the giving utility μ_i. Knowing the sender has a low past giving record, the recipient may have a low μ_i for supporting the charity campaign and therefore, is less likely to give and resend the campaign to other friends.

5.6. A Robustness Check

The reliability of the results presented in Tables 5 and 6 depends on the validity of using the group assignment

Table 6. Results of Second-Stage Regressions on the Effects of Information Seeking

	Second stage					
Variables	*Give* (1)	*Resend* (2)	ln(1 + *Donation amount*) (3)	*Give* (4)	*Resend* (5)	ln(1 + *Donation amount*) (6)
$\widehat{SI}$	0.011	−0.013	0.038	0.006	−0.010	0.026
	(0.976)	(−1.180)	(1.140)	(0.560)	(−0.892)	(0.785)
Target amount	0.000***	0.000	0.000***	0.000***	0.000	0.000***
	(4.392)	(0.379)	(5.336)	(4.656)	(0.146)	(5.486)
# Words	0.000**	0.000	0.000*	0.000**	0.000	0.000**
	(2.367)	(1.368)	(1.937)	(2.576)	(1.278)	(2.103)
# Photos	0.000	−0.000	0.000	0.000	−0.000	0.000
	(0.907)	(−1.323)	(0.072)	(1.020)	(−1.167)	(0.179)
# Supporters	0.000	−0.000	−0.000	0.000	−0.000	−0.000
	(0.206)	(−0.398)	(−1.050)	(0.242)	(−0.212)	(−1.000)
Fraction of goal met	0.024***	0.007	0.091***	0.029***	0.004	0.102***
	(3.341)	(0.904)	(4.197)	(3.954)	(0.533)	(4.670)
Recipient raised funds before	0.011	−0.004	0.013	0.015*	−0.002	0.024
	(1.327)	(−0.590)	(0.549)	(1.859)	(−0.339)	(1.042)
ln(1 + *# recipient donations last month*)	0.038***	0.026***	0.084***			
	(15.072)	(13.209)	(12.186)			
ln(1 + *recipient total donation amount last month*)				0.001***	0.006***	0.003**
				(2.728)	(13.334)	(2.052)
ln(1 + *# sender donations in the past*)	0.012***	−0.005***	0.029***			
	(15.710)	(−8.298)	(12.897)			
ln(1 + *# sender resends in the past*)				0.006***	0.000	0.005*
				(5.321)	(0.356)	(1.725)
Constant	0.023***	0.043***	0.086***	0.037***	0.036***	0.127***
	(8.284)	(16.986)	(10.032)	(12.812)	(13.484)	(14.543)
Campaign-time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Day fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	197,792	197,792	197,792	197,792	197,792	197,792
R^2	0.012	0.005	0.009	0.007	0.005	0.006

Notes. The *t* statistics of estimates are in parentheses. Standard errors are clustered at the case level. Campaign-time fixed effects refer to the date that a case was originated. Day fixed effects refer to the date of the experiment conducted.
*Significant at the 10% level; **significant at the 5%level; ***significant at the 1% level.

as an instrument for information-avoidance or -seeking behaviors. Although this assumption seems reasonable, we use another method to check for the robustness of the results. Let $X1$ be the proportion of individuals who give in G1, let $X10$ be the proportion of information avoiders who give in G1, and let $X11$ be the proportion of information seekers who give in G1. $X2$, $X20$, and $X21$ are similarly defined for G2.

Assume $X11 = X31$ and $X20 = X30$. Based on the information from Tables 2 and 3, we can calculate $X10 = (X1 - X31 \times 0.11)/0.89 = 0.0662$. This amount is higher than $X30 = 0.0635$. That is, avoiding peer information will reduce the giving rate of information avoiders in G3. Note that this calculation is based on the assumption that the proportion of information avoiders in G1 is also 89%. Based on this simple comparison, we find evidence consistent with the results from Table 5. For information seekers, $X21 = (X2 - X30 \times 0.89)/0.11 = 0.0516$, which is less than $X31 = 0.0524$. The difference of 0.0008 represents the effect of seeing peer donation information on the giving propensity of information seekers, again consistent with the result in Table 6.

Next, we evaluate the effects on the propensity to resend. Similar to this exercise, let $X1$ be the proportion of individuals who resent in G1, let $X10$ be the proportion of information avoiders who resent, and let $X11$ be the proportion of information seekers who resent. $X2$, $X20$, and $X21$ are similarly defined for G2. Based on the assumptions that $X11 = X31$ and $X20 = X30$, $X10 = (X1 - X31 \times 0.11)/0.89 = 0.0386$, which is larger than $X30 = 0.0361$. The difference of 0.0025 represents the effect of information avoidance on the resending propensity of information avoiders, which is consistent with the result in Table 5. For information seekers, $X21 = (X2 - X30 \times 0.89)/0.11 = 0.0370$, which is larger than $X31 = 0.0208$. The difference of −0.0162 represents the effect of seeing peer information on the resending propensity of information seekers. It is also consistent with the results in Table 6.

5.7. The Mechanism

We find that information avoidance adversely affected individuals' propensity to give and to promote. The mechanism behind the result is that there is a type of *marginal* individuals, conditional givers, who are positively affected by peers' giving behavior. They choose not to seek the information to avoid the peer comparison pressure. If this is the case, why do we observe that the giving and resending rates among the individuals who do not seek the information are higher than those who do? Recall that there are another three types of individuals in our stylized model. Although never givers will not give no matter what their peers did, always givers will give anyway. As the information does not affect their decisions, both types are also likely to choose not to see the information. Combining the three types of information avoiders, depending on their underlying composition, their giving and resending rates can be higher than the fourth type of individuals (information seekers (when the information is available)).

In addition, the giving and resending decisions of information seekers are affected by whether the senders also gave. Compared with the senders of information avoiders, they were less active for charity in the past, and their giving rate for the current campaign is also low (see Table 3); therefore, the effect of their donation information on information seekers is weaker. Furthermore, the utility of giving (i.e., μ_i) could be positively influenced by the perception of how altruistic the sender is. Information avoiders (in the third type) have senders who typically gave in the past, and as such, they would also give more.[21] This explains why, although information avoidance has a negative impact, the overall giving and resending rates of information avoiders are higher than those of information seekers.

We argue that the mechanism driving the information-avoidance behavior is peer comparison pressure. There could be several alternatives that can explain our findings. The first possible explanation is that strategic responses from recipients in different treatment conditions may play a role that can explain the differences in giving and resending. Specifically, G1 and G3 individuals knew their donation information would be viewed by their friends; therefore, compared with G2 individuals, they may have been more likely to give. Because of this strategic consideration, they may also have been more likely to resend the case to friends to signal their generosity.[22] In this case, we would expect that, conditional on giving, the resend rate in G1 is higher than in G2 and that conditional on not giving, this number is lower in G1 than in G2. The data show that whereas the resend rate conditional on giving in G1 (11.86%) was higher than G2 (11.72%), the difference is not statistically significant. Furthermore, the resending rate conditional on not giving in G1 (3.10%) was also higher than G2 (3.08%), which is inconsistent with the prediction. The difference, however, is also statistically insignificant.

The second possible explanation for information avoidance is inattention. Instead of avoiding information, the majority of individuals might simply not pay attention to the peer donation information. Similarly, one may argue that those individuals who avoid the information do so because they do not perceive the information as valuable. Although these explanations can explain why people did not check the information, the significant differences in the giving and resending rates between G1 and G2 suggest that exposure to the information changes individuals' behaviors. This result will not happen if people do not pay attention to the peer donation information. Furthermore, if the information contains no value, being exposed to the information should not influence one's decisions.

The third potential explanation is that individuals avoid peer donation information because they do not plan to support the campaign. This argument implies reverse causality between information avoidance and the supporting behaviors. Although it works for the first type of individuals who will not give no matter what their senders did, it does not apply to the other two types of information avoiders. In particular, it cannot explain why information avoiders would be more likely to support if they cannot avoid the information.[23]

Another plausible story is that recipients were used to observing full information in G1, as this is the current practice of Waterdrop. When they do not find the donation information in G2, they may interpret that as no giving by the sender, which lowers their propensity to give. Our experimental design, however, can rule out this possibility; when a sender does not give to the campaign, the message in the current practice (i.e., G1) still shows that the sender has helped the case (like the third sender in Figure 3). Therefore, it is unlikely that the recipients interpret no information as no giving.

DellaVigna et al. (2012) argue that potential donors in their study chose to avoid fundraisers because of social pressure. However, our experiment involved no physical interactions. Although one could argue that a similar pressure from friends that pushes individuals to give can still exist even without physical interactions, such pressure exists equally across all treatment conditions. Furthermore, because senders of G3 did not know whether recipients observe their giving information, social pressure, if exists at all, should be the same for information avoiders and seekers. We therefore believe that the internal pressure from peer comparison is what drives the behavioral differences in our findings.

Finally, Andreoni et al. (2017) argue that potential donors avoided bell ringers who made verbal requests because they did not want emphatic stimuli that may have led to suboptimal giving or guilt. This argument might explain our finding that information avoiders are less altruistic. However, our experiment involved no verbal request from senders. Furthermore, the difference across treatment conditions is whether the peer donation information was available. Therefore, seeing information is unlikely to have led to emphatic stimuli as in their experiment.

5.8. The Economic Implications and External Validity of Information Avoidance

We only manipulated a single piece of information—how much friends gave—in the experiment. With such a small difference, 89% of individuals in G3 chose to avoid the peer giving information, and consequently, their giving rate dropped by 3.7%–4.7%. The impact on crowdfunding, however, can be much larger because the resending rate will also be reduced by 5.4%. Table 3 shows that the resending rate of the individuals of G30 is 3.61%, and based on the regression results in Table 5, it will be higher at 3.81% if they cannot avoid the information (as in G1). According to Waterdrop, conditional on resending, a recipient, on average, resends a case to 12 friends. Using the information and assuming that the remaining 11% of information seekers do not change the resending rate (2.08%), a back-of-the-envelope calculation suggests that for every recipient in G1 who reads a message, 0.77 friends, friends of friends, and so on, on average, will receive the resent message. However, if information avoiders are allowed to avoid the peer giving information, the number will be 0.70, an 8.5% drop.[24]

Likewise, we can further calculate the change in total crowdfunding. From Table 3, the giving rate of the individuals in G30 is 6.35%, and it will increase to 6.65% if they cannot avoid the information (using the result from column (4) of Table 5). Further assume that information seekers retain the same giving rate (5.24%), and the giving amount, conditional on giving, is RMB 33.14 for an information avoider and RMB 32.15 for an information seeker (based on the information from Table 3). If recipients are allowed to avoid peer giving information as in G3, the overall crowdfunding amount will drop by 7.7%.[25] According to Waterdrop, 80% of the total donation amount comes from recipients of messages posted by nonfundraisers. Because about RMB 12 billion in total were raised from 2016 to 2018, the drop is equivalent to a decrease of RMB 730 million or U.S. $103 million. This reduction is economically significant, especially considering that our experiment only changed the availability of one piece of information in messages.

Although we find substantial economic impacts, researchers nowadays have been increasingly concerned about the external validity of field or laboratory experiments. We scrutinize this dimension borrowing the 4 criteria, i.e., Selection, Attrition, Naturalness, Scaling, in List (2020). In terms of *selection*, we note that individuals in our experiment are randomly selected based on a random number generated by an algorithm; thus, they are representative of Waterdrop's targeted potential donors.

Attrition should not be a concern as our experiment only lasted for three days. In the long term, different information manipulation conditions may lead to exit or entry of fundraisers and potential donors. However, this is not the focus of our study. In terms of *naturalness*, we only change one piece of information in the message in G2 and G3. Furthermore, the task and choice setting (i.e., giving and resending decisions) for recipients in G2 and G3 are the same as in G1. We therefore believe that individuals were not aware of the experiment we ran and would not make unnatural decisions. Finally, *scaling* is feasible in both horizontal and vertical dimensions. Our theory suggests that peer comparison pressure represents the underlying motivation for individuals to avoid information, which in turn, influences individuals' giving behavior. Although we do not have evidence on whether such pressure is present in other parts of the world (e.g., the United States), the 6.2%–6.5% giving rate in our sample, which is close to the 6.29% giving rate reported by DellaVigna et al. (2012) based on U.S. individuals, suggests that our findings can be horizontally generalized to other charity giving contexts. In terms of vertical scaling, revealing full information has been Waterdrop's current practice, and removing peer giving information or making it optional is an easy, low-cost maneuver. Therefore, scaling up the experiment vertically will have little impact on the implementation cost.

6. Conclusion and Discussion

We study information-avoidance behavior and its consequences on the individual's charity giving and promoting decisions in the context of charity crowdfunding. We find that even when the information can be sought at low cost and no physical or verbal interactions occur with peers when seeking the information, the vast majority of individuals choose to not to seek the information. Using an innovatively designed natural field experiment facilitating the implementation of an IV identification strategy, we show that, compared with the scenario in which the information was exposed, lack of seeking reduced the giving rate by 3.7%–4.7% and the resending rate by 5.4% among information avoiders. This reduction translates into an 8.5% decrease in the total resends on the crowdfunding platform and a 7.7% decline in the total donation amount. These results are very significant, considering that we only manipulated a single piece of information in the messages of donation solicitation. By contrast, we find no significant change in the giving and resending decisions of information seekers when the information was made unavailable. We also find evidence that information avoiders were less active than information seekers in charity giving, whereas their peers who sent the messages gave and resent more in the past.

We argue that the mechanism driving information-avoidance behavior is the pressure from peer comparison. The pressure may come from "self-signaling" revealing that the recipient is less altruistic than her peer or social comparison because the recipient does not want to appear less altruistic than the sender. This mechanism is distinct from what drives the avoidance behaviors in DellaVigna et al. (2012) and Andreoni et al. (2017). We also show evidence contradicting other alternative explanations for the findings.

We believe the study offers new insights for understanding why people choose not to seek information even when the information has value. Our stylized model and empirical findings show that seeing peer information will have a positive effect on the giving and promoting behaviors of potential donors, but many of them will choose not to see the information to avoid the peer comparison pressure. These findings have substantive implications for the design of the information provision in charity crowdfunding. Our results suggest that, from the fundraising charity perspective, individuals should not be given the option to seek the sender's donation information at a low cost. Otherwise, the majority of individuals will choose not to seek the information, resulting in a reduction in the giving and resending rate. The platform should ensure that individuals are exposed to the information in messages. Doing so clearly has a cost. Our stylized model shows that the information can lead to a utility loss to the recipients. Privacy is another concern. Crowdfunding platforms and/or public policy makers should balance the costs and benefits for not only charities and fundraisers but also, potential donors.

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Appendix

Proof of Proposition 1. For G2, given P_j, Equation (3) shows

$$g_i = 1 \Rightarrow \text{ all } \mu_i \text{ subject to (s.t.) } \mu_i \cdot (\delta \cdot (1 - P_j) + P_j) \geq \beta \cdot d.$$

Therefore,

$$Pr(g_i = 1|\text{G2}) = \int \{\mu_i \cdot (\delta \cdot (1-P_j) + P_j) \geq \beta \cdot d\} dF(\mu_i) \tag{A.1}$$

$$= \int \begin{matrix}\{\mu_i \cdot (\delta \cdot (1-P_j)+P_j) \geq \beta \cdot d - \theta \cdot P_j\} \\ -\{\beta \cdot d \geq \mu_i \cdot (\delta \cdot (1-P_j)+P_j) \geq \beta \cdot d - \theta \cdot P_j\}\end{matrix} dF(\mu_i)$$

$$\Rightarrow Pr(g_i = 1|\text{G2}) < \int \{\mu_i \cdot (\delta \cdot (1-P_j)+P_j) \geq \beta \cdot d - \theta \cdot P_j\} dF(\mu_i), \tag{A.2}$$

where the strict inequality is because of the assumption that the density of μ_i is strictly positive everywhere in the distribution function F.

For G1, Equation (2) shows

$$g_i = 1 \Rightarrow \text{ all } \mu_i \text{ s.t. } -\theta \cdot \{g_j = 1\} \leq -\beta \cdot d + \delta \cdot \mu_i \cdot \{g_j = 0\} + \mu_i \cdot \{g_j = 1\},$$

where the right-hand side is the utility of giving and the left-hand side is the utility of not giving. This equation implies

$$\mu_i \cdot (\delta \cdot \{g_j = 0\} + \{g_j = 1\}) \geq \beta \cdot d - \theta \cdot \{g_j = 1\}.$$

Therefore,

$$Pr(g_i = 1|\text{G1}) = \int (P_j \cdot \{\mu_i \geq \beta \cdot d - \theta\} + (1 - P_j) \cdot \{\delta \cdot \mu_i \geq \beta \cdot d\}) dF(\mu_i). \tag{A.3}$$

Given that the indicator functions $\{\cdot\}$ in Equations (A.2) and (A.3) are convex functions, by Jensen's inequality,

$$P_j \cdot \{\mu_i \geq \beta \cdot d - \theta\} + (1 - P_j) \cdot \{\delta \cdot \mu_i \geq \beta \cdot d\} \geq \{\mu_i \cdot (\delta \cdot (1 - P_j) + P_j) \geq \beta \cdot d - \theta \cdot P_j\}.$$

Therefore, combining (A.2) and (A.3), we have

$$Pr(g_i = 1|\text{G1}) \geq \int \{\mu_i \cdot (\delta \cdot (1 - P_j) + P_j) \geq \beta \cdot d - \theta \cdot P_j\} dF(\mu_i) > Pr(g_i = 1|\text{G2}). \quad \square$$

Proof of Proposition 2. For G1, a threshold value $\widehat{\mu}_1(g_j) = (\beta \cdot d - \theta) \cdot \{g_j = 1\} + (\beta \cdot d)/\delta \cdot \{g_j = 0\}$ exists such that

$$g_i = 1 \text{ if and only if (iff) } \mu_i \geq \widehat{\mu}_1(g_j) \text{ and } g_i = 0 \text{ iff } \mu_i < \widehat{\mu}_1(g_j).$$

From Equation (4), holding everything else equal,

$$U_i^{r1}(r_i = 1|\mu_i \geq \widehat{\mu}_1(g_j)) > U_i^{r1}(r_i = 1|\mu_i < \widehat{\mu}_1(g_j));$$

that is, the utility of resend given $\mu_i \geq \widehat{\mu}_1(g_j)$ is larger than the utility of resend given $\mu_i < \widehat{\mu}_1(g_j)$. Therefore,

$$\begin{aligned} Pr(r_i = 1|\mu_i \geq \widehat{\mu}_1(g_j)) &= \int (\alpha \cdot P_k \cdot (\mu_i \cdot (\delta \cdot (1 - P_j) + P_j))) dF(\mu_i|\mu_i \geq \widehat{\mu}_1(g_j)) - c \\ &\geq \int (\alpha \cdot P_k \cdot (\mu_i \cdot (\delta \cdot (1 - P_j) + P_j))) dF(\mu_i|\mu_i < \widehat{\mu}_1(g_j)) - c \\ &= Pr(r_i = 1|\mu_i < \widehat{\mu}_1(g_j)). \end{aligned}$$

That is, the probability of resending conditional on giving is larger than the probability of resending conditional on not giving.

For G2, we can also show that a threshold value $\widehat{\mu}_2(P_j) = (\beta \cdot d)/[\delta + (1 - \delta) \cdot P_j]$ exists such that

$$g_i = 1 \text{ iff } \mu_i \geq \widehat{\mu}_2(g_j) \text{ and } g_i = 0 \text{ iff } \mu_i < \widehat{\mu}_2(g_j).$$

The rest of the proof is similar to G1. $\square$

Proof of Proposition 3. For G2, given P_j, Equation (5) shows

$$r_i = 1 \Rightarrow \text{ all } \mu_i \text{ s.t. } \alpha \cdot (\delta \cdot \mu_i \cdot (1 - P_j) + \mu_i \cdot P_j) \cdot P_k - c \geq 0$$
$$\Rightarrow \mu_i \cdot (\delta \cdot (1 - P_j) + P_j) \geq c/(\alpha \cdot P_k).$$

Therefore,

$$Pr(r_i = 1|G2) = \int \left(\left\{\mu_i \cdot (\delta \cdot (1-P_j) + P_j) \geq \frac{c}{\alpha \cdot P_k}\right\}\right) dF(\mu_i). \tag{A.4}$$

For G1, Equation (4) shows

$$r_i = 1 \;\Rightarrow\; \text{all } \mu_i \text{ s.t. } \alpha \cdot (\delta \cdot \mu_i \cdot \{g_j = 0\} + \mu_i \cdot \{g_j = 1\}) \cdot P_k - c \geq 0;$$
$$\text{i.e., } \mu_i \cdot (\delta \cdot \{g_j = 0\} + \{g_j = 1\}) \geq \frac{c}{\alpha \cdot P_k}.$$

Therefore,

$$Pr(r_i = 1|G1) = \int \left(P_j \cdot \left\{\mu_i \geq \frac{c}{\alpha \cdot P_k}\right\} + (1-P_j) \cdot \left\{\mu_i \cdot \delta \geq \frac{c}{\alpha \cdot P_k}\right\}\right) dF(\mu_i). \tag{A.5}$$

Given that the indicator function $\{\cdot\}$ in (A.5) is a convex function, by Jensen's inequality,

$$P_j \cdot \left\{\mu_i \geq \frac{c}{\alpha \cdot P_k}\right\} + (1-P_j) \cdot \left\{\mu_i \cdot \delta \geq \frac{c}{\alpha \cdot P_k}\right\} \geq \left\{\mu_i \cdot (\delta \cdot (1-P_j) + P_j) \geq \frac{c}{\alpha \cdot P_k}\right\}.$$

Combining (A.4) and (A.5), we have

$$Pr(r_i = 1|G1) \geq Pr(r_i = 1|G2). \quad \square$$

Proof of Proposition 4. Because $\mu_i < \beta \cdot d \Rightarrow \mu_i < (\beta \cdot d)/[\delta + (1-\delta) \cdot P_j]$, the utility of $\{S_i = 0\}$ in (9) is equal to zero. For the expected utility of $\{S_i = 1\}$ in (9), $\mu_i < \beta \cdot d \Rightarrow P_j \cdot max\{-\theta, -\beta \cdot d + \mu_i\} < 0$. Also, because $\mu_i < \beta \cdot d \Rightarrow \mu_i < (\beta \cdot d)/\delta$, $(1-P_j) \cdot max\{0, -\beta \cdot d + \delta \cdot \mu_i\} = 0$. Combining both terms, the expected utility of $\{S_i = 1\}$ is smaller than the utility of $\{S_i = 0\}$.

For those with utility $\mu_i \geq \beta \cdot d$, we need to look at two different cases. First, for those with $\beta \cdot d \leq \mu_i < (\beta \cdot d)/[\delta + (1-\delta) \cdot P_j]$, the utility of $\{S_i = 0\}$ in (9) is equal to zero. The expected utility of $\{S_i = 1\}$ is equal to $P_j \cdot (\mu_i - \beta \cdot d) > 0$. Therefore, the optimal choice is $\{S_i = 1\}$. Second, for those with $(\beta \cdot d)/[\delta + (1-\delta) \cdot P_j] \leq \mu_i < (\beta \cdot d)/\delta$, the utility of $\{S_i = 0\}$ in (9) is equal to $\delta \cdot \mu_i \cdot (1-P_j) + \mu_i \cdot P_j - \beta \cdot d$. The expected utility of $\{S_i = 1\}$ is equal to $P_j \cdot (\mu_i - \beta \cdot d)$. The difference between the latter and the former is

$$\begin{aligned} &P_j \cdot (\mu_i - \beta \cdot d) - (\delta \cdot \mu_i \cdot (1-P_j) + \mu_i \cdot P_j - \beta \cdot d) \\ &= (1-P_j) \cdot \beta \cdot d - \delta \cdot \mu_i \cdot (1-P_j) \\ &> (1-P_j) \cdot \beta \cdot d - \delta \cdot (1-P_j) \cdot (\beta \cdot d)/\delta \;\left(\text{because } \mu_i < (\beta \cdot d)/\delta\right) \\ &= 0. \end{aligned}$$

Therefore, the optimal choice is still $\{S_i = 1\}$.

For those with utility $\mu_i \geq (\beta \cdot d)/\delta$, they will give no matter what their peers did. It is straightforward from Equation (9) that the utility remains the same for $S_i = 0$ or $S_i = 1$. $\square$

Proof of Proposition 5(a). The proof follows strictly from the proof of Proposition 1. Because from Proposition 4 (ignoring those with $\mu_i \geq (\beta \cdot d)/\delta$),

$$Eg_i(S_i = 0|G3) = \int \{\mu_i \cdot (\delta \cdot (1-P_j) + P_j) \geq \beta \cdot d\} dF(\mu_i|\mu_i < \beta \cdot d) \tag{A.6}$$

$$= \int \frac{\{\mu_i \cdot (\delta \cdot (1-P_j) + P_j) \geq \beta \cdot d - \theta \cdot P_j\}}{-\{\beta \cdot d \geq \mu_i \cdot (\delta \cdot (1-P_j) + P_j) \geq \beta \cdot d - \theta \cdot P_j\}} dF(\mu_i|\mu_i < \beta \cdot d)$$

$$\Rightarrow Eg_i(S_i = 0|G2) < \int \{\mu_i \cdot (\delta \cdot (1-P_j) + P_j) \geq \beta \cdot d - \theta \cdot P_j\} dF(\mu_i|\mu_i < \beta \cdot d). \tag{A.7}$$

Also,

$$Eg_i(S_i = 0|G1) = \int (P_j \cdot \{\mu_i \geq \beta \cdot d - \theta\} + (1-P_j) \cdot \{\delta \cdot \mu_i \geq \beta \cdot d\}) dF(\mu_i|\mu_i < \beta \cdot d). \tag{A.8}$$

Given that the indicator functions $\{\cdot\}$ in Equations (A.7) and (A.8) are convex functions, by Jensen's inequality, we have

$$\begin{aligned} Eg_i(S_i = 0|G1) &\geq \int \{\mu_i \cdot (\delta \cdot (1-P_j) + P_j) \geq \beta \cdot d - \theta \cdot P_j\} dF(\mu_i|\mu_i < \beta \cdot d) \\ &> Eg_i(S_i = 0|G3). \quad \square \end{aligned}$$

Proof of Proposition 5(b). The proof follows strictly from the proof of Proposition 3. From Proposition 4,

$$Er_i(S_i = 0|G3) = \int \left(\left\{\mu_i \cdot (\delta \cdot (1-P_j) + P_j) \geq \frac{c}{\alpha \cdot P_k}\right\}\right) dF(\mu_i|\mu_i < \beta \cdot d). \tag{A.9}$$

Also,

$$Er_i(S_i = 0|G1) = \int \left(P_j \cdot \left\{\mu_i \geq \frac{c}{\alpha \cdot P_k}\right\} + (1-P_j) \cdot \left\{\mu_i \cdot \delta \geq \frac{c}{\alpha \cdot P_k}\right\}\right) dF(\mu_i|\mu_i < \beta \cdot d). \tag{A.10}$$

By Jensen's inequality,

$$P_j \cdot \left\{\mu_i \geq \frac{c}{\alpha \cdot P_k}\right\} + (1-P_j) \cdot \left\{\mu_i \cdot \delta \geq \frac{c}{\alpha \cdot P_k}\right\} \geq \left\{\mu_i \cdot (\delta \cdot (1-P_j) + P_j) \geq \frac{c}{\alpha \cdot P_k}\right\}.$$

Combining (A.9) and (A.10), we have

$$Er_i(S_i = 0|G1) \geq Er_i(S_i = 0|G3). \quad \square$$

Proof of Proposition 6. The proof of the proposition strictly follows the proof of Proposition 5, except the distribution is replaced by $dF(\mu_i|\mu_i \geq \beta \cdot d)$, following the result from Proposition 4. $\square$

Endnotes

[1] We choose such terminology following the definition in Golman et al. (2017). However, there is no cost involved, and as we will discuss later in the paper, when the information has no value, not

obtaining information could be a default for most individuals. Therefore, "lack of seeking" is perhaps a more precise term. We thank two anonymous reviewers for pointing out the difference.

[2] We can evaluate the impacts of information avoidance (seeking) on information avoiders (seekers) by directly comparing G1 and G3 (G2 and G3) without using the IV approach. That is, instead of running regressions, we directly calculate the effects of information avoidance on information avoiders, assuming that the proportions of information seekers and avoiders are the same in G1 and G3. Using IV regressions, however, helps us calculate the standard error of the treatment effect, and thus, we can speak to whether the effect is significant from a statistical perspective. Another benefit is that the IV regressions do not need the assumption that G1 and G3 have the same proportions of information seekers and avoiders. We adopt both approaches (see Section 5.6 for the non-IV approach) and find very similar results.

[3] Well-known crowdfunding websites include GoFundMe, FundRazr, and Fundly in the United States. The George Floyd Memorial Fund raised about U.S. $15 million in less than three months after the tragedy. In China, the Free Lunch for Children campaign raised RMB 128 million in small individual donations and caused county governments in multiple provinces to launch free lunch programs (Tsai and Wang 2019).

[4] G1, G2, and G3 correspond to the three treatment conditions in the field experiment.

[5] We find from the field experiment that the correlations between recipients' and message senders' giving amounts are generally small, with correlation coefficients ranging between 0.02 and 0.06. The key difference comes from whether to give and to resend decisions.

[6] Note that a self-signaling utility gain also arises from giving without comparing their giving with that of their peers. This gain is absorbed by μ_i.

[7] For simplicity, we assume the recipient is risk neutral. Adding risk aversion (such that the utility of giving is lower) does not change the results in this section.

[8] The cost is not just the effort of resending, which is very low in our experiment. It also captures other psychological costs: for example, the concern that her message causes a disruption for *k*.

[9] Waterdrop calls the sender and the recipient friends because it believes this relationship is the most common.

[10] About 20% of senders in our data did not give.

[11] The campaigns in the experiment were originated as early as March 2017.

[12] We also conducted an analysis using the full sample that includes the observations for which the message sender is also the fundraiser, and the results are qualitatively identical.

[13] Although finding the sender's donation information from Waterdrop was still possible, recipients had to search Waterdrop's mobile app.

[14] We learned from Waterdrop that, because of the technical challenges when constructing the variable, social distance can have a large measurement error. We also find many observations with the value missing. Because of this issue, we do not use the variable for our main empirical analyses.

[15] Why the differences are statistically significant is unclear; however, judging by the small magnitude of the estimates, the main findings in the paper are unlikely to be affected.

[16] Strictly speaking, individuals of this type do not avoid the information; rather, they simply choose not to seek the information.

[17] The reported standard errors in the table (and Table 6) have been corrected for the two-stage estimation process.

[18] We have also used $\widehat{AI}_i$, obtained from the specification in column (1) of Table 4. The estimation results are highly consistent. They are not reported in Table 5 to save space.

[19] We also ran another regression using the donation amount (without taking log) as the dependent variable. Results are very similar.

[20] Given that these control variables may correlate with ε_i in Equation (11), we do not claim that the coefficients represent the causal effects.

[21] Another possibility is because of self-signaling. Recipients may obtain utility from giving because doing so helps them retain the perception of being altruistic. The self-signaling effect may be weakened if the recipient knows the sender's actual giving information because the information might make the recipient wonder whether she is under peer pressure rather than acting out of pure altruism. As a result, information seekers may give less. This factor is not captured in our stylized model.

[22] In this case, being assigned to different treatment conditions may directly influence the giving and resending decisions, which will make the group assignment an invalid instrument for information avoidance or information seeking.

[23] We acknowledge that the second and third explanations can still be secondary factors that might explain some of information-avoidance behaviors.

[24] The calculation is as follows. For G1, the total number of resends including the one received by the original recipient is $1/(1-(3.81\% \times 89\% + 2.08\% \times 11\%) \times 12) = 1.768$. For G3, the total number of resends is $1/(1-(3.61\% \times 89\% + 2.08\% \times 11\%) \times 12) = 1.703$. Excluding the original recipient, the change is -8.5%.

[25] The calculation is that for G1, after an individual receives a message, the total giving amount from the individual along with all her friends who follow up on the campaign she sends them will be RMB $(33.14 \times 6.65\% \times 89\% + 32.15 \times 5.24\% \times 11\%) \times 1.77 = 3.797$. For G3, the total giving amount will be RMB $(33.14 \times 6.35\% \times 89\% + 32.15 \times 5.24\% \times 11\%) \times 1.70 = 3.505$, representing a 7.7% drop relative to the giving amount of G1.

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