The asymmetry of altruistic giving when givers outnumber recipients and vice versa: A dictator game experiment and a behavioral economics model

Abstract

The behavior of altruistic giving is influenced by the numbers of givers and recipients available in a group. Two independent lines of research have addressed the effect. On the one hand, research on the bystander effect shows that a person gives less when givers outnumber recipients than if they are equal in number. On the other, studies of congestible altruism have found that a person gives more when recipients outnumber givers than if they are equal in size. An interesting question is whether giving decreases at a different rate when givers outnumber recipients than it increases the other way around. Answering the question helps illuminate whether the two effects of collective giving, which the literature has discussed separately, are governed by the same rule. We conducted a multi-person dictator game experiment to investigate people's giving behavior in different group sizes of givers and recipients. We found that giving decreases more rapidly when givers outnumber recipients than it increases the other way around. A behavioral economics model is proposed to show how people's belief about the selfishness of other givers can account for the asymmetry of the two effects. Extending the experiment finding, we simulate giving in more generalized giver-recipient networks to examine how the asymmetry of the two effects influences the extents to which altruistic giving improves distributional inequality.

Keywords: Altruistic Giving, Bystander Effect, Congestible Altruism, Dictator Game, Two-Mode Networks

1. Introduction

Examples of altruistic giving, such as donations to charity organization and disaster relief, are ubiquitous in daily life. Although altruism is part of human nature, it varies across individuals and social contexts. In particular, humans' altruism is influenced by two numeric facts: How many other givers are available? And how many people need help? The first number—the number of givers—is captured by a well-documented phenomenon in social psychology called the "bystander effect" (Darley & Latane, 1968; Fischer et al., 2011), according to which people give less when there are more givers available. The second number—the number of recipients—is addressed in studies of "congestible altruism" (Andreoni, 2007), which indicate that people give more as the number of recipients increases.

The two effects of collective giving can be pieced together by comparing the number of givers (g) with the number of recipients (r). The bystander effect argues that giving is lower when $g > r$ than when $g = r$. Congestible altruism, on the other hand, suggests giving is higher when $g < r$ than when $g = r$. Put together, the two effects suggest that giving decreases as the ratio of g/r increases. An interesting question is: How does giving change with respect to g/r? Does it decrease more or less rapidly in the bystander effect (g/r >1) than it increases in the congestible altruism effect (g/r <1)? The question touches on a fundamental inquiry of whether the bystander effect and congestible altruism, while discussed separately in the literature, are two sides of the same coin governed by the same behavioral rule.

The (a)symmetry of the bystander effect and congestible altruism is worth studying for both theoretical and practical reasons. Psychologists have shown that a positive and a negative change of a person's status could impose different effects on his/her behavior. For example, people react differently to economic losses and gains (Kahneman & Tversky, 1984; Kahneman & Tversky, 1992); rewards and punishments have different effects on incentivizing people's behavior (Balliet et al., 2011); and a promotion and a demotion of social status have different effects on influencing people's prosocial behavior (Clark, Masclet & Villeval, 2010; Charness & Villeval, 2017). These examples show that an identical magnitude of an effect could lead to asymmetrical outcomes when the effect is maneuvered to one direction than another. In fact, research on the asymmetry of human behavior has inspired the advancement of the behavioral and decision sciences over the past decades (Kahneman, 2002). Sharing a similar interest, here we investigate whether human altruism has an asymmetric feature when givers outnumber recipients versus the other way around. The investigation helps enhance our understanding of the mentalities that underlie the altruistic behavior of economic advantaged people (givers) when they are a majority versus a minority in a group.

The (a)symmetry of altruistic giving also has practical implications for organizational management and philanthropy campaigning. Organizational leaders are constantly facing the challenge of how to allocate resources to group members to maximize work performance and minimize distributional inequity. Understanding how givers—those endowed with resources in the group—perform when they are a majority versus a minority in the group would make it possible to provide useful suggestions to leaders with respect to the allocation of power and resources to colleagues and subordinates. Similarly, in philanthropic organizations, campaign organizers must consider how to raise funds for the needy. As donors' motivation for giving is influenced by how much their donation would make a difference, which is a function of the number of donors and recipients that the donor perceives, understanding how donors behave in different group sizes of givers and recipients available would help fundraisers design campaigns in a more efficacious manner.

To assess the (a)symmetry between the bystander effect and congestible altruism, we manipulate the number of givers and the number of recipients in a multi-person dictator game experiment (Study 1). Our study shows that giving drops more rapidly when givers outnumber recipients (the bystander effect) than it increases the other way around (the congestible altruism effect). To explain the asymmetry of the two effects, we modify Fehr and Schmidt's (1999) inequality-aversion model, originally a one-giver-versus-one-recipient model, to a multi-person context (Study 2). We show that a giver's belief about other givers' selfishness can explain the asymmetry: When a giver believes that more (less) than half of other givers are less generous than him/her, giving drops more (less) rapidly in the bystander effect than it increases in congestible altruism.

To understand how the asymmetry of the two effects unfolds, we simulate giving in (two-mode) networks between givers and recipients and examine how distributional inequality improves by the transfers of wealth from givers to recipients (Study 3). The simulation shows that the asymmetry of the two effects could make a difference. When givers are less than recipients, a rapid increase of givers' altruism decreases inequality; in contrast, when there are more givers than recipients, a rapid decrease of givers' altruism nevertheless helps prevent inequality from worsening.

2. Literature

There are at least three different lines of research in psychology and economics addressing how the numbers of givers and recipients influence givers' altruism. One line of research compared what if the giver is alone versus when there are multiple givers around. Another stream of research studied the condition of one recipient compared to the presence of multiple recipients. Finally, there is a third line research arguing that people's giving behavior may not be sensitive to the quantities of recipients.[1] In this paper, we focus on the comparison of the magnitude of the former two effects. We discuss how the setting of our study is different from the final line of research in the concluding section.

2.1 The Bystander Effect

In social psychology, the bystander effect is one of the most well-noted characteristics of helping behavior (Fischer et al., 2011). It argues that people's motivation to help is contingent on the availability of other helpers. The bystander effect can be explained from multiple perspectives. First, researchers argue that uncertainty about their own competency and qualifications may undermine people's willingness to help (Darley & Latane, 1970). As the number of helpers increases, people become more likely to posit that there are more capable others available to help the needy. Second, helping could be construed as collective action, and people may delay their efforts until enough helpers take action (Latane´ & Dabbs, 1975; MacCoun, 2012). The threshold number of active helpers to motivate a person's action could be a function of group size. People may raise their thresholds when they see more helpers are available. Third, the presence of other helpers works to release a person's moral responsibility (Darley & Latane, 1968; Falk, & Szech, 2013). Thus, the more helpers available, the more the responsibility is shared and thus the less likely people act to help. Furthermore, scholars argued that the reduction of responsibility is accelerating as the number of helpers increases. For example, Cryder and Loewenstein (2012) contended that "although we would expect the strongest increase when only one person is

[1] We appreciated a reviewer for reminding us of this line of research.

responsible, we would also expect greater helping when two people are responsible instead of three, for example, or when three are responsible instead of four" (Cryder and Loewenstein, 2012, p.443).

While the bystander effect can be explained by different theories, it is not easy to tell them apart through observations of real life cases of altruistic giving. In this regard, behavioral game experiments can be a promising method to distinguish the multiple motives that underlie people's giving behavior. In laboratory environments, researchers can manipulate and control different features of giving behavior, such as givers' wealth (capability to help), the decisional process (simultaneous or sequential), and the provision of information about how many givers and recipients are available. Each feature could respond to the core construct of a theory of the bystander effect. Panchanathan et al. (2013), for example, compared people's giving behavior when they acted alone versus when there were other givers in the experiment. In their experiment, each giver had the same amount of endowment and made simultaneous decisions of giving with other givers. The result shows that, in line with the bystander effect, people's giving declines as the number of givers increases.

2.2 Congestible Altruism

While the bystander effect addresses the influence of the number of givers, another line of research investigates whether the number of recipients makes a difference in people's giving behavior, and if so, under what circumstances. Compared to the long history of the bystander effect research, the investigation of the number of recipients is relatively young and the results are somewhat inconclusive. Some studies show that people give more when the number of recipients increases (Andreoni, 2007; Soyer & Hogarth, 2011), while others report the opposite result that people are more attentive to the needs of an individual than a group (Kogut & Ritov, 2005a; Kogut & Ritov, 2005b). To reconcile the inconsistency, researchers have located factors, such as identifiability (Kogut & Ritov, 2005b), perceived efficacy (Sharma & Morwitz, 2016), choice overload (Scheibehenne, Greifender & Todd, 2009), and jointness (Hsee et al., 2013) to circumscribe the conditions under which people behave more or less altruistically to a collectivity versus an individual. In this paper, by congestible altruism we mean the research findings that giving increases as the number of recipients increases.

2.3 An Integrated View of the Two Effects

Studies of the bystander effect and those of congestible altruism are both concerned with how group size influences people's giving behavior. Although one investigates the impact of the size of givers while the other addresses the recipients, in theory they are not as separate as how they are treated in the literature. We can use the ratio of the number of givers over that of recipients to link together the two effects. The bystander effect argues that giving is less when $g/r > 1$ than $g/r = 1$, whereas congestible altruism argues giving is greater when $g/r < 1$ than $g/r = 1$. Put together, the two effects suggest that giving decreases as g/r increases. The question is *how* it declines over g/r. Would giving change at a different rate in the condition of $g/r \geq 1$ than $g/r \leq 1$? Technically, g/r is not on the same scale between $g/r > 1$ and $g/r < 1$. Thus, to examine whether giving drops at different rates in $g/r > 1$ and $g/r < 1$, in what follows we use $\ln(g/r)$ to evaluate its relationship with giving. In so doing, $g/r = 1$ will be on the central point that divides the axis of $\ln(g/r)$ into two symmetric halves, allowing us to examine changes of giving on the same scale for $g/r > 1$ and $g/r < 1$.

There are three possible ways in which giving decreases along $\ln(g/r)$: (1) giving decreases at the same rate in $g/r \geq 1$ as in $g/r \leq 1$, suggesting a *linear* relationship between giving and $\ln(g/r)$; (2) giving decreases more rapidly in $g/r \geq 1$ than in $g/r \leq 1$—a *concave* relationship; and (3) giving decreases less rapidly in $g/r \geq 1$ than $g/r \leq 1$—a *convex* relationship. To assess which relationship stands, we conduct a game experiment to seek some empirical evidence.

3. Study 1: The Dictator Game Experiment

3.1 Design

We modify the conventional two-person Dictator game to a multi-person context. Different group sizes of givers $g = \{1, 8, 15\}$ and recipients $r = \{1, 8, 15\}$ are manipulated in the game. We test seven combinations of group sizes: $(g, r) = (1, 1), (8, 8), (15, 15), (1, 8), (1, 15), (15, 1), (8, 1)$. The first three scenarios capture the condition of $g/r = 1$, while the latter four address $g/r < 1$ and $g/r > 1$, respectively. The order of the seven scenarios is randomized to each participant in the experiment.

In each scenario, each participant, playing the role as the dictator, decides whether to share with recipient(s) the money ($200 in local currency and roughly twice the minim um hourly wage in the country). When there is more than one recipient, the dictator's giving would be equally shared by each recipient. Most importantly, the dictator is informed of how many other dictators (including zero) are joining him/her in making the giving decision. Detailed instructions for the game experiment can be found in the Appendix.

We use the strategy method, popularly used in experimental economics research, to collect people's giving decisions (Selten, 1967). Participants make a giving decision in each of the seven scenarios. For each participant, a randomly selected scenario is used to calculate his/her final payoff.

3.2 Subjects

A total of 108 participants (53 females; average ages=21.75 years) were recruited to our experiment from a large public university in the country. They were assigned to eight sessions held over the course of one week in a computer lab on campus.

3.3 Procedure

The experiment was conducted as a survey operated on the online platform, Qualtrics. Each participant received thorough instructions on the game rules before starting the experiment. A session was concluded when all participants completed the survey. Each of them was paid a show-up fee ($150 in local currency). We held a lottery for each of them to choose a scenario from which we calculate their additional payoffs. We contacted each participant one week later to pay them the payoffs.

We emphasized to the participants that the rules of the game were real and that participants' decisions would determine how much they and others would receive in the experiment. Although the interaction in our experiment was not on a real time basis, we assured participants that their decisions would be paired up with others' to calculate payoffs after we collected their experiment data. The experiment was approved by the institutional review board of the institution that funded the research.

3.4 Result

Participants' giving decisions (out of the endowment of $200) vary across different conditions of the number of givers and recipients. For the seven combinations of (g, r) tested in the experiment: (1, 1), (8, 8), (15, 15), (1, 8), (1, 15), (15, 1), (8, 1), the mean of giving in each of the conditions are: 58.44, 51.80, 50.91, 73.61, 76.32, 22.14, and 27.18. The respective standard deviations are: 44.68, 43.07, 45.88, 63.16, 69.52, 39.20, and 40.29. Figure 1 shows more clearly participants' giving against different combinations of group sizes of givers and recipients. As noted, taking a log transformation of g/r divides the axis into two symmetric halves, making it easier to compare the relationship with giving for $g/r \geq 1$ and $g/r \leq 1$. Our goal is to check whether the slopes are different in the two segments.

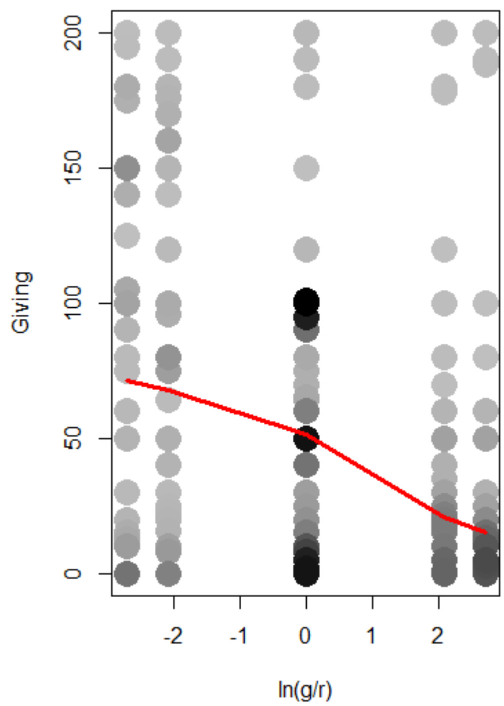

Figure 1—Distribution of giving over different group sizes of givers and recipients. The horizontal axis denotes the log value of the number of givers over that of recipients. Denser colors of the data points represent higher frequencies. The red curve shows the Lowess fitting.

The smooth-fit curve (Lowess regression) in Figure 1 shows that the slope is slightly flatter for $g/r \leq 1$ than $g/r \geq 1$. To assess more accurately the difference in slopes, we run a Tobit regression on giving separated by $g/r \geq 1$ and $g/r < 1$, specified in the following equation:

$$Y = a + b_1 ln\left(\frac{g}{r}\right) \mathrm{I}\left(\frac{g}{r} \geq 1\right) + b_2 ln\left(\frac{g}{r}\right) \mathrm{I}\left(\frac{g}{r} < 1\right) \qquad \ldots [1]$$

where Y represents the amount of giving; g and r are the numbers of givers and recipients in a scenario, respectively; and I is an indicator variable equal to 1 if the condition specified within the parenthesis is satisfied, and 0 otherwise.[2] Tobit regression is adopted here as the dependent variable giving is bound between 0 and 200 (endowment). As each participant made multiple giving decisions in the experiment, to address the repeated-measure issue we follow a conventional method to cluster standard errors of the regression coefficients by participants (Wooldridge, 2003; Arai, 2009).

Table 1 reports the estimation result for equation [1]. In model 1, as expected giving decreases with ln(g/r). Furthermore, the result shows that the two regression coefficients are different ($b_1 < b_2$). To know whether the difference of b_1 - b_2 is statistically significant, we follow the approach proposed by Clogg et al. (1995) to conduct the Z test for the difference of the coefficients.[3] The result shows that the difference is significant (Z = -3.28; p-value = 0.0005).

[2] Note that the regression result remains the same if we move the cases of $g/r = 1$ to the second regressor; that is, $Y = a + b_1 ln\left(\frac{g}{r}\right) \mathrm{I}\left(\frac{g}{r} > 1\right) + b_2 ln\left(\frac{g}{r}\right) \mathrm{I}\left(\frac{g}{r} \leq 1\right)$.

[3] The formula for the test is: $\mathrm{Z} = \frac{b_1 - b_2}{\sqrt{SE_{b_1}^2 + SE_{b_2}^2}}$, where SE stands for standard errors of the regression coefficients.

Table 1—Tobit regression results for equation [1] (Number of cases=756)

	Estimates	
	Model 1	Model 2
Variables		
Intercept	45.63***	49.52***
	(5.34)	(5.54)
$ln\left(\frac{g}{r}\right) \mathrm{I}\left(\frac{g}{g} \geq 1\right)$	-15.19***	-15.44***
	(1.61)	(1.61)
$ln\left(\frac{g}{r}\right) \mathrm{I}\left(\frac{g}{r} < 1\right)$	-8.11***	-7.86***
	(2.07)	(2.02)
N		-0.25
		(0.15)

**** p < 0.001, ** p < 0.01, * p < 0.05*

- Standard errors are within the parentheses

We also consider whether group size (the number of givers and recipients N=g + r) influences the estimation result, as is specified in equation [2].

$$Y = a + b_1 ln\left(\frac{g}{r}\right) \mathrm{I}\left(\frac{g}{g} \geq 1\right) + b_2 ln\left(\frac{g}{r}\right) \mathrm{I}\left(\frac{g}{r} < 1\right) + b_3 N \qquad \text{..... [2]}$$

The result of model 2 in Table 1 shows that the main effects (b_1 and b_2) remain significant, while the effect of group size is not. In fact, if we repeat the previous approach (Clogg et al., 1995) to examine the difference between b_1 and b_2 in model 2, the evidence for the difference is even stronger (Z = -3.53; p-value = 0.0002).

We also use an alternative way—the interaction effect—to check for a difference in the slopes of the relationships. The idea is that we can treat $g/r \geq 1$ and $g/r \leq 1$ as two “groups.” While they are originally set on the opposite sides of the axis of ln(g/r), we can horizontally move one group to the other side so that the two groups will share the same values of ln(*g/r*).[4] More importantly, if giving drops at different rates in the two groups, it would be shown by an interaction effect when we regress giving on ln(*g/r*) with respect to the two groups. Following this method, indeed we found a significant interaction effect between the two groups (p-value = 0.008).

Our multi-person dictator game experiment reveals that the slope of the bystander effect is steeper than that of the congestible-altruism effect, suggesting that giving has a concave, negative relationship with ln(*g/r*). It means that when there are more givers than recipients, adding one more giver to the game would induce a greater reduction in giving than the increment of giving triggered by the addition of one more recipient when there are more recipients than givers. What accounts for the asymmetry? Below we present a modified behavioral economics model to address this question.

4. Study 2: An Adapted Inequality-Aversion Model

We adapt Fehr and Schmidt's (1999) inequality-aversion model to illustrate the conditions under which an individual exhibits a stronger or weaker bystander effect than congestible altruism. Inspired by earlier work by Panchanathan et al. (2013), we generalize the model to encompass multiple factors for how a giver shares with others in the game.

The model is presented in the following equation:

[4] We deliberately add a constant value of $-1\times\ln(1/15)$ to each data point for $g/r \leq 1$. In so doing, the data of $g/r \leq 1$, originally negative or zero on ln(*g/r*), now become zero or positive and share the same values with the data of $g/r \geq 1$ on the axis ln(*g/r*).

$$U = x - \alpha\, g\, p\left(\bar{x} - x\right) - \beta g\left(1 - p\right)\left(x - \underline{x}\right) - r I\left(\frac{\left(g\, p\left(E - \bar{x}\right) + g\left(1 - p\right)\left(E - \underline{x}\right) + \left(E - x\right)\right)}{r} - x\right) \quad \ldots\ldots[3]$$

$$let\ D = \frac{\left(g\, p\left(E - \bar{x}\right) + g\left(1 - p\right)\left(E - \underline{x}\right) + \left(E - x\right)\right)}{r}$$

$$then\ I = \begin{cases} \alpha & if\ D > x \\ -\beta & if\ D < x \\ 0 & otherwise \end{cases}$$

Equation [3] shows the utility (U) of a giver consists of four parts. The first part is the remaining payoff x that the focal giver enjoys after giving out E-x, where E is the endowment. The second part represents envy—a reduction in utility, weighted by α, when a giver compares with the wealthier givers (with a proportion of p). The third part refers to guilt—also a reduction in utility, weighted by β, derived from comparing with the poorer givers (with a proportion of 1-p). According to the original model (Fehr and Schmidt, 1999), the weight of envy ($0 \le \alpha < 1$) and empathy ($0 \le \beta < 1$) of a person to other's payoff would be less than that to oneself (weight = 1). The final part is a loss of utility in the comparison with the recipients, regardless whether they are wealthier or poorer than the focal giver. Details of each part are elaborated as follows.

The second and third parts of equation [3] represent a loss of utility when a giver compares with the wealthier and the poorer givers. Suppose that the focal giver believes a proportion (p) of other givers would donate *less* than s/he does. Given that each giver has an endowment, giving less means that these givers would end up being wealthier than the focal giver. Accordingly, the remaining proportion 1-p of the givers are the poorer ones, who are believed to donate more than the focal giver does. We further assume that wealthy givers, on average, leave $\bar{x}$ payoff for themselves and the poor givers keep $\underline{x}$ for themselves. Specifically, we assume that $\bar{x} = x + \left(E - x\right)u$ and $\underline{x} = v x$, where u and v are two parameters to represent the gap in wealth between the focal giver and the wealthy and the poor givers, respectively. The two parameters are bound between 0 and 1; that is, $0 < u < 1$ and $0 < v < 1$, to make sure that the wealthier (poorer) givers give less (more) than the focal giver.

The fourth element of equation [3] addresses the comparison with the recipients. Since in the game the donations from givers are equally distributed to each recipient, represented by the term D in the equation, the question at stake is whether *all* of the r recipients are wealthier or poorer than the focal giver. If $D > x$, it suggests that a giver would have a reduction in utility (envy) weighed by α when comparing with the recipients, who are wealthier than him/her; in contrast, if $D < x$, a giver would have a loss of utility (guilt) weighed by β when comparing with all of the recipients, who are poorer than the focal giver.

In what follows, we aim to fit the inequality-aversion model described by equation [3] to the laboratory experiment data to see what combination of parameter values of the model best account for the pattern of the asymmetry of the bystander effect and congestible altruism we observed in the laboratory experiment. The parameter values being tested are listed in Table 2. We tested the same numbers of givers and recipients as in the laboratory experiment. The endowment is also set to E=200 as in the experiment.[5]

To be more specific, for each pair of the numbers of givers (g) and recipients (r), we ran through each combination of parameter values in Table 2 to search for the optimal giving (E-x) that would maximize the utility of a giver, as specified by equation [3]. As optimization of equation [3] is mathematically intractable by derivative because of the conditional variable I in the last term, we turned to numeric simulation to search for the utility-maximizing giving (E-x).

[5] In fact, the numeric simulation shows that endowment size (E) does NOT make a difference in influencing the giving behavior of the model.

Table 2—Parameter values tested for the numeric experiment (gray areas replicate the laboratory experiment setting and they are fixed rather than the explanatory parameters)

(g, r) – the number of givers and recipients	(1, 1), (8, 8), (15, 15), (1, 8), (1, 15), (15, 1), (8, 1)
E (endowment)	200
p (proportion of givers expected to be less generous than the focal giver)	0.1, 0.2,…….0.9
α (weight of loss of utility due to envy)	0, 0.1,…...……1
β (weight of loss of utility due to guilt)	0, 0.1………... 1
u (gap from the wealthy givers; a larger value means a larger gap)	0.1, 0.2,…….0.9
v (gap from the poor givers; a smaller value means a larger gap)	0.1, 0.2,…….0.9

There are a total of 88,209 (9×11×11×9×9) combinations of parameter values in Table 2 (in non-gray cells). For each combination, we searched for the optimal amount of giving (E-x) that would maximize the utility function specified by the parameter values imported to equation [3]. We then compared the relationship of the optimal giving and ln(g/r) for $g/r \geq 1$ (bystander effect) and $g/r \leq 1$ (congestible altruism). To be more specific, we collected the regression coefficients (Tobit regression, same as being used to analyze the experiment data in Study 1) of the optimal giving on ln(g/r)) for $g/r \geq 1$ (bystander effect) and $g/r \leq 1$ (congestible altruism) respectively. Among the 88,209 combinations of parameter values, we located those whose result of the regression coefficients is closest to the results of the laboratory experiment in Table 1. We found four parameter combinations that *minimize* the absolute difference in the regression coefficients from our experiment finding: They are (p=0.8, α=0, β=0.5, 0.6, 0.7 **or** 0.8, u=0.9, v=0.2). These parameters generated regression coefficients of -17.24 for the bystander effect and -15.20 for the congestible altruism effect.

Searching for the optimal parameter values of the Fehr-Schmidt model (equation [3]) that replicates our experiment finding is only one purpose of the numeric simulation. After all, these parameter values simply inform us why the participants behaved in the way we observed in the experiment. A broader and more interesting question that our one-time experiment cannot answer is *under what circumstances* would the bystander effect be greater or lesser than the congestible altruism effect. To this end, we found the varieties of the results over the 88,209 parameter values valuable to address the question. Here, we attempt to check how the difference in the regression coefficients between the bystander effect and congestible altruism is influenced by the five parameters, p, α, β, u, and v in the model.

We first deleted simulation cases that generate a positive relationship between giving and $\ln(g/r)$, which was never found in literature. We then focused on the remaining cases (n=64,838) and ran an ordinary regression on the difference of the two regression coefficients: $\triangle b = b_2 - b_1$, where $b_1 < 0$ as in equation [1] is the Tobit regression coefficient of the bystander effect, whereas $b_2 < 0$ is the regression coefficient of the congestible altruism effect.

The regression results are reported in Table 3. The results suggest that the asymmetry of the two effects become even more widened when people are more envious of the richer (represented by the effect of α); less empathetic to poorer (represented by β), and, in the meantime, a higher proportion (p) of givers are believed to give very little (represented by u) to recipients, and the remaining more generous givers donate much less than the focal giver (represented by v).

Table 3—Ordinary least-squared regression on the difference in the regression coefficients of the bystander effect and congestible altruism: $\triangle b = b_2 - b_1$ (Number of cases=64,838)

Variables	Estimates
Intercept	81.57^{***} (5.17)
p (proportion of givers believed to be less generous than the focal giver)	36.88^{***} (4.59)
α (weight of loss of utility due to envy)	59.99^{***} (3.80)
β (weight of loss of utility due to guilt)	-36.47^{***} (4.21)
u (gap from the wealthy givers; a larger value means a larger gap)	187.60^{***} (4.38)
v (gap from the poor givers; a larger value means a smaller gap)	-138.92^{***} (4.53)

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

† Standard errors are reported in the parentheses

The finding above is built on the foundation of the inequality-aversion model by Fehr and Schmidt (1999). To what extents the model truly reflects people's mentality in the experiment needs to be verified in the future—a point we would briefly comment in the concluding section.

5. Study 3: Simulations of Giving in Networks

So far, we have addressed a condition of g givers and r recipients in a group where each giver is facing the same recipients with other g-1 givers—the view of a complete group. In this section, we relax the assumption and extend the experimental setting to a more generalized structure of the relationship between givers and recipients—networks.

We expect that as group size increases, givers do not share the same recipients with one another, for the following reasons. First, people may differ in their preferences regarding whom they want to help, and the heterogeneity could be more salient as group size increases. Second, our attention to the needy is constrained by cognitive capacity and influenced by philanthropy advertisements. For example, online crowdfunding platforms strategically promote collective giving by inviting donors to different groups to encourage them to donate as a collectivity (Ai et al., 2016). This suggests that the recipients to whom givers consider donating could vary across one another. Thus, rather than a complete group, a more generalized structure to represent the relationships of givers and recipients is a *network*, or to be more precise, a two-mode network (also called a bipartite graph), where each giver is linked to some but not all recipients. The two-mode network is also more representative of how large-scale donations are operated in online crowdfunding. In what follows, we simulate giving distributed from givers to recipients in two-mode networks. We are interested in how the asymmetry of the bystander effect and congestible altruism influences the improvement of distributional inequality caused by altruistic giving.

Our simulation model is described as follows. Consider a two-mode network of N nodes, consisting of G givers and R recipients. Each giver is randomly linked to an average of L recipients ($L < R$). Same as in previous sections, we assume givers allocate giving in a complete group view, but different from before, here a giver can be assigned to multiple complete groups in a network. Suppose a giver is endowed with E units of payoffs and is assigned to a total of c complete groups in the network. The giver will allocate E/c payoff to each complete group in which s/he is involved.

To know the complete groups in which a giver is involved in a network, we use social network tools to decompose a network into a set of cliques. In network science, a clique is a subgraph, in which all nodes are linked to one another (Wasserman & Faust, 1994). Applied to the two-mode network here, a clique is a set of givers and recipients in which givers are linked to all of the recipients. As an example, consider the network in Figure 2. The network can be decomposed into three smaller cliques of different sizes. A giver, such as A in Figure 2, is involved in two cliques. Note that different cliques may overlap in nodes, but not in links.

Details of the decomposition method can be found in the Appendix.

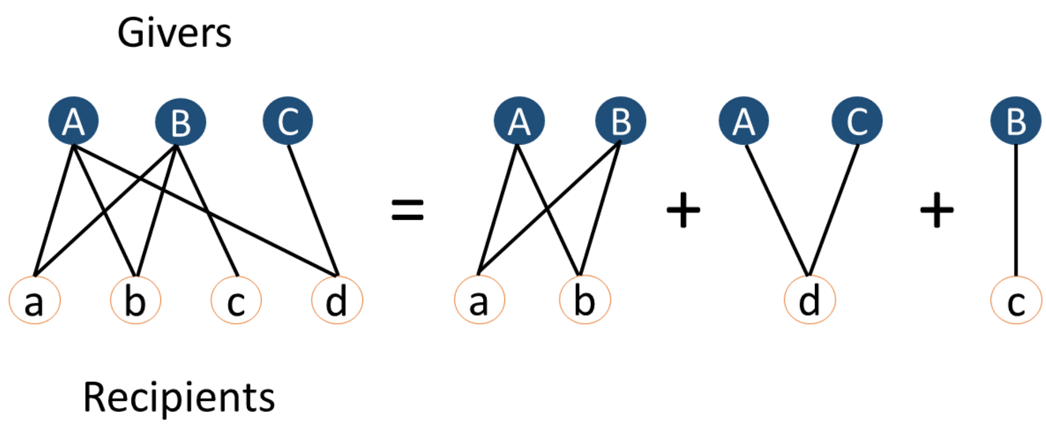

Figure 2—Illustration of the decomposition of a two-mode network into a set of cliques.

We consider a linear model, as in sections 3 and 4, to simulate how givers share payoffs in each clique. We assume that a giver's allocation decision is governed by the following equation in a clique composed of g givers and r recipients:

$$P = a + \text{b}\ln\left(\frac{g}{r}\right) \qquad \ldots\ldots. \quad [4]$$

Here, P denotes the proportion of the endowment a giver would share. The parameter a represents people's baseline generosity, which is insensitive to the number of givers and recipients. We set a = 0.3 to correspond to the giving level, as concluded by a meta-study that analyzed decades of research on dictator game experiments on the one-giver-versus-one-recipient case (Engel, 2011). The parameter b controls the magnitudes of the bystander effect and congestible altruism. We set the values for b as follows to represent that giving decreases *more* rapidly in the bystander effect than in congestible altruism. The values of the coefficients b attempt to replicate the laboratory experiment finding reported in Table 1. As here we are addressing the *proportion* (P) of giving, to be compatible with the regression coefficients in Table 1 (model 1), the value of b is set to be -15/200=-0.075 (as the endowment E is 200 in the experiment) in the following equation:

$$b = \begin{cases} -0.075 & if\ \frac{g}{r} > 1 \\ -0.04 & if\ \frac{g}{r} < 1 \\ 0 & if\ \frac{g}{r} = 1 \end{cases} \qquad \ldots\ldots \quad [5]$$

Similarly, the following equation represents the condition in which giving decreases *less* rapidly in the bystander effect than in congestible altruism.

$$b = \begin{cases} -0.04 & if\ \frac{g}{r} > 1 \\ -0.075 & if\ \frac{g}{r} < 1 \\ 0 & if\ \frac{g}{r} = 1 \end{cases} \qquad \ldots\ldots \quad [6]$$

To recapitulate, we generate random two-mode networks to represent the interactions between givers and recipients. We then decompose each network into a set of cliques, and in each clique, following equation [4] we calculate and distribute giving from givers to recipients. We then calculate the inequality level, measured by the Gini coefficient of the payoffs of givers and recipients. Figure 3 presents the result of how inequality changes over different values of $\ln(G/R)$.[6] Each data point represents the average result over replications of random two-mode networks (network density=0.5).[7]

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[6] Note again that *G* and *R* represent the number of givers and recipients, respectively, that we exogenously set up in the network. They are different from the lower case notations of the numbers of givers (g) and recipients (r) in a *clique*, which are endogenously determined by the network.

[7] Other parameter values set for the simulation in Figure 3 can be found in the Appendix.

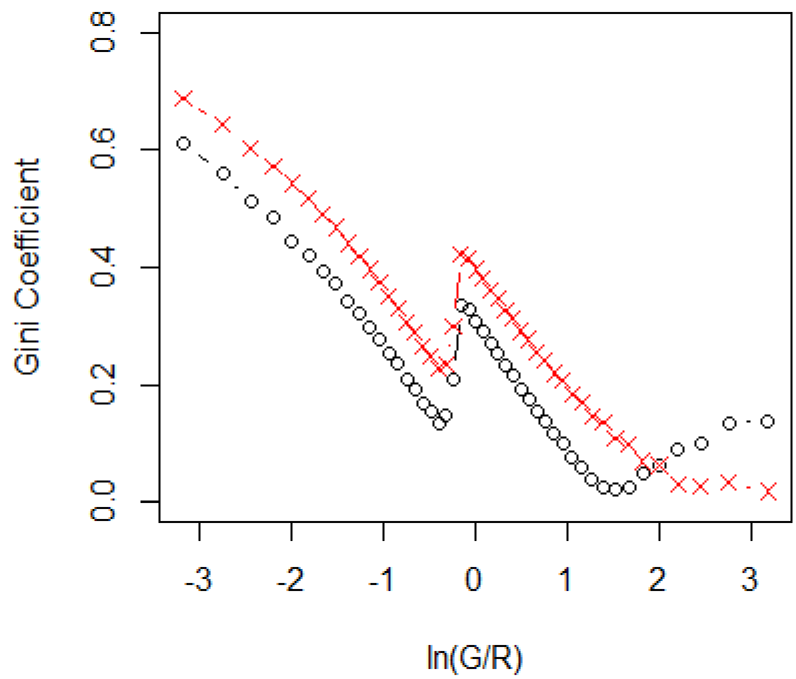

Figure 3—Post-giving inequality levels with different magnitudes of the bystander effect and congestible altruism. The symbol of red cross (black circle) reports the case of equation [5] ([6]) where giving changes at a more (less) rapid rate in the bystander effect than congestible altruism.

Figure 3 shows that in general inequality declines as ln(G/R) increases. As only givers have economic resources to change the payoff distribution, the more givers, the more inequality would improve. Moreover, "stronger" congestible altruism, represented by equation [6], improves inequality further. However, when ln(G/R) exceeds a certain level, inequality turns from decreasing to increasing. This is because when there are few recipients, they receive huge concentrations of giving, which could make them even richer than some givers. These few "rich" recipients ultimately could end up worsening instead of improving the distributional inequality. Under the circumstance, "stronger" bystander effect (equation [5]), while suggesting a more rapid decline in giving, helps prevent inequality from rising rapidly.

We can also relax the assumption of random networks and extend the simulation model to other network topologies. One possible direction is to consider whether the centralization of networks makes a difference. We generate networks where givers are linked disproportionally to a small set of "popular" recipients. We compare it with our original random-network setting, where the distribution of links is less centralized, to see how network topology makes a difference in the results. Details of the generation of the network are reported in the Appendix. Figure 4 presents the simulation results. The pattern is similar to what we found in Figure 3: inequality declines as ln(*G*/*R*) increases. What is novel is that compared to random networks, economic inequality is higher in networks where links are more unevenly distributed across recipients. The difference is more profound for the congestible altruism effect (ln(*G*/*R*)<0) than the bystander effect (ln(*G*/*R*)>0).

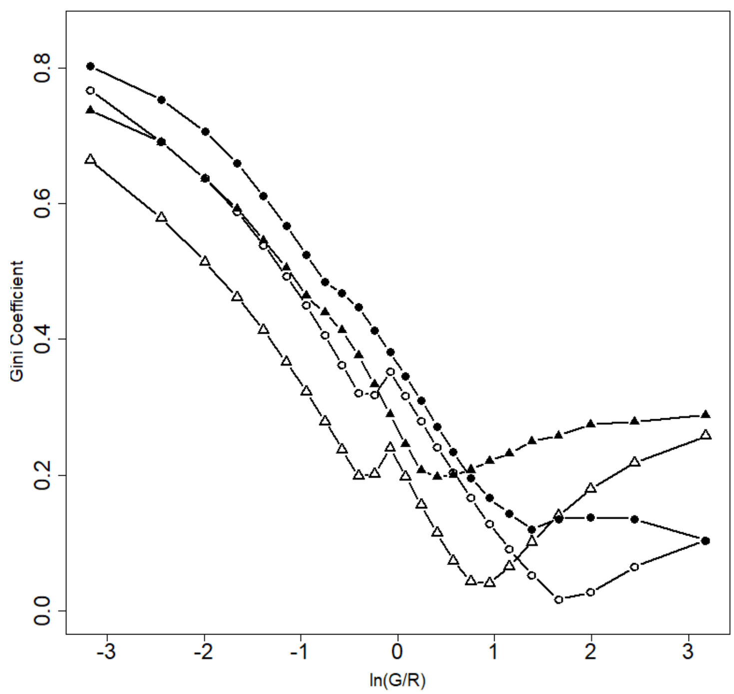

Figure 4—Post-giving inequality levels with different magnitudes of the bystander effect and congestible altruism. The symbol of circle (triangle) reports the case of equation [5] ([6]) where giving changes at a more (less) rapid rate in the bystander effect than congestible altruism. Empty symbols refer to random networks in Figure 3, whereas filled symbols represents networks where links are more unevenly distributed across recipients.

6. Discussion

We investigated whether altruistic giving changes at different rates when givers outnumber recipients than the other way around. The mentalities that underlie people's giving behavior could be different in the two conditions. When givers dominate the group, most people in the group are equally resourceful and there are only a few in need of financial help. People give less in this condition not only because they expect many other givers are available to help the few recipients—the free-riding mentality, but also because they fear that too much giving, according to the inequality-version model, could put them in inferior economic positions to those of many other givers. In contrast, when a group is filled with recipients, the very few givers are likely to feel responsible for helping the great number of the economic disadvantaged recipients—the mentality of heroic altruism. Furthermore, their giving will not have much influence on their economic positions in the group, as there are only a few others as equally resourceful as they are. The free-riding mentality makes a person more selfish, while the heroic altruism mentality makes a person more altruistic. While whether humans are selfish or altruistic in nature remains a topic of debate (Miller, 1999; Zaki & Mitchell, 2013), scholars generally agree that people are likely to be drawn to either selfishness or altruism depending on the mechanisms at work. The question is whether the attractions are of equal strength: Would it be easier to become selfish when the selfishness-eliciting mechanism is triggered than to become altruistic when the altruism-promotion mechanism is activated? We argue that a comparison of the velocity of behavioral changes, as we exemplified in the paper, could provide a new direction to the debate about the human nature of selfishness and altruism.

It is noteworthy that people's giving decision may not always be sensitive to the number of recipients, as earlier research suggested (Kahneman & Ritov, 1994; Baron, 1997; Frederick & Fischhoff, 1998). In a comprehensive review article, Barron (1997) listed and critiqued a number of reasons to why people's decisions are insensitive to the quantities of valuable goods they want to give. For example, there is a "budget constraint" bias, which leads people to believe that if they donate money to a national park, for instance, another national park of a similar kind would not be equally financed (Barron, 1997, p.75). As another example, there is a "availability" bias that argued that the goods people think of when making the giving decision are *not of the same type* of another good when they make a similar giving decision, for example, donation for medical insurance for transplants of different organs (Barron, 1997, p.76). We argued that our study design—the multi-person dictator game—is immune to the kinds of biases for at least two reasons. First, the object of donation in our study is money and the value is objective to every participant. The ambiguity of the effect of the good being evaluated, such as the uncertainty of how much a person's donation would help reduce the casualty of traffic accidents (Barron and Greene, 1996), is not expected to occur in our study. Second, the number of givers and recipients is relatively small and was made very clear in our experiment. As pointed out by Barron (1997, p.84), people usually have difficulty in assessing how much their donation would help reduce the death rates in a big city such as Philadelphia (1.5 million at that time). In contrast, the number of givers and recipients are relatively small and cognitively manageable in our experiment. We believe the reasons and others not fully discussed here may explain why in our study people's giving decisions are sensitive to the quantities of actors in the experiment.

Our study sheds light on the operation of online crowdfunding. On a large charity donation platform, it is rather implausible for a donor to have contacts with every recipient. Accordingly, how to allocate the contacts between donors and recipients to motivate donors' giving remains a challenge. We show that giving could change at different rates in different group sizes of givers and recipients. This suggests that once some critical point is crossed, people's giving could increase more rapidly thereafter. Understanding where the transitions take place is important, as it would help fundraisers judge whether it is worth their efforts to reorganize the contacts between givers and recipients to pursue a rapid increase of donation. As shown by our simulation model, the extent to which the increase makes a difference in shortening the gap in wealth between donors and recipients will depend on the networks of contacts between them.

There are issues left open for future study. First, more experimental work is needed to confirm that our experimental finding is not attributable to the limitation of small sample size and particular cultural and social influences affecting our participants (Henrich, Heine & Norenzayan, 2010). Conducting the experiment across a wider spectrum of cultural and social contexts would help increase the replicability of behavioral science research (Open Science Collaboration, 2015). Moreover, it would also introduce a richer set of explanatory variables at the societal level to analyze the asymmetry of the two effects of giving behavior. Second, although we propose a modified inequality-aversion model to explain why the bystander effect is stronger than congestible altruism, the model's validity remains unverified. It is also an open question whether there are other competing theories to account for our experimental finding. We suggest future study can use more state-of-the-art methods to assess people's physical reaction and brain activities to verify the theory and test the explanatory power of different models for the asymmetry of the bystander effect and congestible altruism that we found in our study.

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Appendix—

(1) Parameter values set for the simulation in Figure 4

N	50
G	2, 3,…..,48
R	*N-G*
L	*R*× *0.5*
E	1,000

Note: As is known in computer science (e.g., Yan & Gregory, 2009), clique detection is a computational complex task—while it takes only dozens of minutes to run our simulation model for *N*=50, it could take days or even weeks for run the same model for *N*=100 or larger. Here we report the results in Figure 4 for a smaller group size (*N*=50). We show below that there is no qualitative difference in the result between *N*=50 and *N*=100.

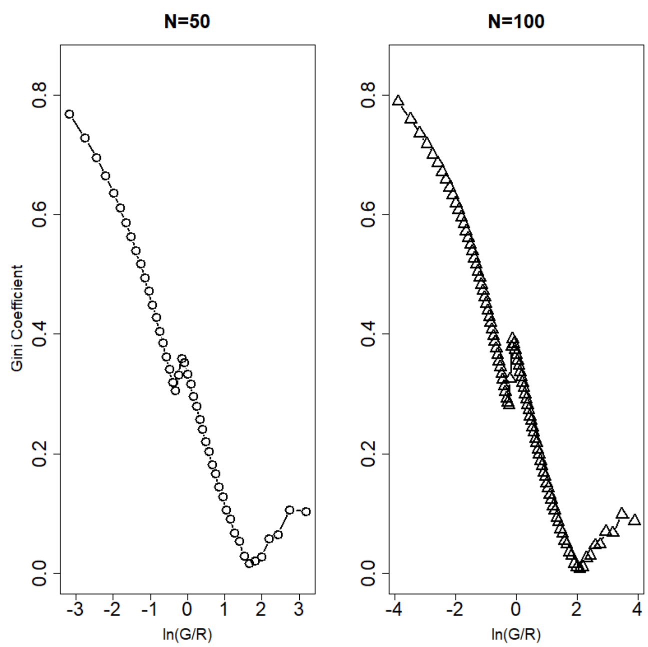

Figure S1— Comparison of the results for *N*=50 and *N*=100.

Reference:

Yan, B., & Gregory, S. (2009, November). Detecting communities in networks by merging cliques. In *Intelligent Computing and Intelligent Systems, 2009. ICIS 2009. IEEE International Conference on* (Vol. 1, pp. 832-836). IEEE

(2) Network Decomposition—

We run the simulation model in the statistical platform *R*. There are a number of supporting tools (libraries) in the platform to conduct network analysis. Here we used one of the most popular packages, "*sna*" (Butts, 2008).

The process of decomposition is described as follows. For a network, we use the function "*clique.census*" provided by the package to pin down the distribution of cliques of the network. We look for the largest clique; if there are more than one largest clique, we choose one where the number of givers and the number of recipients are the most approximate. For the chosen clique, we calculate and distribute giving from givers to recipients in the clique. We then remove the links of the chosen clique from the network. For the remainder of the network, we repeat the process until all of the links are removed, thus concluding the decomposition process.

To ensure that the algorithm of the decomposition works, we compare the set of removed links with the links of the original network prior to decomposition. The test shows that the two sets of links are identical.

Reference—

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(3) Network Formation Mechanisms—

We consider a network formation dynamics similar to the classic "preference attachment" model proposed by Barabasi and Albert (1999). Each giver **takes turns** assigning a fixed number of ties to recipients. The probability of a recipient *i* receiving a tie from a giver is:

$$\mathrm{P}_i = \left(\frac{d_i}{\sum_i d_i}\right)^k$$

where d_i is the network degree of recipient *i* (the number of ties received by *i* so far). Parameter k controls the strength of biases toward linking to the more connected. As long as $k > 1$, each giver is more likely to send ties to recipients who already received more ties from other givers.

Reference—

Barabási, A. L., & Albert, R. (1999). Emergence of scaling in random networks. *Science*, *286*(5439), 509-512.

(4) Instruction Script—

Welcome to the experiment! First, we would like you to turn off your electronic devices to make sure that they will not cause any disturbance during the experiment.

Today’s experiment will last for about 30 minutes. You will engage in a series of scenarios, and in each scenario you will make a decision. Your decision will determine both your and other participants’ payoffs in the experiment. At the end, we will let you make a lottery draw to decide which scenario to pay you. We emphasize that the rules of the game are real, and there is no deception in the experiment. Your identity will not be revealed in the experiment. Please make decisions at your will.

In the following experiment, you and other participants are playing a game. There are two roles in the game: a decision maker and a recipient (called alter). You are one of the decision makers in the game. In each game, you will be given an amount of money and decide whether to keep the money for yourself or give some or all of it to alters. The money you give, if any, will be added to the money given by other decision makers and evenly distributed to each alter.

For example, suppose that you and another decision maker are facing three alters. Each of you has $200.

You

Decision Makers

$200 $200

Alters

Suppose you decide to give x dollars and keep 200-x dollars to yourself, while the other decision maker gives y dollars and keeps 200-y for him/herself. Then, the sum of your giving (x+y) dollars will be distributed to the three alters, and each of them will receive (x+y)/3 dollars.