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GROUP SIZE AND CONFORMITY IN CHARITABLE GIVING: EVIDENCE FROM A DONATION-BASED CROWDFUNDING PLATFORM IN JAPAN

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Group size and conformity in charitable giving: Evidence from a donation-based crowdfunding platform in Japan

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Abstract

A charitable donor typically imitates the majority contribution of other donors. This study examines the relationships between majority size and this so-called donor's conformity behavior, by empirically investigating the impacts of multiple earlier donations on the donation of a subsequent donor to JapanGiving, a donation-based crowdfunding platform in Japan. This analysis is possible because the platform's webpage displays the previous donation amounts in chronological order, thus allowing us to examine the modal amount of more recent donations. By using data on 9,989 actual donations, our

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dynamic panel analyses suggest that when the two most recent donations are identical, a subsequent donor is likely to match the last donation. In other words, when the last donor imitates the donation of the penultimate donor, the subsequent donor is also likely to imitate this amount. Additionally, the likelihood increases when the number of most recent continuous modal donations increases. These results support the notion that a donor's conformity behavior is more likely to occur when a greater proportion of the other donors give a similar amount. Furthermore, the effects of continuous modal donations are strongly observed for low monetary ranges. We discuss that individuals would obtain an excuse for less cooperation due to others' behaviors or initiating further cooperation among a large number of less cooperative others would become harder. Our findings connect economic studies of charity and social psychology studies of conformity and could help improve the effectiveness of fundraising by charities.

Keywords: Charitable giving, Conformity, Free-ride, Dynamic panel model, Crowdfunding, Fundraising management

JEL Classification Codes: D64, H41, C99

1. Introduction

The literature shows that a charitable donor is often influenced by other donors and an influenced donor imitates the others' contributions. (Alpizar et al., 2008; Frey & Meier, 2004; Shang & Croson, 2009). For example, Shang and Croson (2009) find that potential donors make larger donation amounts on average when they know about another's donation than when they do not. This so-called conformity behavior by donors also matters in practice. Indeed, charities deliberately provide information about previous donations (e.g., in their solicitation letters, brochures, and homepages) to solicit new donations (The Behavioral Insights Team, 2013; Hardwick, 2014; Prior, 2014).

Then, when is a charitable donor more likely to conform to others' contributions? This issue in donors' conformity behavior remains a subject of debate and analysis. Answering the question can aid fundraising activities by charities. If we reveal a secret that aids in prompting donors' conformity behavior, it must enable charities to collect donations more effectively and achieve fundraising targets at a faster pace.

One method[1] of investigation involves providing potential donors with information on multiple donors making a similar donation amount. Seminal studies in social psychology revealed that an individual's conformity behavior is likely to appear when a large number of other people behave in a similar way (Asch, 1951; Asch, 1955). In other words, when one individual imitates the choice of another, a third individual is likely to match their choice. Furthermore, the likelihood increases with the number of others who have made a similar choice.

[1] Previous studies have explored the issues in other ways. For instance, Shang et al. (2008) show that donor conformity depends on similarities between donors in that when donors obtain information about another donor of the same sex, they are more likely to be influenced by the other donor. Croson and Shang (2013) find that donor conformity depends on the contribution level of the other donor. When donors see another's extremely high contribution, they are less likely to be influenced by it. Jones and Linardi (2014), among others, find that donor conformity depends on the visibility of his/her contribution. That is, donors are more likely to be influenced by other donors when their own contribution is visible.

If that is the case with charitable giving, providing information regarding multiple donors could influence potential donors more strongly if and when more of the multiple donors have donated the same amount as compared with other times when they may not donate the same amount in such high numbers. That is, subsequent donors' contribution could mirror the majority contributions of multiple donors. However, few study has found this "majority effect" in everyday situations, including real charitable giving, to the best of our knowledge.

We study the causal impact of majority size on donors' conformity behavior, by using a dataset of 9,989 actual donations on a donation-based crowdfunding platform, JapanGiving, and a dynamic panel modeling approach. JapanGiving is the largest donation-based crowdfunding platform in Japan as well as an affiliate of the world's largest platform, JustGiving in the United Kingdom.[2] As an online fundraising intermediary, JapanGiving connects nonprofit organizations (NPOs) and fundraisers with potential donors. The main feature of JapanGiving that can be exploited for the analysis in this study is that its fundraising campaign webpage displays previous donation amounts in chronological order. Potential donors would see the four or five most recent individual donations and combinations of previous donations when accessing the page and donating at different times.

In other words, to exploit causality from majority size on donors' conformity behavior, we investigate the effects of informing subsequent donors regarding the monetary contributions that multiple previous donors already made to JapanGiving. Our empirical models include variables to explain representative combinations of previous donations, and the main variables are the modal amount among the five most recent donations and their appearance along the sequence. Using these variables, we examine the effect of the conformity behavior of previous donors on that of subsequent

[2] The platform's name changed from JustGiving Japan to JapanGiving in January 2015.

donor. This implies that our model specifications include lagged dependent variables as independent variables, and this modelling causes a downward bias in fixed effects estimates (Nickell, 1981). We use a dynamic panel modelling approach, excluding the bias. We further introduce our model specification and identification strategy in Section 4.

Our data, models, and empirical strategy are based on those propounded by Smith et al. (2015), who use a large sample of data from JustGiving and Virgin Money Giving in the United Kingdom whose webpages also display previous donations chronologically. Their analyses show that a new donation amount responds affirmatively to large and small donations among previous donations, changes in their modal amount, and the mean amount of previous donations. Getting an idea from the literature, we examine the significance of the number of people making donations of a similar size in terms of the likelihood of people following previous donations.

Our empirical analyses provide findings that are consistent with those in laboratory studies in social psychology. When the two most recent donations are identical, a subsequent donor is likely to match the last donation. In other words, when the last donor imitates the donation of the penultimate donor, the subsequent donor is likely to match their amount. Furthermore, we find that the likelihood increases when the number of the most recent continuous modal donations increases. These results support the notion that a donor's conformity behavior is more likely to occur when a greater proportion of other donors give a similar amount as compared with when they do not.

Our study, which applies the findings from social psychological studies of conformity to the economic analysis of charitable giving and adopts a dynamic panel modeling approach to test the empirical hypotheses, is the first to discover the effect of majority size on conformity behavior in real charitable giving. The presented findings can assist fundraising activities by suggesting that charities alter the presented donation amounts accordingly to achieve their fundraising targets at a faster pace.

2. Literature review

In social psychology, Asch (1951, 1955) produces seminal works regarding majority size and individuals' conformity behavior. In his laboratory experiment, he presents two cards to experimental subjects. He writes just one line on one card and multiple lines on the other card. He asks subjects to select a line from the multiple lines on the latter card that equals the line on the former card. The main finding is that when a subject knows that more of the group has selected the wrong choice, he/she is more likely to match this wrong choice. The Asch's conformity experiments have been replicated by an extensive experimental literature (see Bond, 2005; Tanford & Penrod, 1984). Most results have been found in the laboratory setting; however, recent studies start to complement these conformity experiments by using more natural observations and assessing conformity behavior in everyday situations (Claidière et al., 2012; Claidière et al., 2014).

To conduct a similar investigation in natural settings, including real charitable giving, researchers need to inform potential donors about combinations of multiple donations. Hence, because employing a field experiment for the analysis would require a large number of treatments, few relevant studies of charitable contributions has been undertaken. In this strand of the research, Martin and Randal (2008) use a see-through donation box in an art gallery to investigate how compositions of visible bills and coins influence new donations. However, they do not track and record each individual donation and cannot draw conclusions on how each donor reacted to the stimulus. In a laboratory experiment, Samek and Sheremeta (2014) analyze the effects of recognizing (i) only the largest or smallest donations and (ii) all multiple donations. However, their work does not shed light on how other combinations affect new donations.

Websites are ideal for displaying various information patterns (Blake et al., 2015; Johnson et al., 2014; Lewis & Reiley, 2014). Hence, researchers can track and record detailed data on website visitors, such as when they visited, what information they saw, and which activity they undertook. By using this information, they can then compute the effects of the treatment information on a visitor's activity. However, if treatment information on websites is not randomly assigned to visitors, an econometric method is necessary to identify the causality from the treatment information to a visitor's activity.

Smith et al. (2015) apply a dynamic panel modeling approach, a method of causal inference, to a large sample of micro panel data of real donations recorded on JustGiving and Virgin Money Giving.[3] As noted in the Introduction, these crowdfunding platforms display previous donations chronologically. The authors examine the effects of other donors by investigating how previous donations affect subsequent donations on these platforms. They use the dynamic panel modeling approach to exclude downward bias in the fixed effects estimates, finding that a £10 rise in the arithmetic mean of all previous donations increases a new donation amount by £2.50. Their study thus establishes positive causality running from previous to new donations.

3. Study setting

Between its launch in March 2010 and December 2014, JapanGiving attracted 111,700 donations totaling ¥121.4 million (US$1.5 million at the 2011 exchange rate)[4] in contributions.[5] NPOs and

[3] Bøg et al. (2012) use a small sample of cross-sectional data from JustGiving, finding a systematic positive correlation between contributions in the early stage of a fundraising campaign and those in its later stage.
[4] 1 US dollar was equivalent to 79.8 Japanese yen in 2011.
[5] Donors can also register with JapanGiving and can donate by credit card or through Internet banking.

fundraisers register with JapanGiving and create fundraising webpages for their causes. They first solicit friends, families, and colleagues for donations, who in turn are expected to share the URL of the fundraising webpage and the solicitation message or their donations with their social and professional associates. Accordingly, most donors on a webpage are likely to belong to an NPO's or fundraiser's existing networks.

We use data from the 9,989 donations made via JapanGiving from February 2011 to December 2011.[6] All sampled donors viewed the same webpage design during this period.[7] JapanGiving records the monetary amounts of donations, their dates and times, and the recipient organizations (see the example in Figure 1). Information is displayed chronologically on one electronic page. A donor therefore sees the last four or five donations prominently. First, we identify the order of donations within a campaign webpage from the time and date data. Subsequently, we use the amounts donated and their sequence to capture the information that each donor saw when he/she visited the webpage. We identify donors by randomly assigned IDs and gather no personal information.

[Figure 1 is here]

4. Empirical strategy

4.1. Model specifications and variables

To examine the spread of conformity behaviors, we first investigate whether positive causality runs from the conformity behavior of a previous donor to that of a new donor. In other words, when a

[6] The total number of donations in this period was 67,595. Most pertained to the reconstruction process from the Great East Japan Earthquake and Tsunami in 2011. We selected the sample for our analysis from the 67,595 donations by following the procedure in Section 4.2 and obtained a plausibly homogeneous sample.
[7] Although JapanGiving sometimes changes the website's design, no changes were made in the period during which those 9,989 donations were made.

previous donor imitates the donation of another previous donor, to what extent is a subsequent donor likely to match their amount. In the second model specification, we investigate whether a new donor's conformity behavior is more likely to occur when more previous donors conform.

4.1.1. Model specification (1)

The first model specification is as follows:[8]

$$y_{i,t} = \alpha + \gamma y_{i,t-1} + z'_{i,t}\delta + u_{i,t}, \qquad (1)$$

$$y_{i,t} = 1, \text{ if } d_{i,t} = d_{i,t-1}$$

$$y_{i,t} = 0, \text{ if } d_{i,t} \neq d_{i,t-1}$$

Empirical Hypothesis 1: When the two most recent donations are identical, a new donor is likely to match the last donation.

where $d_{i,t}$ refers to the amount of the t^{th} donation to campaign webpage i.

The dependent variable $y_{i,t}$ is a dummy that takes 1 when $d_{i,t}$ exactly equals $d_{i,t-1}$, and 0 otherwise. In other words, we define that the t^{th} donor conforms to the $t-1^{th}$ donor when $d_{i,t}$ and $d_{i,t-1}$ are identical. Note that this dependent variable expresses the conformity behavior of the t^{th} donor and does not alone identify why he/she conforms. The independent variable $y_{i,t-1}$ is the first lag of the dependent variable $y_{i,t}$. This variable expresses whether the $t-1^{th}$ donor conforms to the $t-2^{th}$ donor. Its parameter γ represents the effect of the $t-1^{th}$ donor's conformity

[8] To examine the existence of donor conformity, we estimated the following model: $d_{i,t} = \alpha + \gamma d_{i,t-1} + z'_{i,t}\delta + u_{i,t}$. The estimated results showed that γ is small and insignificant. This result implies that a new donor does not respond only to a change in the last donation and this led us to examine combinations of multiple previous donations.

behavior on that of the t^{th} donor.

Here, we test the hypothesis that when the last donor imitates the amount that the penultimate donor made, a subsequent donor is likely to match their amount. We assume that a subsequent donor looks particularly at the last donor's behavior among previous donors. This assumption is plausible because the most recent donation is displayed at the top of a list of previous donations on a JapanGiving campaign webpage, making it more visible to the subsequent donor.

We define the dependent and independent variables in the above ways and use these variables to test the first hypothesis, because it allows us to use a simple dynamic panel model, which provides a solution for the problem of endogeneity. As we will explain details in Section 4.1.3, econometricians have developed methods of causal inference for the dynamic panel model, and the methods have been applied in several empirical studies. Conversely, if we define that the t^{th} donor conforms when $d_{i,t}$ equals $d_{i,t-3}$, $d_{i,t-4}$, or $d_{i,t-5}$, using a dynamic panel model would be unsuitable. Therefore, adapting the definitions of our variables and model specification is a simple and pragmatic strategy. If $\gamma > 0$ holds, it confirms our first empirical hypothesis, suggesting positive causality running from the conformity behavior of a previous donor to that of a new donor.

Some might argue that the definition of the dependent variable is too strict because it judges that the t^{th} donor does not conform to the $t - 1^{th}$ donor even when $d_{i,t}$ and $d_{i,t-1}$ are almost, but not exactly, the same. This definition could thus underestimate the parameters in our model. Nevertheless, we define this so for the following three reasons. First, if we find the directionality of the expected parameter from the underestimated results, this strongly supports our hypothesis. It can also provide academic and practical implications. Second, many of social psychology studies examine whether one individual's choice exactly equals others' choices, to the best of our knowledge. Third, this definition is based on the JapanGiving payment system, which provides nine options for donated amounts.[9] Over 90 percent of all donations concur with the amounts presented in these options. Donors could decide their contribution by choosing from the options, and they could make a binary decision of whether they select the option that other previous donors selected.

The control variables $z'_{i,t}$ include some of the information that the t^{th} donor sees on the webpage, such as the number of previous donations and target completion rate. $z'_{i,t}$ also includes the duration from the inception of the webpage to the date of the t^{th} donation. Furthermore, we use monthly, weekday, and time zone dummies to accommodate common shocks among the time intervals.

4.1.2. Model specification (2)

In the second model specification, we further explore a spread of conformity behaviors. Here, we assume—in the same way as in the first model specification—that a subsequent donor looks at the last donor's behavior. However, we additionally assume that he/she considers the behaviors of the last five donors. The second model subdivides $y_{i,t-1}$ into several cases to test the second empirical hypothesis:

$$y_{i,t} = \alpha + \gamma_1 y_{i,t-1} + \gamma_2 \mathrm{T2}_{i,t} + \gamma_3 \mathrm{T3}_{i,t} + \gamma_4 \mathrm{T4}_{i,t} + \gamma_5 \mathrm{OT1}_{i,t} + \gamma_6 \mathrm{OT2}_{i,t} + z'_{i,t}\delta + u_{i,t}, \qquad (2)$$

$$y_{i,t} = 1, \text{ if } d_{i,t} = d_{i,t-1}$$

$$y_{i,t} = 0, \text{ if } d_{i,t} \neq d_{i,t-1}$$

Empirical Hypothesis 2: When the number of the most recent continuous modal donations increases, a new donor is more likely to match the modal amount.

[9] These are (proportion of donations consistent within the nine options): ¥500 (2.0 percent share), ¥1,000 (8.5 percent), ¥2,000 (13.3 percent), ¥3,000 (12.2 percent), ¥5,000 (25.8 percent), ¥10,000 (25.4 percent), ¥30,000 (3.1 percent), ¥50,000 (0.9 percent), and ¥100,000 (0.9 percent).

[Figure 2 is here]

As shown in Figure 2, the first lagged dependent variable $y_{i,t-1}$ is a dummy that takes 1 when $d_{i,t-1}$ at least equals $d_{i,t-2}$. Next, $\mathrm{T1}_{i,t}$, $\mathrm{T2}_{i,t}$, $\mathrm{T3}_{i,t}$, and $\mathrm{T4}_{i,t}$ are dummies that take 1 when only the two most recent donations of $d_{i,t-1}$ and $d_{i,t-2}$ are identical, when the three most recent donations of $d_{i,t-1}$, $d_{i,t-2}$, and $d_{i,t-3}$ are identical, when the four most recent donations of $d_{i,t-1}$, $d_{i,t-2}$, $d_{i,t-3}$, and $d_{i,t-4}$ are identical, and when all five of the most recent donations are identical, respectively. In all these treatments, $y_{i,t-1}$ takes 1. $\mathrm{T1}_{i,t}$ explains the largest variation among the five most recent donations, whereas $\mathrm{T4}_{i,t}$ explains the smallest variation. We define the degree of conformity behaviors among the five most recent donors to be lowest in the former case, with the degree of conformity behaviors rising in the order of $\mathrm{T2}_{i,t}$, $\mathrm{T3}_{i,t}$, and $\mathrm{T4}_{i,t}$.

We interpret the parameters in the following way. γ_1 exhibits the effect of treatment 1 on the probability that the dependent variable $y_{i,t}$ takes 1. $\gamma_1 + \gamma_2$, $\gamma_1 + \gamma_3$, and $\gamma_1 + \gamma_4$ are the effects of treatment 2, treatment 3, and treatment 4, respectively. The second model specification adds cross-terms with the lagged dependent variable into the first model specification. This simple enhanced version of the first model specification allows us to regard the second model specification as a dynamic panel model.

We explain the degree of conformity behaviors among the last five donors by examining the most recent continuous modal donations. In particular, we consider the difference in the salience of modal donations between larger and smaller variations. For example, a subsequent donor could easily recognize when the last and penultimate donations are identical, which may strengthen the pressure to conform; by contrast, he/she might not do so when two donations of the modal amount appear at an interval. In addition, the pressure to conform might weaken in this case because a subsequent donor could find more recent donors who did not conform. However, the latter case could also generate more or less pressure to conform to the last donation, and ignoring this case leads to the underestimation of the parameters, particularly γ_1 and γ_2. We therefore construct a covariate of the other treatments 1 $\mathrm{OT1}_{i,t}$ to explain the case, and we add it into the second model specification.

Furthermore, we must deal with the case where modal donations appear among the other four recent donations (i.e., all donations except the last). In this case, a subsequent donor might donate the modal amount; however, our dependent variable does not judge whether the subsequent donor conforms because his/her donation amount is different from that of the last donation. If we do not consider this case, it then causes the overestimation of the parameters of γ_1, γ_2, γ_3, and γ_4. The second model specification thus includes a covariate of the other treatments 2 $\mathrm{OT2}_{i,t}$ to explain the case, controlling for its effect.

4.1.3. Bias corrections in dynamic panel models

In model specifications (1) and (2), the error term is decomposed as $u_{i,t} = \eta_i + \nu_{i,t}$. η_i is a constant page-specific effect that captures the unobserved inter-donor preference correlations on that page; $\nu_{i,t}$ is a random error term. In view of the characteristics of the error term, the OLS estimates of γ and γ_{1-4} are likely to be upward-biased because of unobserved correlations. To exclude this bias, we use fixed effects linear probability models to estimate the above two equations. However, the fixed effects estimates of γ and γ_{1-4} are likely to be downward-biased (Nickell, 1981), since the two model specifications are a dynamic panel model that includes lags of the dependent variable. A correlation thus remains between the treatment variables and error term even after we eliminate the constant page-specific effect by first differencing.

We address this downward bias by adopting the following two methodologies. The first is the generalized method of moments (GMM) for dynamic panel estimations, particularly Difference GMM (Arellano & Bond, 1991) and System GMM (Blundell & Bond, 1998). The second methodology is the half-panel jackknife fixed effects estimation developed by Dhaene and Jochmans (2015).

In Difference GMM, we use as instruments the several period lags of the dependent variable that influence just the differenced independent variable after we eliminate the constant page-specific effect by first differencing. System GMM adds the level moment condition to the moment conditions of Difference GMM and estimates the equation. These methodologies have been applied in several empirical studies, and Smith et al. (2015) also adopt Difference GMM for their estimations.

We use the second methodology to deal with the downward bias since GMM estimates are not always stable because of the problems of weak instruments, too many instruments, and non-stationarity of the dependent variable (Bun et al., 2015; Roodman, 2009a). To avoid these problems, econometricians have developed another methodology, by which they directly exclude the downward bias in the fixed effects estimates and obtain reliable estimates (Bun & Carree, 2005; Dhaene & Jochmans, 2015; Hahn & Kuersteiner, 2002; Kiviet, 1995). We adopt the half-panel jackknife fixed effects estimation method developed by Dhaene and Jochmans (2015) has been applied in recent empirical studies (Hospido, 2012, 2015). In this method, we first assume that the fixed effects estimator includes downward bias B and that B decreases as the time T dimension increases. Next, we estimate the fixed effects estimates of $\hat{\theta}_{nT}$ by using the full panel dataset; $\hat{\theta}_{nT}$ includes downward bias B/T. We also divide the full panel into halves and estimate the fixed effects values of $\hat{\theta}_{nT,1}$ and $\hat{\theta}_{nT,2}$ by using the subsamples. $\hat{\theta}_{nT,1}$ and $\hat{\theta}_{nT,2}$ that include common downward bias $2B/T$. Finally, we obtain the half-panel jackknife estimator without the downward bias by substituting $\hat{\theta}_{nT}$, $\hat{\theta}_{nT,1}$, and $\hat{\theta}_{nT,2}$ for $2\hat{\theta}_{nT} - \frac{\hat{\theta}_{nT,1}+\hat{\theta}_{nT,2}}{2}$. We check whether our main estimation results are stably observed when we use Difference GMM, System GMM, and the half-panel jackknife fixed effects estimation.

4.2. Preliminary identification analysis

Our identification strategy for the parameters of $y_{i,t-1}$ and $\mathrm{T2}_{i,t} - \mathrm{T4}_{i,t}$ assumes that donors' attributes and characteristics do not depend on t after controlling for a constant page-specific effect by using dynamic panel estimations. Ordinal regressions corroborate this assumption by directly adding the variables of attributes and preferences into the equation: however, we gathered no personal information for its protection. Subsequently, we justify the assumption by confirming that the distribution of donated amounts on a webpage is stationary throughout the campaign. In that case, we can judge that plausibly homogeneous donors visit the campaign webpage and donate there. This subsection delineates examples to confirm this assumption.

First, we consider that the distributions of donated amounts, number of donors per webpage, and length of the campaign are skewed because of a few successful fundraisers[10] and generous donors (Smith et al., 2015). We exclude from the analysis webpages that have single donations exceeding ¥500,000 (US$6,266), webpages with fewer than 25 or more than 100 donations, and webpages with donations made more than 50 days after their inception. Furthermore, we exclude some exceptional donations, including continuous donations made by an identical donor and donations made by JapanGiving founders before a campaign webpage opened to the public.

[10] One of the most successful fundraisers is Dr. Shinya Yamanaka, a Japanese Nobel Prize-winning stem cell researcher. He raised more than ¥20,000,000 (US$250,656) from 1,913 donors; the largest single donation in his campaign was ¥1,000,000 (US$12,533).

Second, we exclude the first three donations on each webpage because their donors are more likely to be the fundraiser's friends, family, and colleagues, and tend to donate different amounts (Agrawal et al., 2015; Smith et al., 2015).[11] The data indicate that the mean of the first three donations (¥17,467) significantly exceeds the mean of the remaining donations (¥8,568) with 1% statistical significance. Therefore, we exclude them. Furthermore, we exclude the fourth and fifth donations because our analysis focuses on the effects of the last five donations.

Finally, we verify that amounts without the initial five donations are sufficiently stationary throughout the entire campaign. Then, we use the Kolmogorov–Smirnov test to compare the distribution of monetary amounts donated in the first half and second half of the campaign. The null hypothesis is that the two sample groups have identical distributions, and the test does not reject this in 291 out of 359 campaign webpages ($p > 0.100$). Thus, the 9,989 data points across the 291 campaign webpages are plausibly homogeneous.

As shown in Table 1, the arithmetic mean donation is ¥8,823 (US$111). The mean number of donations per campaign webpage is approximately 47,[12] and the mean target price is ¥997,724 (US$12,504). The number of campaigns with final target completion rates of 100 percent or more is 98. The arithmetic mean donation on JapanGiving might be higher than normal donations in Japan. One possible explanation is that most samples donated for the reconstruction process from the Great East Japan Earthquake and that such donations are likely to be higher. The Japan Fundraising

[11] Agrawal et al. (2015) use data from a Canadian crowdfunding platform, showing that early donors have closer relationships with fundraisers. Smith et al. (2015) report that the average amount of the first three donations is systematically larger than the average of the remainder in JustGiving UK; therefore, they exclude the initial three donations from their analysis.

[12] As we have explained, our analyses use the sample, which excludes the exceptional donations from the donations per campaign webpage. Therefore, the number of our sample, 9,989, is inconsistent with the number, which is calculated out by multiplying the number of donation per campaign webpage, 47, by the number of campaign webpage, 291. The number of donation per campaign webpage in our sample is around 34.

Association (2012) reports that relief money or donations averaged around ¥10,000 nationally at this time.

[Table 1 is here]

5. Basic analysis

This section first presents the estimation results of model specification (1), testing the first empirical hypothesis that when the two most recent donations are identical, a new donor is likely to match the last donation. Next, we present the estimation results of model specification (2), testing the second empirical hypothesis that when the number of the most recent continuous modal donations increases, a new donor is more likely to match the modal amount. We run the regressions, considering the control variables' effects, several fixed effects, and serial correlation effects.

5.1. First hypothesis test results

Table 2 presents the results of the OLS estimations, fixed effects model estimations, and dynamic panel model estimations. In the Difference GMM and System GMM estimations, we use more than the two-period lags of the dependent variable and more than the three-period lags of the donation amount as instrumental variables. In addition, we collapse these instrumental variables to deal with the problem of excessive instrumental variables because too many instrumental variables could over-fit the endogenous variables as well as weaken the Hansen test of over-identifying restrictions.[13,14] The Arellano–Bond test for serial correlation does not reject the null hypothesis of no second-order serial

[13] The econometric software STATA provides a "collapse" option (Roodman, 2009b).

[14] Several empirical studies in macroeconomics have reported plausible causal effects using GMM estimations, but these results suffered from problems associated with excessive instruments (Bazzi & Clemens, 2013). After collapsing the instruments to address these problems, most analyses showed no evidence that supported causality.

correlation, implying that more than the two-period lags are valid as instruments. The Hansen test indicates that the instrument set is plausible.[15]

[Table 2 is here]

Our findings confirm the first empirical hypothesis. Table 2 shows that all the dynamic panel estimates of γ are positive and statistically significant at the 1 percent level. We find that when the last two donations are identical, the likelihood that a new donor matches the last donation increases by 13.6–13.7 percent. This finding also supports the notion of positive causality running from the conformity behavior of the most recent donor to that of a new donor.[16]

As discussed in Section 4.1.1, the magnitudes can be underestimated because we define that the $t-1^{th}$ donor conforms to the $t-2^{th}$ donor when $d_{i,t-1}$ and $d_{i,t-2}$ are identical, and this definition allows the control group to include the case where $d_{i,t-1}$ and $d_{i,t-2}$ are similar. The above results show that even when employing this strict definition, the magnitudes exceed 13.6. This finding implies that we cannot ignore the extent to which the conformity behavior of previous donors influences that of a new donor.

5.2. Second hypothesis test results

The model specification (2) subdivides $y_{i,t-1}$ into five cases. We estimate this model, testing that when the number of the most recent continuous modal donations increases, a new donor is more likely to match the modal amount.

[15] The estimated results are consistent with the theoretical predictions for biases. The fixed effects estimate is smaller than the OLS estimate, while the OLS estimate is biased upward. All the dynamic panel estimates of γ lie between the OLS and fixed effects estimates. The fixed effects estimate is biased downward. However, the biases may not always generate as the theoretical predictions in model specifications with covariates.

[16] Even the fixed effects estimate with downward bias shows a positive and statistically significant effect. From the fixed effects estimation results, our data show that the conformity behavior of the previous donor is causative of new donor behavior.

Before presenting the estimation results, we reintroduce the parameters associated with the key independent variables. First, γ_1 is the parameter of the first lagged dependent variable, which takes 1 when at least the last two donations are identical. Second, γ_2, γ_3, and γ_4 are the parameters for the three most recent continuous modal donations (treatment 2), the four most recent continuous modal donations (treatment 3), and the five or more most recent continuous modal donations (treatment 4). The baseline is the two most recent continuous modal donations (treatment 1). Third, we interpret the parameters in the following ways. γ_1 exhibits the effect of treatment 1 on the probability that the dependent variable, $y_{i,t}$, takes 1. $\gamma_1 + \gamma_2$, $\gamma_1 + \gamma_3$, and $\gamma_1 + \gamma_4$ are the effects of treatment 2, treatment 3, and treatment 4, respectively.

[Table 3 is here]

[Figure 3 is here]

Our findings confirm the second empirical hypothesis. As shown in Table 3, all the dynamic panel estimates of $\gamma_1 \cdot \gamma_2 \cdot \gamma_3 \cdot \gamma_4$ are positive and statistically significant at least at the 10 percent level.[17] Our additional tests in Figure 3 show that the effects of treatments 2, 3, and 4 are 2.2 times, 3.4 times, and 6.2 times, respectively, larger than treatment 1.[18] In other words, the effect rises in the order of treatment 1, 2, 3, and 4. These results imply that as the number of the most recent continuous modal donations increases among the last five donations, a new donor is more likely to match the last donation. This finding confirms our second empirical hypothesis as well as supports our contention that when more previous donors have contributed similarly in monetary terms, a new donor's conformity behavior is more likely to occur. The likelihood increases not strictly linearly but

[17] Similarly, in model (1), the Arellano–Bond test and Hansen test imply that our instrumental variables are valid and plausible.

[18] As an example, we use the Difference GMM estimations to conduct the additional tests and present the test results.

continuously with the number of the most recent continuous modal donations.

The effect of treatment 1 is smaller than those of treatments 2–4 because a new donor might recognize that the two most recent continuous modal donations are not the majority among the last five donations. That is, when facing those cases, a subsequent donor might not think that many previous donors contribute the same amount as the last donation. On the contrary, the three or more most recent donations are identical in treatments 2–4, and thus a new donor might recognize that the last donor belongs to the majority.

The other treatments have parameters that are consistent with our expectations. $\mathrm{OT1}_{i,t}$ explains the cases in which donations identical to the last donation appear at intervals. The results show that these cases generate some pressure to match their donation amount. In addition, $\mathrm{OT2}_{i,t}$ explains the cases where modal donations appear among the other four recent donations without the last donation. This parameter shows a negative sign, indicating that a subsequent donor might match the amount of the modal donation. Therefore, we again recognize that we need to control for these two cases when identifying $\gamma_1 \cdot \gamma_2 \cdot \gamma_3 \cdot \gamma_4$.

6. Further analysis

6.1. Heterogeneity between monetary amount ranges

Section 5 showed that when the two most recent donations are identical, a subsequent donor is likely to match the last donation. The likelihood further increases when the number of the most recent continuous modal donations increases. This section conducts additional analysis, within the limitations of data availability, to discuss why donors conform in this manner and thus deepen the interpretation of our findings.

In advance, we introduce the major following mechanisms to explain the relationship between others' behaviors and individual conformity (Kameda & Hastie, 2015; Zafar, 2011): (1) image-related concern (Andreoni & Petrie, 2004; Bernheim, 1994; Rege & Telle, 2004) and (2) social learning (Banerjee, 1992; Bikhchandani et al., 1992). Social psychology calls the first mechanism normative conformity and the second one informational conformity. In the first mechanism, people stick to a similar choice because they want to be considered generous. People who care about their own reputation tend to avoid their own choice inconsistent with others' choices because departures from social trends can impair their social status. In the second mechanism, people learn about the best choice from information about others' choices and hence make the same choice. Although they might determine their best choice independently, doing so can be costly or time-consuming. In addition, Carpenter (2004) proposes another mechanism, namely (3) free-riding in providing a public good. In the third mechanism, people would obtain an excuse for less cooperation from others' free-riding behavior, or initiating more cooperation among a large number of free-riders would become harder. The other recent studies indicate that donors are often reluctant to give are looking for some excuses to avoid donations (Exley & Petrie, 2018; Klinowski, 2016; Reyniers & Bhalla, 2013).

To explore which mechanism works better, we examine the heterogeneity in the effect of continuous modal donations across monetary amount ranges. More concretely, we construct interaction terms between the dummies for the ranges in the amounts donated and variables of continuous modal donations. We then use the variables to investigate the extent to which the effect of continuous modal donations differs across these ranges.

The effects should differ by mechanisms in the following ways. First, if an image-related concern shapes donors' conformity behavior in our sample, we find a more strongly positive effect of continuous modal donations in higher monetary ranges. Recall that most of the donations in our sample are for the reconstruction process from the Great East Japan Earthquake in 2011; therefore, there exists a social norm that expects donors to give a higher amount. Second, if social learning explains our results, the effect of continuous modal donations is the same across these ranges. Third, if free-riding causes our results, we find a stronger positive effect of continuous modal donations in lower monetary ranges.

[Table 4 is here]

Table 4 presents the results that support the third mechanism of free-riding. The effects of the most recent three or more continuous modal donations are positive and statistically significant in the ranges of ¥1–¥29,999 in the half-panel jackknife estimation (at least at the 10 percent level).[19] However, the effect is largest in the lowest range of ¥1–¥1,999, and it reduces as the range elevates. In addition, the effect loses statistically significance in the range of ¥30,000 or more. These results imply that when the most recent three or more continuous modal donations are identical in lower monetary ranges, a subsequent donor is more likely to match the modal amount, but the likelihood decreases in higher ranges.

Our analysis also finds that donation amounts between ¥5,000 and ¥29,999 themselves have positive and statistically significant effects. This result implies that when the last donor contributes ¥5,000–¥29,999, a subsequent donor is likely to contribute a similar range even if he/she does not see the most recent continuous modal donations in this range. In our samples, the average donation amount

[19] Using Difference or System GMM for this model specification might be unsuitable because it includes a large number of the interacted variables, generates too many instrumental variables, and could produce unstable estimation results. In fact, Hansen tests indicate that the estimation results are weakened by the many instruments. Therefore, we mainly use for the discussion the results of the half-panel jackknife estimation, which are not impeded by this problem. However, since, in our sample, the Difference and System GMM estimations present similar results to the half-panel jackknife estimation, we report them for readers' reference.

is ¥8,822, and more than 50 percent of the samples donate in these high ranges of ¥5,000–¥29,999, as discussed in Section 4. These sample characteristics could cause the above effects.

In sum, when the most recent three or more continuous modal donations are identical in the low range of ¥1–¥1,999, a subsequent donor is most likely to match the modal amount. If he/she did not see the most recent continuous modal donations, he/she could contribute in the higher ranges of ¥5,000–¥29,999. The information on previous modal donations in lower ranges would provide a subsequent donor with an excuse, which allows him/her to behave in a less cooperative manner (i.e., save money). An alternative explanation is that since a large number of previous donors make a lower donation, it creates an unspoken rule that does not allow a subsequent donor to behave initially in a more cooperative manner.

These findings call fundraisers' attention to the information on previous modal donations in such lower amount ranges, which could encourage subsequent donors to stick to lower ranges when deciding on their donation amount. Fundraisers must thus enhance subsequent contributions by newly providing information on another single donation or multiple modal donations of higher amounts. However, modal donations of too high amounts would not have conformity effects on a new donor.

6.2. Sample selection issues

Some might still argue that the most recent continuous modal donations hold positive effects because information on modal donations attracts different groups of donors. For example, fundraisers might ask their friends and colleagues to donate a lower monetary amount, say ¥1–¥1,999. If so, this does not allow us to interpret our estimation results in the way of Section 6.1. This concern relates to sample homogeneity. Although we recognize that our dynamic panel approach accommodates this problem, we take another approach to readdress this concern in this subsection. However, it is difficult to directly test the existence of sample selection bias because we lack information on webpage traffic and donor characteristics. Instead, we use information on the arrival rate of donations (i.e., the duration from the $t-1^{th}$ donation to the t^{th} donation). Since the arrival of a different group of donors would coincide with changes in arrival rates, we can investigate the existence of sample selection bias indirectly by investigating continuous changes in modal donations and the arrival rate of subsequent donations. For the analysis, we use the dependent variable that explains the duration from the $t-1^{th}$ donation to the t^{th} donation. If information on continuous modal donations attracts different cohorts of donors, the continuous modal donations should exert statistically significant effects on the dependent variable.

[Table 5 is here]

The results in Table 5 assuage this concern. They show that continuous modal donations do not display any statistically significant effects in the key ranges of monetary amounts. Again, we found from Section 6.1 that when the most recent three or more continuous modal donations are identical in the low range of ¥1–¥1,999, a subsequent donor is most likely to match the modal amount. Table 5 shows that in this and some higher ranges, the continuous modal donations do not influence when a subsequent donor appears and gives.[20]

These findings do not support the possibility of sample selection bias. Fundraisers might ask their friends and colleagues to make donations of a similar amount. If so, continuous modal donations should have a statistically significantly positive impact in lower ranges. However, this is not the case.

[20] Although the most recent at least two continuous modal donations exhibit a negative impact in the range of ¥10,000–¥29,999, its significance level is relatively weak (the 10 percent level). In addition, the most recent three or more continuous modal donations have a strongly negative impact in the range of ¥30,000 or more. However, the treatment itself does not have the effect which promotes donors' conformity behavior. Also, the low frequency of the treatment could create this result. Therefore, these findings do not disturb our interpretations.

In addition, these findings do not support the other cases of sample selection. For example, a donor might seek out a campaign webpage that displays the last continuous modal donations and donate there. If so, his/her information should have statistically significant positive impacts. Again, this is not the case. Conversely, a donor might rather avoid a campaign webpage that displays continuous modal donations. If so, his/her information should have statistically significant negative impacts. However, once again, this is not the case.

7. Discussion and conclusion

In this study, we investigated how presenting the amounts of multiple previous charitable contributions publicly (i.e., on the campaign webpage) affects subsequent donations. By using data from a donation-based crowdfunding platform in Japan, we found that when the number of the most recent continuous modal donations increases among the last five donations, a subsequent donor is more likely to match the modal amount. This finding implies that a donor conforms to the majority's behavior and that donor conformity is strengthened when the size of the majority expands.

Our findings are consistent with those of social psychological studies of conformity. The extensive experimental literature in this area finds that people mirror the majority's behaviors and choices. Hence, we contribute to raising the external validity of social psychological studies. Our findings imply that the laboratory experimental results in social psychology are similarly observed in real charitable giving contexts, which is one of everyday occurrences. Although laboratory studies of conformity started in the 1950s, relatively a few studies have established similar results in everyday situations (Claidière et al., 2012; Claidière et al., 2014).

Next, this finding contributes to economic studies of charity. Several economic studies have shown that presenting a single donation influences a subsequent donor and demonstrated the likelihood of matching the presented donation (Alpizar et al., 2008; Shang & Croson, 2009). Our findings show that presenting multiple donations of a similar amount further strengthens the likelihood.

We found from further analysis that when the most recent three or more continuous donations are identical in lower monetary ranges, a subsequent donor is more likely to match the modal amount, indicating that our sample's donors conform by free-riding. Information on previous modal donations in lower ranges could provide a subsequent donor with an excuse that may allow them to behave in a less cooperative manner (i.e., save their money). Alternatively, since a large number of previous donors make lower donations, it could create an unspoken rule that does not allow a subsequent donor to behave initially in a more cooperative manner.

These findings practically contribute to improving online peer-to-peer fundraising activities by charities. Knowing previous modal donations of a lower amount could encourage subsequent donors to stick to lower ranges. In these situations, charities should aim to enhance subsequent contributions by newly providing information on higher donations. On the contrary, even if the effects of the most recent three or more continuous donations weaken, they remain positive and statistically significant in some higher ranges. These findings indicate that charities can control the amounts contributed by subsequent donors by presenting multiple donations of a similar amount. Our study can contribute to these multiple objectives because we connect economic studies of charity and social psychological studies of conformity.

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Tables and Figures

Figure 1. JapanGiving webpage (JG MARKETING Co. Ltd., 2014)

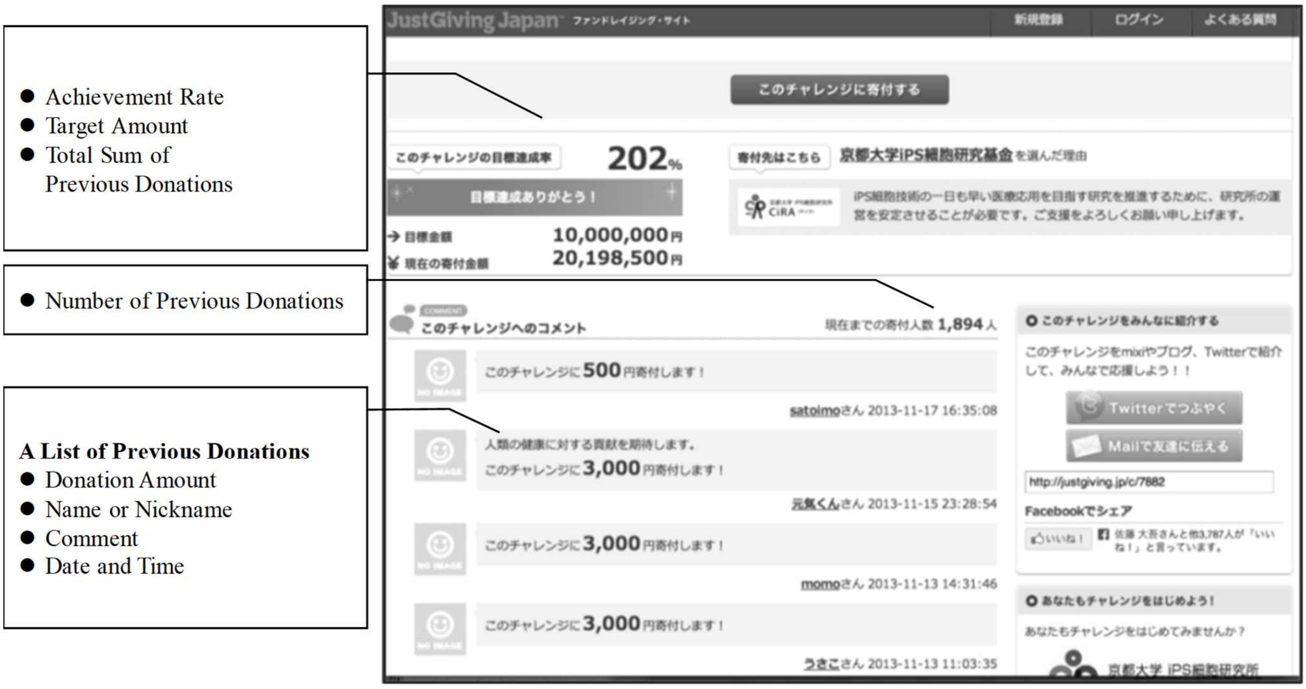
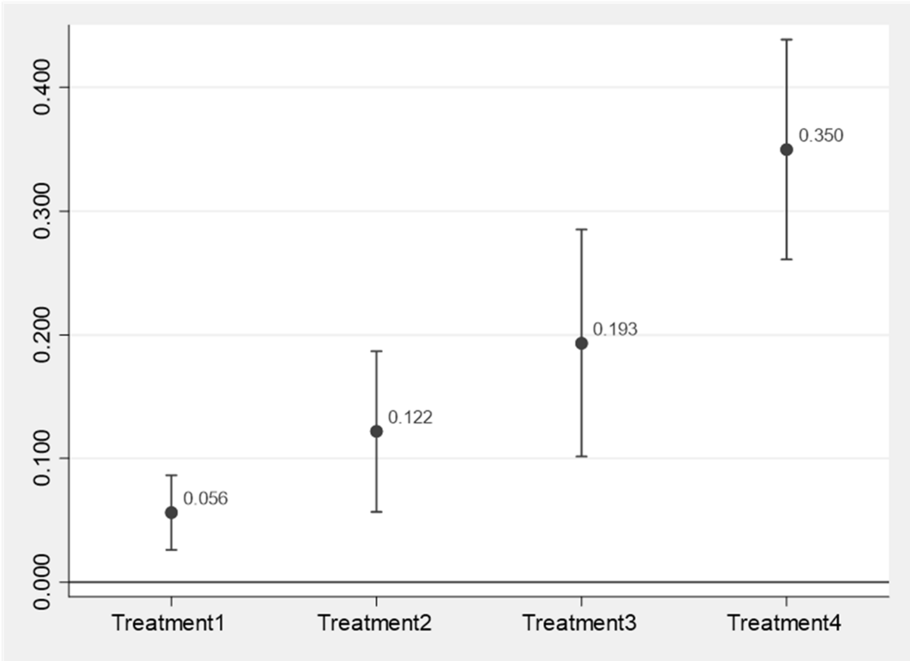


Figure 2. Main independent dummy variables

Main Independent Dummy Variables	$y_{i,t-1}$	$T1_{i,t}$	$T2_{i,t}$	$T3_{i,t}$	$T4_{i,t}$	$d_{i,t-1}$	$d_{i,t-2}$	$d_{i,t-3}$	$d_{i,t-4}$	$d_{i,t-5}$
First Lagged Dependent Variable: At Least **Two** Continuous Modal Donations	1	Baseline	*	*	*	●	●	*	*	*
Treatment 1 (Baseline): **Two** Continuous Modal Donations	1	Baseline	0	0	0	●	●	X	Y	Z
Treatment 2: **Three** Continuous Modal Donations	1	Baseline	1	0	0	●	●	●	Y	Z
Treatment 3: **Four** Continuous Modal Donations	1	Baseline	0	1	0	●	●	●	●	Z
Treatment 4: **Five** Continuous Modal Donations	1	Baseline	0	0	1	●	●	●	●	●

Notes: The circular marks explain donations of an identical amount. X, Y, and Z explain donations that are different from this amount. The asterisk marks imply that the donation amount is not conditional.

Figure 3. Effects on the probability that the dependent variable takes 1



Notes: As an example, we use the Difference GMM estimates to calculate out each treatment effect.
The effect of Treatment 1 (Two continuous modal donation): $\gamma_1 = 0.056$
The effect of Treatment 2 (Three continuous modal donation): $\gamma_1 + \gamma_2 = 2.2 \times \gamma_1 = 0.122$
The effect of Treatment 3 (Four continuous modal donation): $\gamma_1 + \gamma_3 = 3.4 \times \gamma_1 = 0.193$
The effect of Treatment 4 (Five continuous modal donation):$\gamma_1 + \gamma_4 = 6.2 \times \gamma_1 = 0.350$

Table 1. Descriptive statistics

	Mean	Std. Dev.	Min	Max
Donation Unit, N=9,989				
Donation Amount (Japanese Yen)	8,822.585	19190.530	100	500,000
Campaign Webpage Unit, N=291				
Number of Donations	46.856	19.091	25	100
Target Price (Japanese Yen)	997,723.800	1,621,552.000	77,777	10,000,000
Target Completion Rate	0.822	0.733	0.017	7.297
Over 100% (Dummy Variable)	0.337	0.473	0	1

Note: Our analyses use the sample, which excludes the exceptional donations from the donations per campaign webpage. Therefore, the number of our sample, 9,989, is inconsistent with the number, which is calculated out by multiplying the number of donation per campaign webpage, 47, by the number of campaign webpage, 291. The number of donation per campaign webpage in our sample is around 34.

Table 2. Basic analysis: Hypothesis 1 test results

	(1)	(2)	(3)	(4)	(5)
Linear Probability Model	OLS	Fixed Effects	Difference GMM	System GMM	Half-Panel Jackknife
Model 1:					
Lag1.dependent variable	0.163***	0.104***	0.136***	0.137***	0.136***
	(0.016)	(0.014)	(0.015)	(0.015)	(0.015)
(t-1)th Donation Amount (Log-transformed)	-0.006	-0.011**	-0.057***	-0.054***	-0.010**
	(0.006)	(0.004)	(0.007)	(0.006)	(0.004)
Number of Previous Donations	-0.000	-0.001*	-0.001	-0.002	-0.001
	(0.000)	(0.000)	(0.003)	(0.002)	-0.001
Target Completion Rate	-0.002	-0.005	-0.129	-0.015	-0.013
	(0.013)	(0.013)	(0.115)	(0.026)	-0.037
From Inception of the Webpage	-0.001	0.001	0.004	-0.001	0.002
	(0.001)	(0.001)	(0.004)	(0.002)	-0.002
Arellano-Bond test for AR(1), p-value	-	-	0.000	0.000	-
Arellano-Bond test for AR(2), p-value	-	-	0.922	0.914	-
Hansen test, p-value	-	-	0.374	0.452	-
(over-ID restrictions)	-	-	(13)	(17)	-
FE Campaign Webpage	NO	YES	YES	YES	YES
FE Monthly	YES	YES	YES	YES	YES
FE Weekday	YES	YES	YES	YES	YES
FE Time Zone	YES	YES	YES	YES	YES

Notes:
1. The number of donations is 9,989 and the number of campaign webpages is 291.
2. Cluster robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.
3. The dependent variable is a binary variable that takes 1 when the (t)th donation amount is equal to the (t-1)th donation amount.

Table 3. Basic analysis: Hypothesis 2 test results

						(1)	(2)	(3)	(4)	(5)
Linear Probability Model						OLS	Fixed Effects	Difference GMM	System GMM	Half Panel Jackknife
Model 2: The Five Most Recent Donations	**t-1**	**t-2**	**t-3**	**t-4**	**t-5**					
Lag1.Dependent Variable	●	●	*	*	*	0.051***	0.022	0.056***	0.058***	0.046***
						(0.014)	(0.014)	(0.015)	(0.015)	(0.014)
T1 variable	●	●	X	Y	Z	Baseline	Baseline	Baseline	Baseline	Baseline
T2 variable	●	●	●	Y	Z	0.121***	0.070**	0.066*	0.072**	0.100***
						(0.030)	(0.030)	(0.034)	(0.033)	(0.032)
T3 variable	●	●	●	●	Z	0.194***	0.114***	0.137***	0.124***	0.153***
						(0.036)	(0.034)	(0.047)	(0.045)	(0.036)
T4 variable	●	●	●	●	●	0.366***	0.246***	0.294***	0.292***	0.306***
						(0.038)	(0.035)	(0.045)	(0.044)	(0.044)
OT1 variable						0.161***	0.120***	0.113***	0.109***	0.134***
						(0.014)	(0.013)	(0.017)	(0.016)	(0.014)
OT2 variable						-0.025**	-0.081***	-0.056***	-0.058***	-0.051***
						(0.012)	(0.013)	(0.020)	(0.019)	(0.013)
(t-1)th Donation Amount (Log-transformed)						-0.007*	-0.011***	-0.049***	-0.046***	-0.010**
						(0.005)	(0.004)	(0.006)	(0.005)	(0.004)
Number of Previous Donations						-0.000	-0.001**	-0.002	-0.003*	-0.001
						(0.000)	(0.000)	(0.003)	(0.001)	(0.001)
Target Completion Rate						-0.001	-0.006	-0.132	-0.022	-0.011
						(0.009)	(0.013)	(0.132)	(0.026)	(0.035)
From Inception of the Webpage						-0.001	0.001	0.005	0.000	0.002
						(0.001)	(0.001)	(0.004)	(0.002)	(0.002)
Arellano–Bond test for AR(1), p-value						-	-	0.000	0.000	-
Arellano–Bond test for AR(2), p-value						-	-	0.346	0.414	-
Hansen test, p-value						-	-	0.224	0.387	-
(over-ID restrictions)						-	-	(28)	(37)	-
FE Campaign Webpage						NO	YES	YES	YES	YES
FE Monthly						YES	YES	YES	YES	YES
FE Weekday						YES	YES	YES	YES	YES
FE Time Zone						YES	YES	YES	YES	YES

Notes:
1. The number of donations is 9,989 and the number of campaign webpages is 291.
2. Cluster robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.
3. The dependent variable is a binary variable that takes 1 when the (t)th donation amount is equal to the (t-1)th donation amount.
4. The circular marks explain donations of an identical amount. X, Y, and Z explain donations that are different from this amount. The asterisk marks imply that the donation amount is not conditional.

Table 4. Further analysis: Heterogeneity between monetary ranges

Linear Probability Model		(1) OLS	(2) Fixed Effects	(3) Difference GMM	(4) System GMM	(5) Half-Panel Jackknife
(t-1)th Donation Amount Ranges	1 - 1,999 yen	Baseline	Baseline	Baseline	Baseline	Baseline
	2,000 - 4,999 yen	0.024	0.016	0.007	0.011	0.016
		(0.016)	(0.016)	(0.021)	(0.020)	(0.016)
	5,000 - 9,999 yen	0.103***	0.095***	0.094***	0.094***	0.095***
		(0.018)	(0.018)	(0.025)	(0.024)	(0.018)
	10,000 - 29,999 yen	0.088***	0.081***	0.077***	0.079***	0.084***
		(0.018)	(0.018)	(0.024)	(0.024)	(0.019)
	30,000 yen or more	-0.111***	-0.117***	-0.158***	-0.152***	-0.113***
		(0.014)	(0.017)	(0.027)	(0.026)	(0.017)
Lag1. dependent variable × (t-1)th Donation Amount Ranges	1 - 1,999 yen	0.050	0.000	0.084*	0.089*	0.028
		(0.040)	(0.035)	(0.048)	(0.048)	(0.036)
	2,000 - 4,999 yen	0.045*	0.009	0.068**	0.058*	0.042*
		(0.023)	(0.024)	(0.032)	(0.030)	(0.025)
	5,000 - 9,999 yen	0.030	0.008	0.019	0.024	0.032
		(0.024)	(0.025)	(0.030)	(0.029)	(0.025)
	10,000 - 29,999 yen	0.048**	0.025	0.060**	0.061**	0.044*
		(0.023)	(0.022)	(0.028)	(0.028)	(0.023)
	30,000 yen or more	0.066	0.038	0.092	0.108*	0.052
		(0.071)	(0.069)	(0.074)	(0.063)	(0.070)
T1 variable		Baseline	Baseline	Baseline	Baseline	Baseline
T2, T3, or T4 variable × (t-1)th Donation Amount Ranges	1 - 1,999 yen	0.438***	0.299***	0.250***	0.300***	0.371***
		(0.095)	(0.091)	(0.093)	(0.097)	(0.129)
	2,000 - 4,999 yen	0.132***	0.053	0.138**	0.166***	0.103**
		(0.048)	(0.048)	(0.062)	(0.063)	(0.049)
	5,000 - 9,999 yen	0.206***	0.130***	0.093*	0.088*	0.166***
		(0.037)	(0.034)	(0.051)	(0.049)	(0.036)
	10,000 - 29,999 yen	0.180***	0.100***	0.107**	0.095**	0.140***
		(0.036)	(0.034)	(0.043)	(0.043)	(0.037)
	30,000 yen or more	0.142	0.094	0.306	0.324	0.193
		(0.139)	(0.147)	(0.530)	(0.490)	(0.219)
Other Treatments		YES	YES	YES	YES	YES
Number of Previous Donations		YES	YES	YES	YES	YES
Target Completion Rate		YES	YES	YES	YES	YES
From Inception of the Webpage		YES	YES	YES	YES	YES
Arellano–Bond test for AR(1), p-value		-	-	0.000	0.000	-
Arellano–Bond test for AR(2), p-value		-	-	0.464	0.557	-
Hansen test, p-value		-	-	0.024	0.057	-
(over-ID restrictions)		-	-	(55)	(73)	-
FE Campaign Webpage		NO	YES	YES	YES	YES
FE Monthly		YES	YES	YES	YES	YES
FE Weekday		YES	YES	YES	YES	YES
FE Time Zone		YES	YES	YES	YES	YES

Notes:
1. The number of donations is 9,989 and the number of campaign webpages is 291.
2. Cluster robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.
3. The dependent variable is a binary variable that takes 1 when the (t)th donation amount is equal to the (t-1)th donation amount.
4. The regression includes control variables and four types of fixed effects.

Table 5. Further analysis: Sample selection issues

Fixed Effects Model		(1) Time until the next donation (in hour)
(t-1)th Donation Amount Ranges	1 - 1,999 yen	Baseline
	2,000 - 4,999 yen	-0.492
		(3.361)
	5,000 - 9,999 yen	0.534
		(3.344)
	10,000 - 29,999 yen	1.435
		(3.488)
	30,000 yen or more	-7.808
		(4.825)
Lag1. dependent variable × (t-1)th Donation Amount Ranges	1 - 1,999 yen	-6.527
		(7.185)
	2,000 - 4,999 yen	-2.108
		(4.038)
	5,000 - 9,999 yen	-1.329
		(3.385)
	10,000 - 29,999 yen	-6.806*
		(4.035)
	30,000 yen or more	17.299
		(18.293)
T1 variable		Baseline
T2, T3, or T4 variable × (t-1)th Donation Amount Ranges	1 - 1,999 yen	8.021
		(16.176)
	2,000 - 4,999 yen	9.175
		(9.946)
	5,000 - 9,999 yen	1.955
		(6.426)
	10,000 - 29,999 yen	3.839
		(5.976)
	30,000 yen or more	-112.044***
		(28.734)
Other Treatments		YES
Number of Previous Donations		YES
Target Completion Rate		YES
From Inception of the Webpage		YES
FE Campaign Webpage		YES
FE Monthly		YES
FE Weekday		YES
FE Time Zone		YES

Notes:
1. The number of donations is 9,878 and the number of campaign webpages is 290.
2. Cluster robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.
3. The dependent variable explains the duration from the (t-1)th donation to the (t)th donation.
4. All regressions include control variables and four types of fixed effects.