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Conformity in Charitable Giving: Evidence from Empirical Analysis of Japanese Online Donations

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ABSTRACT

We investigate the impacts of multiple earlier donations on the amounts that subsequent donors contributed to JapanGiving, an online fundraising platform, during 2011. The platform's webpage displays amounts of the preceding five donations in chronological order. In our model, using data for 9,984 donations, we construct variables to explain information a donor sees on the webpage. The main variables are the modal amount among the preceding five donations and their appearance along the sequence. We find that when more of the preceding five donations are identical, a new donor will more likely match the modal amount. However, this is not observed when the last two sequential donations are identical. Only the most recent three or more modal donations influence a new donor to match the modal amount. Our findings connect economic studies of charity and social psychology studies of conformity.

Keywords: *conformity, social preference, charitable giving, online dataset, natural experiment*
JEL Classification Number: H41, D64, C99

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1. Introduction

When is a charitable donor more likely to be influenced by other donors? How does an influenced donor determine his/her contribution? These issues in donor conformity remain unsolved, although economists revealed the other findings about it. Seminal field experiments investigated the impact of disclosures about other donors' contributions (Frey and Meier, 2004; Alpizar et al., 2008; Shang and Croson, 2009). For example, Shang and Croson (2009) randomly inform potential donors about another's donation, finding significant differences in average donations between informed and uniformed groups. However, in doing so, they merely demonstrate that conformity in charitable giving exists. It remains unclear when a donor is more likely to conform to other donors.

One method[2] to investigate broader issues is to provide potential donors information about multiple donors. Social psychology studies report that individual conformity strengthens when a larger number of people behave in a similar way (Asch, 1955; Asch, 1956; Rosenberg, 1961; Milgram et al., 1969; Wilder, 1977; Latanē and Wolfe, 1981; Clark and Maass, 1990). If that is the case with charitable giving, providing information about multiple donors could influence potential donors more strongly when more of the multiple donors have donated the same amount. That is, their

[2] Previous studies have explored the issues in other ways. Shang et al. (2008) find that a donor's conformity depends on similarities between themselves and the other donors. Their findings indicate that when they obtain information about another donor of the same gender, they are more likely to be influenced by the other donor. Croson and Shang (2013) find that a donor's conformity depends on the contribution level of another donor. Their findings indicate that when they see another donor's extremely high contribution, they are less likely to be influenced by it. Jones and Linardi (2014) and other literature find that a donor's conformity depends on the visibility of their contribution. That is, they are more likely to be influenced by other donors when their own contribution is visible.

contribution could mirror the majority contributions of multiple donors.

This study empirically investigates the effects of informing potential donors about the amounts that multiple donors have already contributed to a fundraising website. Our analysis employs a novel dataset and model. First, we use data from 9,984 donations presented on the real website of JapanGiving. The distinctive feature of JapanGiving is that its fundraising page displays amounts of each previous individual donation in chronological order. Potential donors can see the most recent four or five individual donations and combinations of previous donations that arise as a result of accessing the page at different times. Second, our empirical model uses variables to explain representative combinations of previous donations. Using the data and the model, we find which combination most increases the likelihood a new donor will match the modal norm established by previous donations.

We assume random variation in the above variables. Our introductory analysis backs up this assumption by confirming that the distribution of donated amounts on a webpage is stationary throughout the campaign. This result plausibly indicates that donations are homogeneous within each webpage.

Several findings emerge from our empirical analysis. The main finding is that when more among the five previous donors contribute a same amount, it is more likely that a new donor will match their modal amount. This result indicates that donor conformity increases in the above circumstance. However, we also find that this phenomenon does not appear when the two most immediately previous donors give the same amount. Only three or more successive modal donations significantly affect the likelihood that a new donor matches the modal amount.

These results are robust to regression-to-the-mean bias and sample-selection bias. Suppose the modal amount is larger or smaller than the previous arithmetic mean. It remains likely that a new donor matches the modal amount in both cases. Furthermore, information about continuous modal donations does not influence when a new donor appears on a webpage and donates. This result addresses the concern that different cohorts of donors arrive at a webpage accordingly with the amount combinations of multiple donations.

This is the first study to determine when a donor is more likely to be influenced by other donors in an environment that reveals amounts of previous contributions. Our findings connect economic studies of charity and social psychology studies of conformity. Furthermore, our findings assist charitable fundraising by demonstrating that fundraisers could enhance contributions by providing information about continuous modal donations.

This paper is organised as follows. Section 2 discusses previous studies. Section 3 introduces JapanGiving and the data recorded on its website. Section 4 explains econometric strategies. Section

5 presents the basic estimated results, and Section 6 provides further analysis of the estimated results. Section 7 discusses the study's implications, limitations and future research.

2. Literature Review

We apply findings from psychological studies of conformity to the economic analysis of charitable giving. In social psychology, the Asch conformity experiment (1955) has been followed by an extensive literature (Asch, 1956; Rosenberg, 1961; Milgram et al., 1969; Wilder, 1977; Latanē and Wolfe, 1981; Clark and Maass, 1990). Their common finding is that people are more likely to choose the option that more of others have chosen.

To conduct a similar investigation into charitable giving, researchers would need to inform potential donors about combinations of multiple other donations. Using randomised control trials for the analysis would require a large number of treatment groups, therefore, few studies of charitable contributions have been undertaken. 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 did not track and record each individual donation and so did not investigate how each donor reacts to the stimulus. Second, in a laboratory experiment, Samek and Sheremeta (2014) analyse the effects of recognising only the largest or smallest among multiple donations and the effect of recognising all the multiple donations. However, it remains unclear how the other combinations affect new donations.

How can we measure effects of displaying various patterns of information? The marketing literature suggests that a website is ideal for such an investigation (Blake et al., 2014; Johnson et al., 2014; Lewis and Reiley, 2014), because the Internet lets researchers provide a website's visitors extensive information. Furthermore, researchers can track and record detailed data about visitors, such as when they visited, what information they detected and which activity they undertook. Researchers use the information to compute effects of treatments' information on a visitor's activity.[3]

Smith et al. (2014) conduct an economic study of charity using online data recorded by JustGiving in the United Kingdom, the webpage of which displays the amount of each previous individual donation. Their main finding is that the amount of new donations rises as the arithmetic mean of all previous donations rises. They use arithmetic means as an indirect indicator of the distribution of all previous donations, perhaps because they are reluctant to assume that donors actually compute them. As a consequence, their study merely demonstrates that conformity or peer pressure exists among online donors. After considering a previous scholarship, we more directly construct variables to explain information a donor actually sees.

[3] Treatments' information might not be randomly assigned to visitors. It must be confirmed empirically from data that visitors are sufficiently homogeneous for identification.

3. Setting

3.1. *Website of JapanGiving*

JapanGiving is an online fundraising intermediary that connects non-profit organisations (NPOs) and fundraisers with potential donors. JapanGiving is the sibling of JustGiving in the United Kingdom[4], the world's largest fundraising platform. Between its public launch in March 2010 and December 2014, JapanGiving attracted 111,700 donations and facilitated ¥121.4 million in contributions.

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

3.2. *Characteristics of donation data*

We use data from 9,984 donations made via JapanGiving from February to December 2011. All sampled donors viewed the same webpage design during this period, although JapanGiving sometimes changed the design. JapanGiving records the amounts of donations, their dates and time,

[4] In 21st January 2015, this platform was renamed from JustGiving Japan to JapanGiving.

and the recipient organisation. We use these data to generate further information. First, we identify the order of donations within a campaign webpage from data about date and time. Then, we use amounts donated and their sequence to calculate totals already donated pending the next donation. These allow us to know what information each donor saw when they visited the webpage. We identified donors by randomly assigned IDs but gathered no personal information.

3.3. *List of previous donations*

The unique feature of JapanGiving is that it lists all previous donations (Figure 1[5]). Its list includes a donor's name, comment, date and time of donation, and contribution. Information is displayed chronologically on one electronic page. A donor sees the amount of each among several preceding donations because the normal browser can display the preceding four or five donations.

[Figure 1 is here]

The donor sees the distribution of the most immediate previous five donations and their variation. They consider the variation as large when the previous five donors gave different amounts and small when each gave identical amounts. If findings from social psychology apply to charitable giving, the influence of the previous five donations is larger in the latter case than in the former. The affected

[5] Figure 1 shows the webpage design in the previous version. The webpage design changed from it to the current version in 4th March 2014.

donation could follow the modal donation among the previous five.

4. Empirical Strategy

4.1. *Model*

This study investigates when a donor is more likely to be influenced by other donors in an environment that reveals amounts of previous contributions. We empirically investigate the effects of amounts contributed by multiple donors using data reported on an actual fundraising website. The tested hypothesis is that when more among the preceding five donors give an identical amount, it is more likely that a new donor contributes the modal amount. We estimate the equation of the following specification:

$$y^*_{c,n} = \alpha + \gamma_1 D_1 + \gamma_2 D_2 + \gamma_3 D_3 + \gamma_4 D_4 + z'_{c,n}\delta + u_{c,n}$$

$$y_{c,n} = 1, \text{if } d_{c,n} = d_{c,n-1}$$

$$y_{c,n} = 0, \text{if } d_{c,n} \neq d_{c,n-1}$$

[Figure 2 is here]

where $d_{c,n}$ refers to the amount of the n^{th} donation to a campaign webpage c.

We use a nonlinear fixed effects model for estimations. The error term is decomposed as $u_{c,n} = \eta_c + \nu_{c,n}$. η_c is a constant page-specific effect that captures unobserved correlations of preferences among donors on that page, and $v_{c,n}$ is a random error term. We use monthly, weekday and time zone dummies to deal with common shocks among time intervals.

The dependent variable $y_{c,n}$ is a dummy that takes 1 when $d_{c,n}$ equals $d_{c,n-1}$, and 0 otherwise. Dummies are appropriate because this dependent variable is based on the JapanGiving payment system. The JapanGiving payment page provides nine options for donated amounts.[6] Over 90% of all donations coincide with amounts presented in the options. That is why donors could decide their contribution by choosing from the options. Furthermore, when modal donations are among the immediately preceding five donations, donors could make a binary decision of whether they select the option that matches the modal amount.

Independent variables D_1, D_2, D_3 and D_4 explain the degree of variation among the immediately preceding five donations. D_1 explains the largest variation, while D_4 explains the smallest variation, as seen in Figure 2. We set the variables in that way to consider the difference in salience of modal donations between the larger and smaller variation. For example, a donor might not recognise when two donations of the modal amount appear at an interval, but they could more easily do so when the immediately preceding first and second donations are identical.

The control variables $z_{c,n}^{\prime}$ include several pieces of information that the n^{th} donor sees on the

[6] They are (proportion of donations consistent within the nine options): ¥500 (1.8%), ¥1,000 (8.5%), ¥2,000 (13.5%), ¥3,000 (12.3%), ¥5,000 (25.9%), ¥10,000 (25.4%), ¥30,000 (3.1%), ¥50,000 (0.8%) and ¥100,000 (0.9%).

webpage, such as the number of previous donors and the target completion rate. Furthermore, $z'_{c,n}$ includes the duration from inception of the webpage to the date of n^{th} donation.

4.2. *Introductory analysis for identification*

Identification of parameters D_1, D_2, D_3 and D_4 depends on the assumption that donated amounts within a webpage are homogeneous during the entire campaign. This subsection examines the samples to confirm this assumption.

First, we consider that distributions of donated amounts, number of donors per webpage and length of campaign are skewed because of a few successful fundraisers[7] and generous donors (Smith et al., 2014). We exclude from analysis webpages that have single donations exceeding ¥500,000, webpages with fewer than 25 or more than 100 donations and donations more than 50 days before inception of the webpage.

Second, we exclude the initial five 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. 2014, Smith et al., 2014).[8] Data indicates that the mean of the first three donations

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[7] 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 from 1,913 donors. The largest single donation in his campaign was ¥1,000,000.

[8] Agrawal et al. (2014) use data from a Canadian crowdfunding platform, showing that early donors have closer relationships with fundraisers and Smith et al. (2014) reported that the average amount of the first three donations is systematically larger than the average of the remaining samples of JustGiving UK. Therefore, we exclude the initial three donations in this analysis.

(¥17,469.79) exceeds the mean of the remaining donations (¥8,572.269) with statistical significance. Thus, we exclude them. Furthermore, we exclude the immediately preceding 4th and 5th donations, because our analysis focuses on effects of the immediately preceding five donations.

Finally, we check that amounts without the initial five donations are sufficiently stationary throughout the entire campaign. We divide donations on a campaign webpage into a first and second half determined by their timing. Next, we use the Kolmogorov-Smirnov test to compare distributions of amounts donated in both halves. The null hypothesis is that the two sample groups have identical distributions, and the test does not reject it at statistical significance in 271 of 325 campaign webpages ($p < 0.100$). Thus, the 9,984 samples in the 271 campaign webpages plausibly are homogeneous.

Before estimations, we introduce simple statistics of our samples. As seen in Table 1, the arithmetic mean donation is ¥8,827.434 (US$110.632 at the 2011 exchange rate[9]). The mean number of donors per campaign webpage is approximately 48, and the mean target price is ¥958,816 (US$12,016.668). The number of campaigns with the final target completion rate of 100 % or more is 90.

[Table1 is here]

[9] 1 US dollar is exchanged with 79.7905 Japanese yen in 2011.

5. Basic Analysis

This section presents results of the empirical analysis. We begin with descriptive results for comparisons of the basement and four treatment groups. We then run a regression analysis, considering control variables' effects and several fixed effects.

5.1. *Descriptive results*

Table 2 reports arithmetic means of the outcome variable $y_{c,n}$, which takes 1 if $d_{c,n} = d_{c,n-1}$. This descriptive comparison shows findings consistent with the prediction that when more of the preceding five donors give the same amount, a new donor more likely will contribute to the modal amount. In Table 2, we find no statistically significant difference between the basement group and treatment group 1. On the other hand, we find a statistically significant difference between treatment groups 1 and 2 (at 1% confidence), between groups 2 and 3 (at 10% confidence) and between groups 3 and 4 (at 1% confidence). The arithmetic mean of the outcome variable in treatment group 2 is 12.7% larger than for treatment group 1. The mean of the outcome variable in treatment group 3 is 8.3% larger than in treatment group 2. The mean of the outcome variable in treatment group 4 is 19.1% larger than in treatment group 4. These findings indicate that a donor is likely to match the immediately preceding first donation when the immediately preceding three or more donations are identical. Interestingly, the likelihood might not increase linearly with increases in number of continuous modal donations.

[Table 2 is here]

5.2. *Regression results*

We confirm the above findings via regression analysis in Table 3, where we regress the outcome variable $y_{c,n}$ on D_1, D_2, D_3, D_4 and the control variables. We use both linear probability and logit models[10], considering several fixed effects.

[Table 3 is here]

Table 3 shows findings consistent with those in §5.1. The two continuous modal donations have no statistically significant effect, but three or more continuous modal donations do. In particular, according to column 1, the size of the effect is larger for the three continuous modal donations than for the two continuous modal donations (at nearly 10% confidence) and it is larger for the five continuous modal donations than for the four continuous modal donations (at 1% confidence). However, there is no statistically significant difference in the size of the effect between the three continuous and four continuous modal donations. As with the descriptive results in §5.1, these

[10] In §6, we will show only the results of a linear probability model, because its results have not been different from those of a logit model. Furthermore, we can look at marginal effects by the former model. See Wooldridge (2010) for details.

findings indicate that a donor is likely to match the immediately preceding first donation when the immediately preceding three or more donations are identical. Again, the likelihood seems not to increase linearly with increasing numbers of continuous modal donations.

We explain the effects of control variables. The increase in the amount of the immediately preceding first donation reduces the likelihood that a new donor matches it, and an increase in the number of previous donors also reduces the likelihood. On the other hand, we find no statistically significant effect for the achievement rate and duration since inception of the webpage. The first finding indicates that it is more difficult for donors to match the previous donation of a higher amount. The second finding indicates that donors in the latter part of a campaign tend not to match the previous donation.

6. Further analysis

This section investigates whether the results in §5 are convincing by addressing several concerns. Observers might argue that we find the effects of three or more continuous modal donations only within a specific range of contributions. This concern relates to the generality of effects. Observers also might argue that regression-to-the-mean bias primarily explains their effects. This concern relates to bias in the effects. Finally, they might conclude that information about the three or more continuous modal donations attracts different groups of donors. This concern relates to sample homogeneity.

6.1. *Heterogeneity between ranges of amounts*

If our results concerning three or more continuous modal donations pertain only to particular ranges of contributions, we cannot conclude that the effects exist generally in our sample. In fact, effects might vary with ranges in amounts donated. A donor might easily contribute a lower amount (e.g. ¥3,000 or US$37.590 at the 2011 exchange rate), but not a higher amount (e.g. ¥30,000 or US$375.906). However, the effects should not vary extremely with ranges in amounts contributed.

To address this concern, we use cross terms between the dummy for ranges in amounts donated and variables of continuous modal donations. We verify whether the effects vary extremely with ranges in amounts using these variables.

[Table 4 is here]

Table 4 shows findings that belay the concern. Effects of the three or more continuous modal donations are statistically significant from zero in the four ranges of ¥1,000–¥1,999, ¥3,000–¥4,999, ¥5,000–¥9,999 and ¥10,000–¥29,999. Table 4 also reports that the effect is not statistically significant from zero for ¥30,000 and higher. This finding indicates that a donor does not match the previous donation of an extremely high amount.

It is unclear why statistical effects do not differ significantly from zero for ranges below ¥1,000 and ¥2,000–¥2,999. Perhaps the narrowness of these ranges explains this phenomenon. A donor might easily raise a contribution below ¥1,000 to ¥1,000–¥1,999, and they might revise a contribution of ¥2,000–¥2,999 to ¥1,000–¥1,999 or ¥3,000–¥4,999. However, we have considered the characteristics of each contribution range by using dummy variables for ranges in amounts. Thus, we cannot determine which explanation clarifies the phenomenon.

6.2. *Regression-to-the-mean bias*

The second concern is that regression-to-the-mean bias primarily explains most of the effects of the three or more continuous modal donations. We share this concern because we verified in §4.2 that amounts donated in our samples are homogeneous and homogeneous samples sometimes regress to the mean. Suppose a new donation is ¥4,000, its immediately preceding three donations are ¥5,000 and the arithmetic mean of previous donations is ¥3,000. It is unclear whether the donation of ¥4,000 recedes to ¥3,000 or remains at ¥5,000.

We address this concern with two variables in the analysis: one to explain the arithmetic mean of amounts donated before the modal donations and another to explain positive or negative differences between the modal and mean amounts. If regression-to-the-mean bias explains the effects of the immediately preceding three or more continuous modal donations, the second variable should have a statistically significant negative impact.

[Table 5 is here]

Table 5 shows findings that arrest the concern: the immediately preceding three or more modal donations exhibit no statistically significant negative effects. Their effects are positive when the modal donation exceeds the previous mean, and they are statistically and significantly positive when the modal donation is below the previous mean. These findings indicate that a donation does not revert to the previous mean when the immediately preceding three or more donations are identical. On the other hand, Table 5 reports that no continuous modal donation has statistically significant negative effects when the modal donation is larger or smaller than the previous mean. We find a negative effect from the immediately preceding two modal donations when the modal donation is below the previous mean. We also find a positive effect from the immediately preceding two modal donations when the modal donation exceeds the previous mean; however, their p-value is larger than that of the immediately preceding three or more continuous modal donations. These findings indicate that a donor is more likely to give the modal amount when they see the immediately preceding three or more modal donations. We address the second concern by the two indications.

6.3. *Sample-selection problem*

The third concern is that information about three or more continuous modal donations attracts different groups of donors, causing a sample-selection problem. It is hard to directly verify the existence of sample-selection bias because we lack information about webpage traffic and donors' characteristics. But, we have information about the arrival rate of donations (i.e. the duration from $n-1^{th}$ donation to n^{th} donation). Since the arrival of a different group of donors would coincide with changes in arrival rates, we can check sample-selection bias indirectly by investigating continuous changes in modal donations and the arrival rate of subsequent donations.

To address this concern we use three dependent variables: (1) Whether a donor appears and donates within one day after the immediately preceding first donation, (2) whether a donor appears and donates within three days after the immediately preceding first donation, (3) whether a donor appears and donates within one week after the immediately preceding first donation. If information about continuous modal donations attracts different cohorts of donors, the three or more continuous modal donations should exert statistically significant effects on these dependent variables.

[Table 6.1 is here]

[Table 6.2 is here]

Results in Tables 6.1 and 6.2 assuage the concern. First, Table 6.1 reports the effects of variables used in §6.1. It shows that any continuous modal donations display no statistically significant effects. Second, Table 6.2 reports the effects of variables used in §6.2. This table shows that any continuous modal donations exhibit no statistically significant effects. These findings indicate that information about continuous modal donations does not have an influence when a donor appears and donates.

The above findings do not support any possibility of sample-selection. For example, a donor might seek out a campaign webpage that displays the immediately preceding three or more continuous modal donations and donate there. If so, their information should have statistically significant positive impacts. However, this is not the case. Next, fundraisers might ask families, friends and colleagues to make donations of particular amounts. If so, some amounts of the immediately preceding three or more continuous modal donations should have statistically significantly positive impacts. Again, this is not the case. Finally, a donor might avoid a campaign webpage that displays the immediately preceding three or more continuous modal donations of higher amounts. If so, their information should have statistically significant negative impacts. However, once again, this is not the case.

7. Discussion, Implications, Limitations and Future Research

7.1. *Discussion and implications*

This study has investigated how knowing the previous amounts of multiple charitable contributions affects subsequent donations. Using data from a Japanese fundraising website, we find that when the number of immediately preceding continuous modal donations increases among the immediately preceding five donations, a subsequent donor is more likely to match the modal amount. This finding is consistent with findings in social psychological studies of conformity.

We use these results to determine when a donor is more likely to be influenced by other donors, particularly in an environment where they browse the amounts of others' contributions. Our main result is that a donor likely will match the immediately preceding first donation when the immediately preceding three or more donations are identical. Furthermore, tests indicate that the effects of the immediately preceding three or more continuous modal donations have several characteristics. The first is that the likelihood a donor will match the immediately preceding first donation does not increase linearly with an increase in number of continuous modal donations. The likelihood rises as the number rises from two to three and from four to five; however, it does not increase as the number rises from one to two or from three to four. Several experiments in social psychology report findings are consistent with ours, suggesting a nonlinear relationship between individual conformity and the number of others with a same option. For example, Asch (1955) shows that individual conformity maximizes when the number of others with a same option increases is three or four. Rosenberg (1961) reports a decrease in individual conformity when the number of others with a same option increases from three to four persons.

The second characteristic is that effects of the immediately preceding three or more continuous modal donations vary somewhat with ranges in amounts. In particular, the likelihood that a donor will equal the immediately preceding first donation falls when the range of amounts donated rises from ¥5,000–¥9,999 to ¥10,000–¥29,999. This finding is consistent with Shang and Croson (2009), who investigate how donors set their contribution by consulting that of another donor. They report that the effect of another donor’s contributions varies with the range in amount. For example, when Shang and Croson (2009) told new donors that another had contributed $75, 24% contributed $75. On the other hand, when they told new donors that another had contributed $180, only 5% contributed $180. These results are derived from the assumption that a donor’s contribution is constrained by their budget. A donor might easily donate a lower amount but not a higher amount.

The third characteristic relates to the second. The effects of the immediately preceding three or more continuous modal donations weakened when the range of amounts donated widens. However, these effects are more persistent than those of the immediately preceding two continuous modal donations. We find no statistical significance for the effects of the immediately preceding two continuous modal donations when the modal amount is ¥1,000–¥1,999, ¥3,000–¥4,999 or ¥5,000–¥9,999. However, we find statistical significance in the effects of the immediately preceding three or more continuous modal donations when the modal amount is within these ranges. No earlier economic or social psychology research has produced these findings. Smith et al. (2014) report that the amount of new donations increases as the arithmetic mean of all previous donations increases. The authors also report that amounts of new donations change accordingly when the modal amount of all previous donations changes. However, they disregard the effects of the number of continuous modal donations.

Our empirical results and exploration of the three characteristics can improve fundraising by charities. Fundraisers attract larger sums by disclosing continuous modal donations because three or more continuous modal donations of higher amounts could have seed money effects on new donation.[11] On the other hand, fundraisers should be careful when there are three or more continuous modal donations of lower amounts. Revealing that information boosts the likelihood, a new donor will contribute the lower amount.

[11] List and Lucking-Reiley (2002) demonstrate seed money effects, suggesting that a 66% target completion rate enhances donor participation and average donated amounts. Our research indicates that the immediately preceding three or more continuous modal donations guide donations to higher amounts, although revealing that information does not influence donor participation.

7.2. *Limitations and future research*

One limitation of this study is that it does not establish its own homogeneous basement and treatment groups. Laboratory and field experimental studies do not share this limitation. Thus, observers might question the homogeneity between the basement and treatment groups. However, we established that our samples are plausibly homogeneous by examining the sample data. In §4.2, we verified that the distribution of donated amounts on a webpage is stationary throughout the campaign. Furthermore, in §6.3, we reject the possibility that information about continuous modal donations attracts different groups of donors. Moreover, we examined the effects of various combinations of multiple donations, because we use online data from JapanGiving. Of course, we can expect one field experiment to address the first limitation and test the similar hypothesis. The new research focuses only on the effects of representative amount combinations of multiple donations.

The second limitation is that we could not explain why effects vary with the number of continuous modal donations. Field experimental studies also feature this limitation. According to Zafar (2011), theoretical studies and laboratory experiments in economics and social psychology use different mechanisms to explain the relationship between individual conformity and others' behaviour. The mechanisms are as follows: (1) social learning (Banejee 1992, Bikhchandani et al. 1992), (2) social comparison (Cialdini 1993, Messick 1999) and (3) image-related concerns (Bernheim 1994, Andreoni and Petrie 2004, Rege and Telle 2004)[12]. The mechanism that explains the relationship depends on context, and it is less clear which mechanism explains the relationship between donor conformity and number of others contributing a similar amount. We expect another experimental research to discover a mechanism. The new research allows participants to browse contributions of multiple other donors.

A third limitation involves the generalisability of our results. Laboratory and field experimental studies share this limitation. Perhaps our conclusions are sensitive to the choices offered on this Japanese website and to its webpage design. We expect other empirical research to strengthen the generalisability. The new research tests the similar hypothesis by using data from websites outside Japan or data collected through channels such as direct mail and by telephone. The first step would be investigating data from JustGiving in the United Kingdom because its webpage resembles that of JapanGiving.

Despite these limitations, our conclusions are robust within our samples. Future experimental or empirical research needs to explore mechanisms of the effects and the same effects outside Japan. This study and future research will deepen understanding of when a donor is more likely to be

[12] (1) Individuals 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. (2) People increase their utility by simply mirroring others' choices. (3) People stick to the same choice because they want to be considered generous. People who care about their own reputation tend to avoid their own choice's coinciding with others' choices, because departures from the social trend can impair their social status.

influenced by other donors. Ours and future findings will aid real fundraising by charities.

Shusaku Sasaki (Osaka University, JSPS Research Fellow)

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Figures

Figure 1. The Fundraising Webpage of JapanGiving

- Target completion rate
- Target price
- Earned value,
  Total sum of past donations

- Number of past donors

A list of past donations
- Donation amount
- Name or Nickname
- Comment
- Date and time

Figure 2. Degrees of Variation in the Preceding Five Donations

		n-1	n-2	n-3	n-4	n-5
Treatment 1 $D_1 = 1$	Preceding **two** continuous modal donations	○	○	X	Y	Z
Treatment 2 $D_2 = 1$	Preceding **three** continuous modal donations	○	○	○	Y	Z
Treatment 3 $D_3 = 1$	Preceding **four** continuous modal donations	○	○	○	○	Z
Treatment 4 $D_4 = 1$	Preceding **five** continuous modal donations	○	○	○	○	○

Notes to figure:
The circular marks explain donations that are equal to the modal amount. On the other hand, X, Y, and Z explain donations that are different from the modal amount.

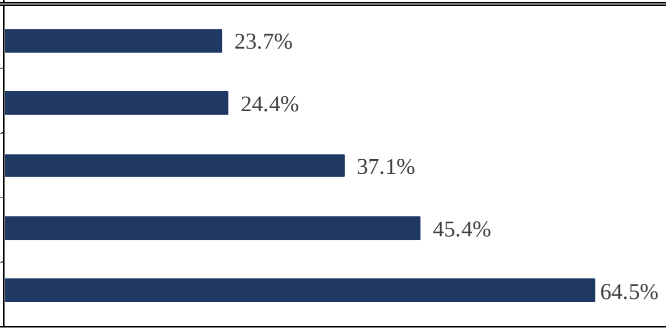
Tables

Table1. Simple Statistics

	Mean	Std. Dev.	Min	Max
Donation Unit, N=9,984				
Donation Amount (Japanese Yen)	8827.434	19411.75	100	500000
Campaign Webpage Unit, N=271				
Number of all donors	48.42066	19.43556	26	100
Target Price (Japanese Yen)	958,816	1470983	77,777	10,000,000
Target Completion Rate (Percent)	0.8187211	0.6657263	0.02465	7.297
Over 100% (Dummy Variable)	0.3321033	0.4718392	0	1

Table 2. Basic Analysis–Descriptive Results

Group Name (Observations)	Mean of the Outcome Variable (Standard Errors)
Basement (N=8,824)	0.237 (0.425)
Treatment 1 (N=327)	0.244 (0.430)
Treatment 2 (N=312)	0.371 (0.484)
Treatment 3 (N=222)	0.454 (0.499)
Treatment 4 (N=299)	0.645 (0.479)



Group Comparison	p-value (two-tailed t-test)	
Basement vs Treatment 1	0.770	No Statistically Significant Difference
Treatment 1 vs Treatment 2	0.000	Statistically Significant Difference at 1% Confidence
Treatment 2 vs Treatment 3	0.054	Statistically Significant Difference at 10% Confidence
Treatment3 vs Treatment 4	0.000	Statistically Significant Difference at 1% Confidence

Table 3. Basic Analysis–Regression Results

The dependent variable is a binary variable, which takes 1 when (n)th donation amount is equal to (n-1)th donation amount.						FE Linear Probability Model (1)	FE Logit Model (2)
(n-1) th donation amount (log-transformed)						-0.0100**	-0.0618**
						(0.00496)	(0.0291)
The preceding five donations							
	n-1	n-2	n-3	n-4	n-5		
Treatment 1	○	○	X	Y	Z	0.0195	0.112
						(0.0242)	(0.135)
Treatment 2	○	○	○	Y	Z	0.0740***	0.347***
						(0.0248)	(0.124)
Treatment 3	○	○	○	○	Z	0.110***	0.479***
						(0.0294)	(0.142)
Treatment 4	○	○	○	○	○	0.243***	1.041***
						(0.0271)	(0.135)
Number of the previous donors						-0.000943*	-0.00512*
						(0.000496)	(0.00277)
Target completion rate (%)						-0.00648	-0.0283
						(0.0215)	(0.115)
From the first donation (Days)						0.000703	0.00399
						(0.00119)	(0.00695)
Constant						0.394	-
						(0.305)	-
R-squared						0.014	-
F-statistics						4.76	-
Log likelihood						-	-4776.5083
Number of donors						9,984	9,984
Number of campaign webpages						271	271
Campaign FE						YES	YES
Month FE						YES	YES
Weekday FE						YES	YES
Timezone FE						YES	YES

Notes to table:

The circular marks explain donations that are equal to the modal amount. On the other hand, X, Y, and Z explain donations that are different from the modal amount. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 4. Further Analysis– Heterogeneity between Ranges of Amounts

The dependent variable is a binary variable, which takes 1 when (n)th donation amount is equal to (n-1)th donation amount	FE Linear Probability Model (1)
Donation Amount Ranges	
1 - 999 yen	Basement
1,000 - 1,999 yen	0.0226
	(0.0352)
2,000 - 2,999 yen	0.0546
	(0.0341)
3,000 - 4,999 yen	0.0410
	(0.0343)
5,000 - 9,999 yen	0.145***
	(0.0335)
10,000 - 29,999 yen	0.128***
	(0.0335)
30,000 - 49,999 yen	-0.106***
	(0.0399)
50,000 yen and more	-0.118***
	(0.0430)
Cross Terms:	
Donation Amount Ranges × **The Preceding Two Continuous Modal Donations**	
1 - 999 yen	-0.0437
	(0.126)
1,000 - 1,999 yen	-0.0172
	(0.0733)
2,000 - 2,999 yen	-0.0128
	(0.0637)
3,000 - 4,999 yen	-0.000434
	(0.0571)
5,000 - 9,999 yen	-0.0589
	(0.0463)
10,000 - 29,999 yen	0.136***
	(0.0474)
30,000 - 49,999 yen	0.307
	(0.246)
50,000 yen and more	-0.00619
	(0.300)
Cross Terms:	
Donation Amount Ranges × **The Preceding Three or More Continuous Modal Donations**	
1 - 999 yen	0.0620
	(0.168)
1,000 - 1,999 yen	0.409***
	(0.0492)
2,000 - 2,999 yen	0.0394
	(0.0476)
3,000 - 4,999 yen	0.140***
	(0.0527)
5,000 - 9,999 yen	0.129***
	(0.0245)
10,000 - 29,999 yen	0.0937***
	(0.0246)
30,000 - 49,999 yen	0.226
	(0.246)
50,000 yen and more	-0.0314
	(0.431)
Constant	0.340
	(0.303)
R-squared	0.042
F-statistics	8.91
Number of donors	9,984
Number of campaign webpages	271
Control Variables	YES
Campaign / Month / Weekday / Timezon FE	YES

Notes to table: Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 5. Further Analysis–Regression-to-the-mean Bias

The dependent variable is a binary variable, which takes 1 when (n)th donation amount is equal to (n-1)th donation amount	FE Linear Probability Model (1)
No Preceding Continuous Modal Donations	
Positive Difference from the Previous Mean - Dummy	-0.0924***
	(0.0119)
Negative Difference from the Previous Mean - Dummy	-0.103***
	(0.0118)
The Preceding **Two** Continuous Modal Donations	
Positive Difference	0.00323
	(0.0204)
Negative Difference	-0.0670***
	(0.0200)
The Preceding **Three or More** Continuous Modal Donations	
Positive Difference	0.0335
	(0.0270)
Negative Difference	0.0876***
	(0.0259)
Constant	0.430
	(0.304)
R-squared	0.019
F-statistics	6.21
Number of donors	9,984
Number of campaign webpages	271
Control Variables	YES
Campaign / Month / Weekday / Timezone FE	YES

Notes to table:

We use two variables in the analysis: one to explain the arithmetic mean of amounts donated before the modal donations and another to explain positive or negative differences between the modal and mean amounts.

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 6.1. Further Analysis–Sample-selection Problem [Part 1]

The dependent variable takes 1 …

(1) when a donor appears and makes a donation **within 1 day** after the immediately preceding first donation.

(2) when a donor appears and makes a donation **within 3 days** after the immediately preceding first donation.

(3) when a donor appears and makes a donation **within 1 week** after the immediately preceding first donation.

	Within 1 day	Within 3 days	Within 1 week
FE Linear Probability Model	(1)	(2)	(3)
Donation Amount Ranges			
1 - 999 yen	Basement	Basement	Basement
1,000 - 1,999 yen	-0.0167	0.00204	0.0103
	(0.0287)	(0.0198)	(0.0138)
2,000 - 2,999 yen	-0.0322	0.00527	0.00509
	(0.0279)	(0.0192)	(0.0133)
3,000 - 4,999 yen	-0.0541*	-0.0126	-0.00535
	(0.0280)	(0.0193)	(0.0134)
5,000 - 9,999 yen	-0.0224	0.0143	0.00189
	(0.0274)	(0.0188)	(0.0131)
10,000 - 29,999 yen	-0.0351	0.00481	-0.000505
	(0.0274)	(0.0189)	(0.0131)
30,000 - 49,999 yen	-0.0534	-0.0268	-0.00940
	(0.0327)	(0.0225)	(0.0157)
50,000 yen and more	-0.0363	0.00108	0.0208
	(0.0348)	(0.0240)	(0.0167)
Cross Terms:			
Donation Amount Ranges × **<u>The Preceding Three or More Continuous Modal Donations</u>**			
1 - 999 yen	-0.0570	0.0510	0.00983
	(0.156)	(0.107)	(0.0748)
1,000 - 1,999 yen	0.00358	-0.0155	-0.0235
	(0.0440)	(0.0303)	(0.0211)
2,000 - 2,999 yen	-0.0584	-0.0212	0.00127
	(0.0405)	(0.0279)	(0.0194)
3,000 - 4,999 yen	0.0716	0.0409	0.00726
	(0.0440)	(0.0303)	(0.0211)
5,000 - 9,999 yen	0.000635	-0.00131	0.00141
	(0.0206)	(0.0142)	(0.00986)
10,000 - 29,999 yen	0.00583	-0.00626	0.00252
	(0.0211)	(0.0145)	(0.0101)
30,000 - 49,999 yen	-0.0871	-0.00426	0.0143
	(0.190)	(0.131)	(0.0910)
50,000 yen and more	-	-	-
	-	-	-
Constant	1.579***	1.354***	1.358***
	(0.125)	(0.0859)	(0.0598)
R-squared	0.247	0.301	0.339
F-statistics	71.52	93.56	111.64
Number of donors	8,573	8,573	8,573
Number of campaign webpages	265	265	265
Control Variables	YES	YES	YES
Campaign / Month / Weekday / Timezone FE	YES	YES	YES

Notes to table: Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 6.2. Further Analysis–Sample-selection Problem [Part 2]

The dependent variable takes 1 …

(4) when a donor appears and makes a donation **within 1 day** after the immediately preceding first donation.

(5) when a donor appears and makes a donation **within 3 days** after the immediately preceding first donation.

(6) when a donor appears and makes a donation **within 1 week** after the immediately preceding first donation.

	Within 1 day	Within 3 days	Within 1 week
FE Linear Probability Model	(1)	(2)	(3)
No Preceding Continuous Modal Donations			
Positive Difference from the Previous Mean - Dummy	0.00705	0.000494	-0.000152
	(0.00962)	(0.00662)	(0.00461)
Negative Difference from the Previous Mean - Dummy	0.00888	-0.00497	0.000817
	(0.00968)	(0.00667)	(0.00464)
The Preceding **Two** Continuous Modal Donations			
Positive Difference	-0.0161	-0.0108	-0.00115
	(0.0166)	(0.0114)	(0.00794)
Negative Difference	-0.0222	-0.0181	-0.00432
	(0.0174)	(0.0120)	(0.00835)
The Preceding **Three or More** Continuous Modal Donations			
Positive Difference	-0.000729	-0.00577	0.00540
	(0.0213)	(0.0146)	(0.0102)
Negative Difference	-0.0237	-0.0139	-0.00236
	(0.0252)	(0.0173)	(0.0121)
Constant	1.551***	1.357***	1.359***
	(0.122)	(0.0843)	(0.0587)
R-squared	0.247	0.300	0.338
F-statistics	90.30	117.99	141.06
Number of donors	8,573	8,573	8,573
Number of campaign webpages	265	265	265
Control Variables	YES	YES	YES
Campaign / Month / Weekday / Timezone FE	YES	YES	YES

Notes to table:

We use two variables in the analysis: one to explain the arithmetic mean of amounts donated before the modal donations and another to explain positive or negative differences between the modal and mean amounts. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1