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Gift Contagion in Online Groups: Evidence From Virtual Red Packets

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Gifts are important instruments for forming bonds in interpersonal relationships. Our study analyzes the phenomenon of gift contagion in online groups. Gift contagion encourages social bonds of prompting further gifts; it may also promote group interaction and solidarity. Using data on 36 million online red packet gifts on a large social site in East Asia, we leverage a natural experimental design to identify the social contagion of gift giving in online groups. Our natural experiment is enabled by the randomization of the gift amount allocation algorithm on the platform, which addresses the common challenge of causal identifications in observational data. Our study provides evidence of gift contagion: on average, receiving one additional dollar causes a recipient to send 18 cents back to the group within the subsequent 24 hours. Decomposing this effect, we find that it is mainly driven by the extensive margin – more recipients are triggered to send red packets. Moreover, we find that this effect is stronger for "luckiest draw" recipients, suggesting the presence of a group norm regarding the next red packet sender. Finally, we investigate the moderating effects of group- and individual-level social network characteristics on gift contagion as well as the causal impact of receiving gifts on group network structure. Our study has implications for promoting group dynamics and designing marketing strategies for product adoption.

Key words: social contagion, social network, red packets, gift giving, online groups

1. Introduction

Individuals belong to many different social groups: kinship groups, friend groups, work groups or organizations, and interest groups. The collective identities developed in these groups deeply shape the behavior of their members (Tajfel et al. 1979, Cialdini and Goldstein 2004, Christakis and Fowler 2007, Chen and Li 2009, Aral and Walker 2012, Bond et al. 2012). Nowadays, social groups are facilitated through digital platforms, especially social network platforms such as Facebook, Line, WeChat, and WhatsApp. These platforms support social groups for a variety of purposes, including relationship maintenance, opinion and information exchange, and event planning (Veinott et al. 1999, Backstrom et al. 2006, Park et al. 2009, Bloom et al. 2015, Liu et al. 2015). In particular, during the COVID-19 pandemic, online work group chats have substituted for conventional in-person meetings (Brynjolfsson et al. 2020); indeed, it was reported that 42 percent of the U.S. labor force worked from home full-time as of June 2020.[1] In China, WeChat groups are widely used for instant work-related communication (Liu et al. 2015, Qiu et al. 2016). Although online work groups offer the convenience of long-distance communication and coordination, they may face challenges related to team building and group solidarity (Holton 2001).

One way to promote group bonding is through the use of group gifts, which are the gifts sent by a group member without specifying recipients. Examples of group gifts include the food items or souvenirs bought by a member to her work group after traveling abroad as well as the small gifts being exchanged at a Christmas or holiday party (the "white elephant" gift exchange). While prior literature focuses on one-to-one gifts and their role in creating interpersonal social bonds (Mauss 2002), few studies have investigated group gifts and their role in promoting in-group interactions and solidarity.

In this study, we are interested in studying the outbreak of sending group gifts in online social groups, indicating the presence of gift contagion (the social contagion of gift giving). Social contagion is defined as "an event in which a recipient's behavior has changed to become 'more like' that of the actor" (Wheeler 1966). Aral et al. (2009) has pointed to the importance of identifying causal effects in the process of social contagion. In the context of group gifts, gift contagion implies that people who receive larger amounts of gifts feel promoted to increase their own subsequent contributions. If gift contagion exists in groups, the actual impact of a given gift would be amplified, leading to stronger social bonds and feelings of group solidarity (Markovsky and Lawler 1994).

To quantify the effect of gift contagion, our study employs a large-scale dataset of 3.4 million users on a large social network platform in east Asia. For anonymous concern, we call the platform we study as ABC thereafter. On the platform, users send online red packets to each other as a type of digital monetary gift. The red packets, especially group red packets, swiftly became extremely popular after being released. For example, more than 700 million people engaged in sending or receiving red packets during one week in 2019.

[1] `https://news.stanford.edu/2020/06/29/snapshot-new-working-home-economy/`

Methodologically, the causal identification of social contagion in observational data is notoriously challenging (Aral et al. 2009, Shalizi and Thomas 2011, Yuan et al. 2021). In particular, the following two confounding factors may hinder valid causal identification of gift contagion. The first confounding is the "temporal clustering." Specifically, group members may send gifts within a short time period independently to celebrate a festival or an event (Aral et al. 2009). The second is homophily, the phenomenon whereby individuals tend to befriend similar others (McPherson et al. 2001). For example, wealthy people tend to cluster in a group and send larger amounts of gifts to each other.

We leverage a natural experiment to overcome the above challenges. Our natural experiment is enabled by a random gift amount allocation algorithm for group red packets. The algorithm splits a red packet into several shares and randomly determines the amount of each share. We utilize this random assignment of received cash amounts to identify the impact of the amount received on a participant's subsequent gifting behavior. We first examine the presence of gift contagion on the platform. On average, receiving one additional dollar causes a recipient to send 18 cents back to the group within the subsequent 24 hours. Moreover, we find that this overall effect is mainly driven by the extensive margin, i.e., receiving red packets significantly promotes the likelihood of giving. Second, we investigate heterogeneity in the effect size of gift contagion across different time periods (festival versus non-festival periods), and across different types of groups (e.g., relative versus classmate groups). Third, our analysis suggests that a social norm exists in that the luckiest draw recipient should send the very first subsequent red packet. Finally, we find that both individual-level network position and group-level network structure affect the strength of gift contagion, respectively.

The rest of the paper is organized as follows. Section 2 describes the institutional background and our data. Section 3 discusses our estimation strategy. Section 4 introduces our hypotheses. Section 5 presents the results. Section 6 concludes.

2. Data

2.1. Background

In our study, we focus on the custom of sending monetary gifts to family members, friends, and other acquaintances in what is known as "red packets" (also known as "red envelopes," or "lucky money"). Red packets are typically sent to others as a way of commemorating festivals or important events. They also function as a means of tightening the social network in East and Southeast Asian cultures, known as the *renqing* and *guanxi* system (Luo 2008, Wang et al. 2008). We summarize the history of red packets in *Appendix A*.

ABC platform enables users to designate private contacts (we use the term "friends" throughout the paper) and to create group chats. Groups are created for a wide variety of purposes, ranging from family members to coworkers and friends. The number of group members ranges between 3

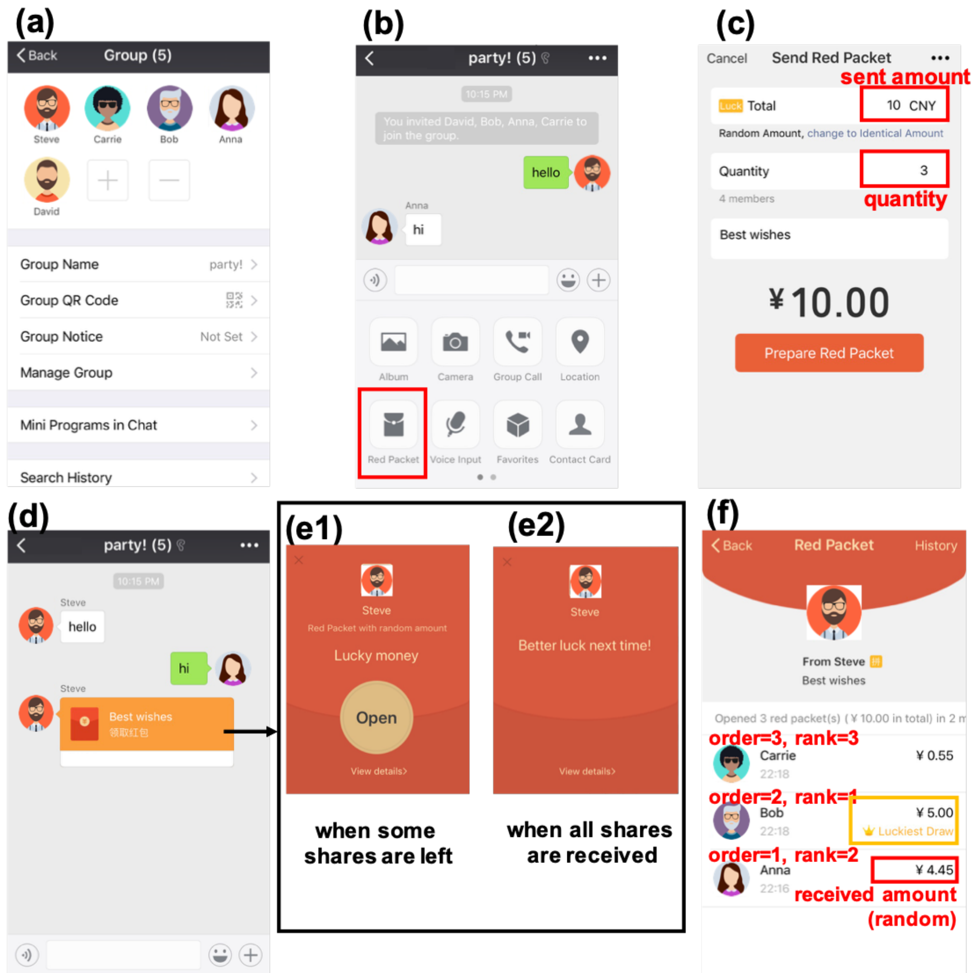

Figure 1 Illustration of group red packets with random amounts

and 500. ABC introduced its online red packet feature in 2014, allowing users to send monetary gifts to either a friend or a group. Its red packets were popularized during the Lunar New Year of 2015 — it was reported that 55% of the Chinese population sent and received red packets on that single day. Because of the popularity of red packets, ABC also benefits from a rapid growth in its mobile payment market share and becomes the second largest mobile payment platform in the country.

Noting there are two types of group red packets, our study focuses on the most popular one – the random-amount, group-designated red packet, as depicted in Figure 1.[2] In this example, Panel (a) provides the basic information about the group, the name of which is "Party!", with five group members in total. Panel (b) presents the user interface of this group, from which a group member can click the "Red Packet" button to send a red packet. Panel (c) shows that a group member (Steve in this example) can choose both the ***total amount*** of the red packet that he would like to send ("Total"=10 CNY) and the ***number of recipients*** ("Quantity"=3). Panel (d) is the interface

[2] The other type is that senders can also choose to split red packets equally.

for the red packet notification, from which a user can click the orange button to choose to receive the packet. Panel (e1) pops up when some shares of the red packet remain. In this example, only the first three users who click the "Open" button can receive a share of this red packet. Panel (e2) pops up when all shares of the red packet have been received by group members. Finally, Panel (f) shows the recipient list, which can be viewed by clicking "View details" in Panel (e). All of the group members, including senders, recipients, and non-recipients, can view the recipient list and see the amount obtained by each recipient. We define the ***order of receiving time*** as group members' respective places in the order at the time when they receive the red packet. In the above setting, the amount that each user receives is randomly assigned by the platform, and is a function of the total amount of the red packet, the number of recipients, and the order of the receiving time. Moreover, the platform designates which user receives the largest amount of a red packet with a "Luckiest Draw" icon and the corresponding yellow text. All group members can observe who is the luckiest draw recipient.

2.2. Data collection

In collaboration with the company, we collect a dataset consisting of randomly-sampled groups with red packet activity from October 1, 2015 to February 29, 2016. To protect user privacy, users' identities were anonymized before we accessed the data. To avoid data sparsity, we restrict our analysis to groups in which the number of red packets sent is at least three times the number of group members. We also filter out groups that might be used for online gambling based on the following criteria: (1) a number of red packets greater than 50 times the number of group members; (2) a name that suggests a gambling focus (containing words such as C /块(Chinese yuan), Ñ (send), ¢ (red), (packet), s (luckiest), 抢(grad), 赌(gamble), 钱(money), 福) (welfare), and 接龙(chain) or Arabic numerals (which indicate the default packet amount set for gambling); or (3) no designated group name, which could also be temporarily created for gambling.[3] In total, this selection process results in 174,131 groups with 3,466,928 group members (3,450,540 unique users).

In our main analyses, we include: (1) the characteristics of 174,131 groups, including the number of group members, the total number of red packets, and the total cash value of the red packets; (2) 3,450,540 unique users in these groups, along with their characteristics, such as the number of in-group friends are also retrieved; and (3) the attributes of each red packet, including the cash amount, the corresponding recipients and the opening time. In total, our sample comprises 36,608,864 red packets. Furthermore, we focus on recipients of "spontaneous red packets," which indicate that no group red packet is sent in the 24 hours prior to this type of red packet. We conduct robustness checks by varying the time window and find that our main results remain robust (*Appendix D.1*). In total, we identify 1,549,720 spontaneous red packets sent to 7,266,446 recipients.[4] Each observation

[3] We show that groups identified as gambling groups appear to exhibit greater levels of gift contagion (*Appendix D.1*).

[4] We exclude observations in which the sender clicks the red packet and receives a share of her own red packet.

refers to a user's received red packet and we have 7,266,446 observations in total. *Appendix B* presents a detailed description of the data.

3. Estimation strategy

3.1. Random assignment algorithm for group red packets

Here we illustrate the random assignment algorithm for red packet amounts. First, the sender determines the total amount of the red packet ($a > 0$) and the number of recipients to receive a portion of the red packet ($n \geq 1$).[5] Then group members choose to open the red packet on a first-come, first-served basis. They do not know the values of a and n until they open the red packet. Let o denote the order of receiving time ($o = 1, 2, ..., n$). The amount received by the recipient with order o, denoted by V_o, is determined by the following algorithm:

1. When $o = 1$ and $o < n$: the amount obtained by the first recipient (order $= 1$) follows a uniform distribution on $(0, \frac{2a}{n}]$. The expected amount is:

$$\mathbb{E}[V_1] = \frac{1}{2} \times (0 + \frac{2a}{n}) = \frac{a}{n}.$$

   When $o = n = 1$, the amount received is a because the only recipient should take all the cash amount.

2. When $1 < o < n$: the amount received follows a uniform distribution on $(0, \frac{2(a - V_1 - \dots - V_{o-1})}{n - o + 1}]$. We have:

$$\begin{aligned}
\mathbb{E}[V_o] &= \mathbb{E}\left[\mathbb{E}[V_o | V_1, ..., V_{o-1}]\right] \\
&= \mathbb{E}\left[\frac{1}{2} \times \left(0 + \frac{2(a - V_1 - \dots - V_{o-1})}{n - o + 1}\right)\right] \\
&= \frac{a - \mathbb{E}[V_1] - \dots - \mathbb{E}[V_{o-1}]}{n - o + 1}.
\end{aligned}$$

   We show that $\mathbb{E}[V_o] = \frac{a}{n}$ by induction:

   First, we have already shown that $\mathbb{E}[V_1] = \frac{a}{n}$.

   Second, assuming that we have $\mathbb{E}[V_{o'}] = \frac{a}{n}$ for all $o' < o$, we have $\mathbb{E}[V_o] = \frac{a - (o-1)\frac{a}{n}}{n - o + 1} = \frac{a}{n}$.

3. When $o = n$: $V_o = a - V_1 - \dots - V_{o-1}$, indicating that the last recipient takes the surplus. Then we have $\mathbb{E}[V_o] = a - \mathbb{E}[V_1] - \dots - \mathbb{E}[V_{o-1}] = \frac{a}{n}$.

[5] In practice, the amount received is rounded to the nearest cent, and is set at least 0.01 CNY.

Therefore, the expectation of the received amount is the same: $\frac{a}{n}$. However, the variance in the amounts is not always the same. For example, when $n > 2$,

$$
\begin{aligned}
\mathrm{Var}(V_1) &= \frac{1}{12} \quad (\frac{2a}{n} \quad 0)^2 = \frac{a^2}{3n^2};\\
\mathrm{Var}(V_2) &= \mathbb{E}\Big[\mathrm{Var}(V_2 j V_1)\Big] + \mathrm{Var}\Big(\mathbb{E}[V_2 j V_1]\Big)\\
&= \mathbb{E}\Big[\frac{1}{12} \quad (\frac{2(a \quad V_1)}{n \quad 1})^2\Big] + \mathrm{Var}\Big(\frac{a \quad V_1}{n \quad 1}\Big)\\
&= \mathbb{E}\Big[\frac{(a \quad V_1)^2}{3(n \quad 1)^2}\Big] + \frac{1}{(n \quad 1)^2}\mathrm{Var}(V_1)\\
&= \Big(\quad \frac{(a \quad \frac{2a}{n})^3}{9(n \quad 1)^2} + \frac{a^3}{9(n \quad 1)^2}\Big) \quad \frac{n}{2a} + \frac{a^2}{3(n \quad 1)^2 n^2}\\
&= \frac{a^2}{3n^2} + \frac{4a^2}{9(n \quad 1)^2 n^2} > \mathrm{Var}(V_1).
\end{aligned}
$$

In addition, we provide the complete proof for variance differences in *Appendix C*.

To show that the random assignment algorithm implemented on the platform functions as described above, we compare the empirical distributions of received amounts from our data to the simulation results generated by the algorithm in Figure 2. In our first comparison example in the upper two rows, we see that the total amount is 10 CNY and the number of recipients is 5 (108,560 observations). In our second comparison example in the bottom two rows, we see that the total amount is 5 CNY and the number of recipients is 3 (38,523 observations). We do not find significant differences between these two distributions generated by the simulation and our empirical data ($p = 0.30$ and 0.36 for the two cases, respectively, two-sided Kolmogorov-Smirnov tests). Additionally, consistent with the random assignment algorithm, the expectation of the amount received is solely determined by the total amount of the gift and the number of recipients ($\frac{10}{5} = 2$ and $\frac{5}{3}$ for the two cases, respectively). Examining the remaining data, we find that the results continue to hold.

Furthermore, we verify the randomization procedure and provide the results in *Appendix C*. The results suggest that, conditional on the total amount of the red packet, the number of recipients, and the order of receiving time, the amount received is not significantly correlated with individual characteristics or historical behaviors. Taken together, these analyses confirm that the amount that a recipient obtains is solely determined by the following three variables: (1) the total amount of the red packet; (2) the number of recipients; and (3) the order of receiving time. This verification enables us to use the following empirical strategy to quantify the causal impact of gift contagion.

3.2. Empirical strategy

We next discuss our empirical strategy, which is used to quantify the impact of the amount received on the recipient's subsequent gifting behavior. We regard the random assignment of received amounts as a stratified randomized experiment (Kernan et al. 1999, Imai et al. 2008, Imbens and Rubin 2015,

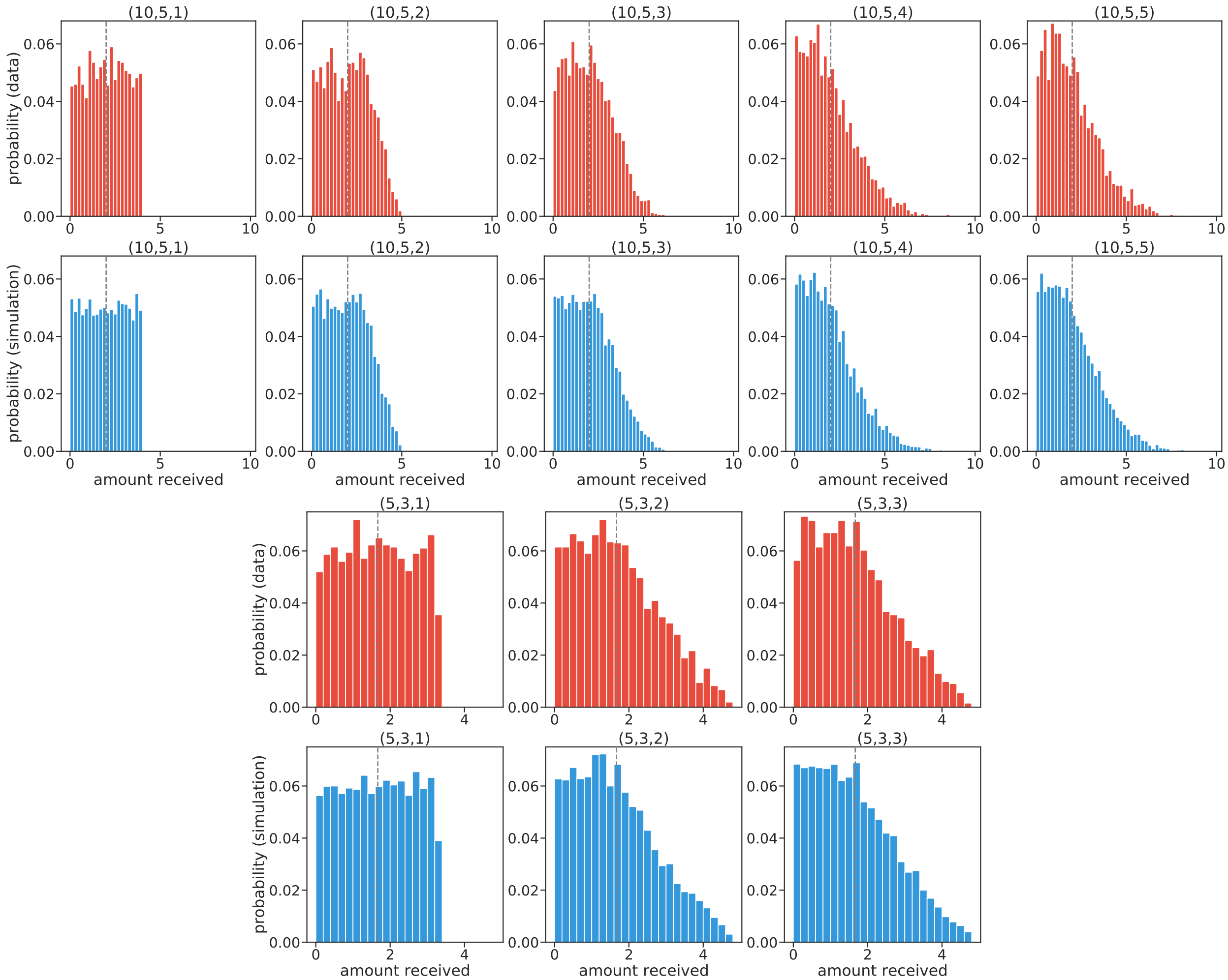

Figure 2 Distributions of received amounts in our dataset (red) and simulation (blue). The top two rows are those with 10 CNY and 5 recipients; The bottom two rows are those with 5 CNY and 3 recipients. A title with (a, n, o) indicates that the total amount of the gift is a CNY, the number of recipients is n, and the order of receiving time is o.

Athey and Imbens 2017), where a stratum is uniquely determined by the total amount of the red packet, the number of recipients, and the order of receiving time. We apply the empirical strategy of stratified randomized experiments proposed by Imbens and Rubin (2015) and conduct the following regression analyses:

$$Y_{gir} = \beta T_{gir} + \sum_{s} \gamma_s B_s(A_r, N_r, O_{ir}) + \epsilon_{gir}. \tag{1}$$

In Eq. (1), g denotes a group, and i denotes a unique user who receives a share of a red packet r. ϵ_{gir} represents the random noise. The dependent variable Y_{gir} is the amount sent by the recipient i in the time interval after receiving a red packet. The selected time intervals are 10 minutes, 1 hour, 3 hours, 6 hours, 12 hours, and 24 hours. The main independent variable T_{gir} is the amount received by user i from red packet r. β is the estimand of interest that specifies the linear relationship between

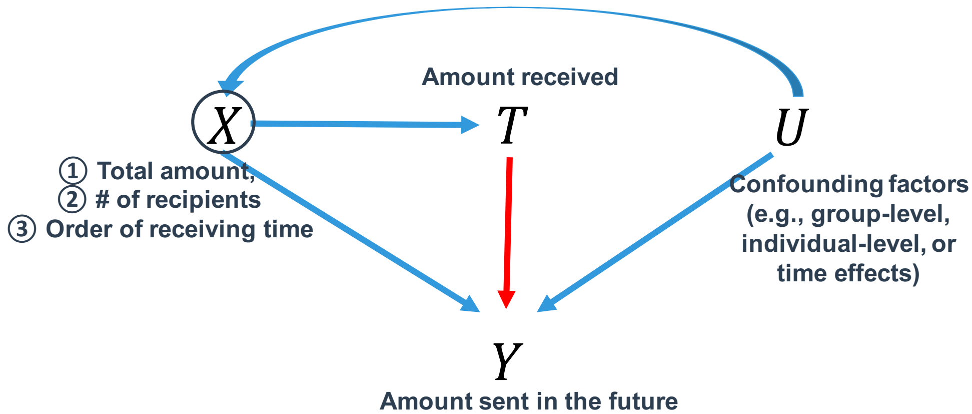

Figure 3 A directed acyclic graph illustrating the causal relationship

T_{gir} and Y_{gir} and measures the degree of gift contagion. A_r, N_r, and O_{ir} refer to the total amount of the red packet r, its number of recipients, and user i's order of receiving time, respectively. Finally, $B_s(A_r, N_r, O_{ir})$ is a dummy variable indicating whether the value of $X_{gir} = (A_r, N_r, O_{ir})$ belongs to the sth stratum. The dummy variable helps control for stratum fixed effects. In total, we have 180,578 strata in our sample.

To address potential data interdependence, we focus on group- versus user-level interdependence, as only 3.1% of the users in our dataset belong to more than one group, data interdependence at the group level is the primary concern. To further address user-level interdependence, our bootstrap identifies any two groups containing the same user as a "cluster." We use the Poisson bootstrap (Efron 1992) at the "cluster" level for 1,000 replicates to estimate the robust standard errors or 95% confidence intervals.

To depict the causal relationship examined by our empirical strategy, we use Pearl's directed acyclic graphs (DAGs) to visualize the causal relationship in our empirical strategy (Pearl 2009). As shown in Figure 3, controlling for X blocks all of the "backdoor" paths from T to Y, which satisfies the backdoor criterion and allows us to identify the causal impact of T on Y. This process provides greater confidence that confounding factors (U), such as temporal clustering and homophily, would not bias our estimation.

We also separate gift contagion into the extensive margin (the increase in the probability of sending red packets) and the intensive margin (the increase in the amount sent conditional on sending) (Hossain and Li 2014, Liu et al. 2014, Bott et al. 2020, Cao et al. 2020). For the extensive margin, we replace the outcome variable in Eq. (1) with a dummy variable $\mathbb{1}[Y_{gir} > 0]$. For the intensive margin, we apply Eq. (1) on observations where $Y_{gir} > 0$. In later analyses, we report the estimations of β in the respective regression as extensive and intensive margins.

This empirical strategy has two advantages in identifying a causal relationship. First, it enables us to fully control for the stratum fixed effect, without requiring a specific functional form for the impact of X. For example, a linear specification, i.e., adding A_r, N_r, and O_{ir} directly into the regression, would lead to an overestimated treatment effect (*Appendix D.2*). Second, we realize that if most strata have few observations, we may fail to measure such within-stratum effects. Fortunately, our sample size is sufficiently large that we have a sufficient number of observations within each stratum. Note that the average number of observations in a stratum is 8.37. Compared to Kizilcec et al. (2018), which relies on the birthday discontinuity to perform a quasi-experiment, we leverage the gift-amount randomization algorithm embedded in the feature to identify the social contagion of gift giving.

4. Hypotheses

To motivate the hypotheses, we construct a simple model by following Charness and Rabin (2002) (see *Appendix E*). In our model, the utility function of a user depends on her own payoff and that of others in the same group, with parameters specifying their respective weight. We theoretically show that a user's sending amount increases with the amount that she receives from the preceding red packet. This leads to our first hypothesis.

Hypothesis 1 (Gift contagion) *The larger the amount a recipient obtains, the larger the amount the recipient will send to the group.*

Next, inspired by the fact that individuals would exchange red packets more often during holiday seasons, we quantitatively show that the size of gift contagion is stronger during festival periods. This leads to the following hypothesis:

Hypothesis 2 (Festival effect) *Gift contagion is stronger during festival periods than during other time periods.*

Similar to the festival effect, we also predict that the strength of gift contagion would be different among different groups. In particular, we expect that the effect would be stronger in groups of relatives. This leads to the following hypothesis:

Hypothesis 3 (Group type effect) *Gift contagion is stronger in groups of relatives than it is in other groups.*

Recall that the user interface highlights the person who is the luckiest draw recipient, and this information is observed by all group members. We thus posit that gift contagion is stronger for the luckiest draw recipients. There are two possible reasons for our conjecture. The first reason is because of the ***amount effect***: luckiest draw recipients receive larger amounts, and thus, they may send a larger amount to others, as we explained in Hypothesis 1. The second reason is that the salience of the luckiest draw recipient information might motivate users to send red packets (referred to as the *luckiest draw e ect*). In our model shown in *Appendix E*, we analytically show that such luckiest draw effect would amplify the size of gift contagion. Hence, we have the following hypothesis:

Hypothesis 4 (Luckiest draw effect) *Gift contagion is stronger for luckiest draw recipients than it is for others.*

Finally, we are interested in the moderating effect of social network characteristics. Again, we quantitatively show that a member who has more friends or who is less clustered in their group would send more, conditional on the same amount received. Therefore, we have the following hypothesis:

Hypothesis 5 (Individual network position on gift contagion)

(a) Gift contagion is stronger for individuals who are less clustered in the group.

(b) Gift contagion is stronger for individuals who have more friends (higher degree) in the group.

5. Results

5.1. Gift contagion in online groups

We first apply a simplistic, non-parametric approach to shed light on the causal effect of the amount received by a user within a group on the probability of that user sending the first subsequent red packet. We depict the probability of sending the first subsequent red packet for the recipients of a given red packet in Figure 4. From this figure, we see a decreasing trend related to the rank of received amounts: those who receive the largest amount have the highest probability of sending the first subsequent red packet. Moreover, the largest difference lies between those who receive the largest amount and those who receive the second largest amount, while the differences between other recipients are much smaller.

Next, we apply the empirical strategy described in Section 3 to quantify the impact of the amount received on the subsequent amount sent, namely, we estimate β in Eq. (1). Figure 5 presents the marginal effects for different timeframes. From the figure, we see an increase in the effect size as the timeframe widens, with the effect stabilizing after the first three hours. In later analyses, we focus on regression results for 10 minutes and 24 hours, respectively.

Result 1 (Gift contagion) *The larger the amount a recipient obtains, the larger the amount she sends to the group.*

Support. *As shown in Columns (1) and (2) in Table 1, the regression coe cients for the amount received are positive and significant at the 1% level (10 minute: 0.1554,* $p < 0.01$*; 24-hour: 0.1850,* $p < 0.01$*).*

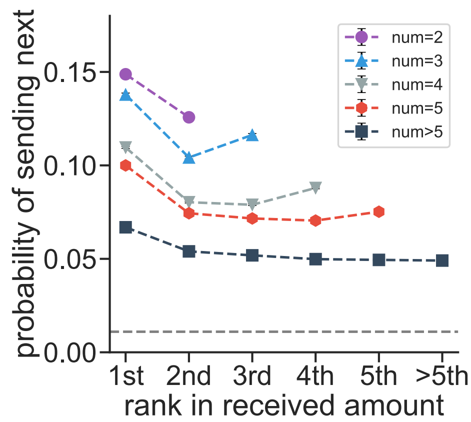

Figure 4 The recipients' probability of sending the first subsequent red packet. "Num" is the number of recipients of a given red packet. The x-axis indicates the rank of received amounts among recipients. For example, "1st" refers to the user who receives the largest amount, i.e., the luckiest draw recipient. "$>$5th" is the average probability among recipients whose rank is below the 5th position. The dashed gray line represents the average probability that a non-recipient sends the first subsequent red packet. The error bars, i.e., the 95% CIs, are much smaller than the markers, and become invisible.

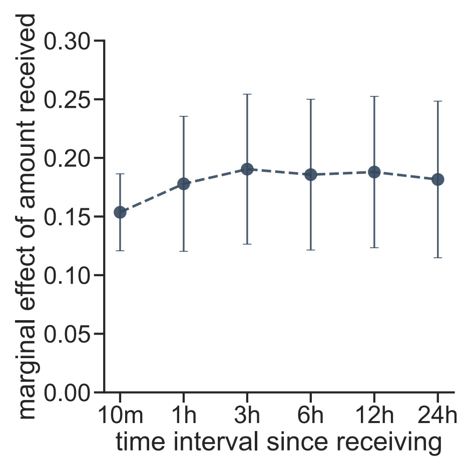

Figure 5 The marginal effects of the amount received on the amount sent within the corresponding timeframes. Error bars are the 95% CIs.

By Result 1, we reject the null hypothesis in favor of Hypothesis 1. Since the gifting behavior is quantitatively measurable in our dataset, we are able to decompose the overall effect to the extensive and intensive margins. This decomposition has received little examination in the previous gift contagion literature. For example, in their study of gift contagion on Facebook, Kizilcec et al. (2018) reports only the overall effect of gift contagion. The extensive margin reflects whether the amount received increases the recipient's likelihood of sending a red packet, while the intensive margin indicates, conditional on sending a red packet, whether the amount received affects the amount sent. As shown in Columns (3) and (4), receiving one more CNY increases the recipient's

Table 1 Regression analyses for gift contagion

	Overall		Extensive		Intensive	
	10 min	24 h	10 min	24 h	10 min	24 h
	(1)	(2)	(3)	(4)	(5)	(6)
Amount received	0.1554***	0.1850***	0.0031***	0.0032***	0.0048	-0.2210*
	(0.0176)	(0.0359)	(0.0001)	(0.0001)	(0.0725)	(0.1374)
Stratum fixed effect	Y	Y	Y	Y	Y	Y
No. of observations	7,266,446	7,266,446	7,266,446	7,266,446	1,060,746	1,370,741
Adjusted R^2	0.0394	0.0396	0.0211	0.0233	0.1517	0.1096

Note: The dependent variable (DV) for Columns (1) and (2) is the amount sent within the respective timeframe. It is coded as zero for those who do not send red packets. The DV in Columns (3) and (4) is the dummy variable for sending red packets. The DV in Columns (5) and (6) is the amount conditioning on sending red packets. Marginal effects are reported. Standard errors clustered at the group and user level are in parentheses. *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.

probability of sending a red packet by 0.31% in 10 minutes ($p < 0.01$) and 0.32% in 24 hours ($p < 0.01$). By contrast, the intensive margin is not significant within 10 minutes ($p > 0.1$), and even becomes negative within 24 hours ($p = 0.055$). Therefore, we conclude that the primary driver of our observed overall effect of receiving a red packet on subsequent behavior is that users are more likely to send packets versus more likely to send a greater amount.

In addition, we test for generalized reciprocity (Yamagishi and Cook 1993, Nowak and Roch 2007), i.e., whether receiving gifts in one group triggers the recipient to send a gift within another group. Again, we apply the estimation strategy in Eq. (1) to estimate the effect, but with the dependent variable being the average amount that the user sends to other groups she belongs to in our sample. Since we sample our data at the group level, our test of generalized reciprocity is restricted to those who belong to multiple sampled groups, which yields 18,910 (3.1%) users in our sample. Altogether, although the sign for the estimated coefficient is positive, it is not significant (see Table A.7 in *Appendix*). This null result may be due to two factors. First, although the number of users is not small, a lack of within-stratum variation may underpower our analysis. Indeed, among 12,671 strata, 7,956 contain only one observation. Second, since users may belong to additional groups that are not in our sample, the lack of all sending and receiving history of a user leads to an underestimation of our effect.

5.2. Heterogeneous effect of gift contagion

The fine-grained information in our large dataset provides opportunities to examine how the effect size of gift contagion varies in multiple dimensions, which further deepens our understanding of gift contagion. For example, Kizilcec et al. (2018) only examine Facebook birthday gifts, while our sample includes the sending of red packets for different purposes, such as celebrating the Lunar New

Table 2 Regression analyses for gift contagion: festival versus non-festival seasons

	Overall		Extensive		Intensive	
	10 min	24 h	10 min	24 h	10 min	24 h
	(1)	(2)	(3)	(4)	(5)	(6)
			Festival			
Amount received	0.1936***	0.2460***	0.0030***	0.0031***	0.0803	-0.0205
	(0.0261)	(0.0531)	(0.0001)	(0.0001)	(0.0831)	(0.1487)
Stratum fixed effect	Y	Y	Y	Y	Y	Y
No. of observations	2,297,290	2,297,290	2,297,290	2,297,290	399,763	545,953
Adjusted R^2	0.0458	0.0493	0.0172	0.0222	0.1626	0.1260
			Non-festival			
Amount received	0.1199***	0.1239***	0.0032***	0.0034***	-0.1571	-0.6609**
	(0.0251)	(0.0520)	(0.0001)	(0.0001)	(0.1514)	(0.3262)
Stratum fixed effect	Y	Y	Y	Y	Y	Y
No. of observations	4,969,156	4,969,156	4,969,156	4,969,156	660,983	824,788
Adjusted R^2	0.0342	0.0318	0.0196	0.0208	0.1861	0.1485

Note: The dependent variable (DV) for Columns (1) and (2) is the amount sent within the respective timeframe. It is coded as zero for those who do not send red packets. The DV in Columns (3) and (4) is the dummy variable for sending red packets. The DV in Columns (5) and (6) is the amount conditioning on sending red packets. Marginal effects are reported. Standard errors clustered at the group and user level are in parentheses. *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.

Year and job promotion. We first examine how the strength of gift contagion differs between festivals and non-festival seasons by running regressions separately, and report the main results below.[6]

Result 2 (Festival e□ect) *The e ect of gift contagion is stronger during festival than non-festival periods, and the di erence is significant in the first 10 minutes.*

Support. *As shown in Columns (1) and (2) of Table 2, the size of the overall e ect is larger during festival than non-festival seasons (10 minutes: 0.1936 versus 0.1199, $p = 0.042$; 24 hours: 0.2460 versus 0.1239, $p = 0.101$).*

By Result 2, we reject the null hypothesis in favor of Hypothesis 2. We also examine the extensive and intensive margins and present the results in Columns (3)-(6), Table 2. From these results, we see that the extensive margin is significant for both festival and non-festival seasons, although the differences are not significant at the 5% level (10 minutes: $p > 0.1$; 24 hours: $p = 0.098$). Additionally, the intensive margin for festival season is larger than non-festival season (10 minutes: $p > 0.1$; 24 hours: $p = 0.074$).

Second, we examine whether the gift contagion effect varies across different types of groups. We identify three group types by inferring a group's composition from group names. (1) *Relative groups*: groups with names containing ¶ (family). (2) *Classmate groups*: groups with names containing [班(class), f /中 f / 中/高中(elementary/secondary/low secondary/high secondary school,

[6] We consider all important dates that people celebrate in China including the Lunar New Year and other festivals.

Table 3 Regression analyses for gift contagion by group types

	Overall		Extensive		Intensive	
	10 min	24 h	10 min	24 h	10 min	24 h
	(1)	(2)	(3)	(4)	(5)	(6)
			Relatives			
Amount received	0.1484***	0.1948***	0.0031***	0.0031***	0.0792	0.0305
	(0.0227)	(0.0443)	(0.0002)	(0.0002)	(0.0816)	(0.1298)
Stratum fixed effect	Y	Y	Y	Y	Y	Y
No. of observations	2,200,404	2,200,404	2,200,404	2,200,404	366,553	472,239
Adjusted R^2	0.0636	0.0552	0.0139	0.0169	0.2169	0.1405
			Classmates			
Amount received	-0.0253	-0.0913	0.0068***	0.0069***	-1.1597**	-1.2252**
	(0.0625)	(0.1245)	(0.0009)	(0.0009)	(0.4202)	(0.5316)
Stratum fixed effect	Y	Y	Y	Y	Y	Y
No. of observations	408,397	408,397	408,397	408,397	47,242	62,616
Adjusted R^2	0.0982	0.1206	0.0082	0.0148	0.2631	0.1956
			Coworkers			
Amount received	0.1267**	0.0627	0.0032***	0.0031***	-0.1841	-0.6356
	(0.0643)	(0.1062)	(0.0005)	(0.0006)	(0.3836)	(0.5495)
Stratum fixed effect	Y	Y	Y	Y	Y	Y
No. of observations	143,297	143,297	143,297	143,297	17,974	23,156
Adjusted R^2	0.1633	0.1723	-0.0067	0.0041	0.3694	0.3236

Note: The dependent variable (DV) for Columns (1) and (2) is the amount sent within the respective timeframe. It is coded as zero for those who do not send red packets. The DV in Columns (3) and (4) is the dummy variable for sending red packets. The DV in Columns (5) and (6) is the amount conditioning on sending red packets. Marginal effects are reported. Standard errors clustered at the group and user level are in parentheses. *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.

respectively), 大 f (college/university), 校(school), J / § (grade)]. (3) *Coworker groups*: groups with names containing l ø (company), 集团(corporate group), 工 \ (work), and 限(limited liability). Table 3 reports the regression results for group type analysis.

Result 3 (Group type e□ect) *The overall e ect of gift contagion is stronger in relative groups than in classmate groups.*

Support. *The e ect size is significantly greater in relative groups than in classmate groups (10 minutes:* 0.1484 *versus* 0.0253, $p = 0.009$*; 24 hours:* 0.1948 *versus* 0.0913, $p = 0.031$*).*

By Result 3, we reject the null hypothesis in favor of Hypothesis 3. In addition, as indicated by Table 3, we find that the overall effect is significant for relative groups, while the effects are not significant for the other two groups.[7] Moreover, we find that the effect on extensive margins is positive and significant across all group types, but not on intensive margins.[8] This suggests that the effect of gift contagion is primarily driven by promoting new participants to join the red packet chain. These results are consistent with the prior literature, which shows that the overall effect on workers'

[7] The overall effect is marginally significant for coworker groups only within 10 minutes ($p < 0.1$).

[8] Surprisingly, the effect on intensive margin is even negative and significant for classmates groups.

productivity is primarily driven by the extensive margin rather than the intensive margin (Hossain and Li 2014, Cao et al. 2020). Additionally, we compare the effect size between group types and find that the extensive margin is significantly higher in classmate groups than in relative groups (10 minutes: 0.0068 versus 0.0031, $p < 0.01$; 24 hours: 0.0069 versus 0.0031, $p < 0.01$) or coworker groups (10 minutes: 0.0068 versus 0.0032, $p < 0.01$; 24 hours: 0.0069 versus 0.0031, $p < 0.01$). By contrast, the intensive margin for classmate groups is significantly smaller than that for relative groups (10 minutes: 1.1597 versus 0.0792, $p < 0.01$; 24 hours: 1.2252 versus 0.0305, $p = 0.022$).

In addition, we investigate how other demographic characteristics, such as gender and age, affect the degree of gift contagion. We find that the effect of gift contagion is stronger for older recipients, and that red packets sent by younger users are more socially contagious. Moreover, although there is no significant gender difference in the overall effect, red packets sent by female users tend to exhibit a higher extensive margin. *Appendix D.2* includes detailed analyses.

5.3. "Luckiest draw" effect

As discussed in Section 4, we posit that luckiest draw recipients may exhibit stronger gift contagion. To examine the behavioral difference between luckiest and non-luckiest draw recipients, we run the regressions in Eq. (1) for these two subgroups separately and report the results in Table 4.

Result 4 (Luckiest draw effect) *Gift contagion is stronger for luckiest draw recipients than non-luckiest draw recipients, and the difference is significant in the 10-minute timeframe.*

Support. *In Columns (1) and (2) of Table 4, the marginal effects for luckiest draw recipients are larger than those for non-luckiest draw recipients (10 minutes: 0.3271 versus 0.0981,* $p = 0.011$*; 24 hours: 0.3985 versus 0.1616,* $p > 0.1$*).*

By Result 4, we reject the null hypothesis in favor of Hypothesis 4. Moreover, we find that the extensive margin for luckiest draw recipients is almost ten times of that for non-luckiest draw recipients (10 minutes: 0.0074 versus 0.0007, $p < 0.01$; 24 hours: 0.0078 versus 0.0008, $p < 0.01$). Conditional on sending red packets, the marginal effect on the amount that a user sends is smaller for luckiest than non-luckiest draw recipients, although the difference is only marginally significant (Columns (5) and (6), 10 minutes: 0.3767 versus 0.2246, $p = 0.064$; 24 hours: 0.8846 versus 0.2030, $p = 0.067$).

It is possible that luckiest draw recipients send more simply because they receive more. To control for this "amount" effect, we implement the following matching procedure. Specifically, we match each luckiest draw recipient with non-luckiest draw recipients by holding the following variables constant: the total amount of the red packet, the number of recipients of that red packet, the order of receiving time, and the amount received by the corresponding recipient. Matching on the first

Table 4 Regression analyses for gift contagion: luckiest versus non-luckiest draw recipients

	Overall		Extensive		Intensive	
	10 min	24 h	10 min	24 h	10 min	24 h
	(1)	(2)	(3)	(4)	(5)	(6)
	Luckiest					
Amount received	0.3271***	0.3985***	0.0074***	0.0078***	-0.3767	-0.8846*
	(0.0836)	(0.1635)	(0.0004)	(0.0004)	(0.2743)	(0.4862)
Stratum fixed effect	Y	Y	Y	Y	Y	Y
No. of observations	1,923,297	1,923,297	1,923,297	1,923,297	296,799	371,698
Adjusted R^2	0.0640	0.0503	0.0348	0.0373	0.1844	0.1222
	Non-luckiest					
Amount received	0.0981***	0.1616**	0.0007***	0.0008***	0.2246	0.2030
	(0.0331)	(0.0807)	(0.0001)	(0.0001)	(0.1720)	(0.3393)
Stratum fixed effect	Y	Y	Y	Y	Y	Y
No. of observations	5,343,149	5,343,149	5,343,149	5,343,149	763,947	999,043
Adjusted R^2	0.0373	0.0413	0.0159	0.0184	0.1543	0.1181

Note: The dependent variable (DV) for Columns (1) and (2) is the amount sent within the respective timeframe. It is coded as zero for those who do not send red packets. The DV in Columns (3) and (4) is the dummy variable for sending red packets. The DV in Columns (5) and (6) is the amount conditioning on sending red packets. Marginal effects are reported. Standard errors clustered at the group and user level are in parentheses. *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.

three variables allows us to control for the effect of unobserved variables, as the backdoor criterion is satisfied (Pearl 2009). Moreover, matching on the received amount allows us to further control for the difference in the amount received.[9] Our matching procedure yields 668,936 luckiest draw recipients and 1,658,283 non-luckiest draw recipients, representing successful matching of 33.7% of our luckiest draw recipients. Additionally, we bootstrap for 1,000 replicates to construct the confidence intervals.

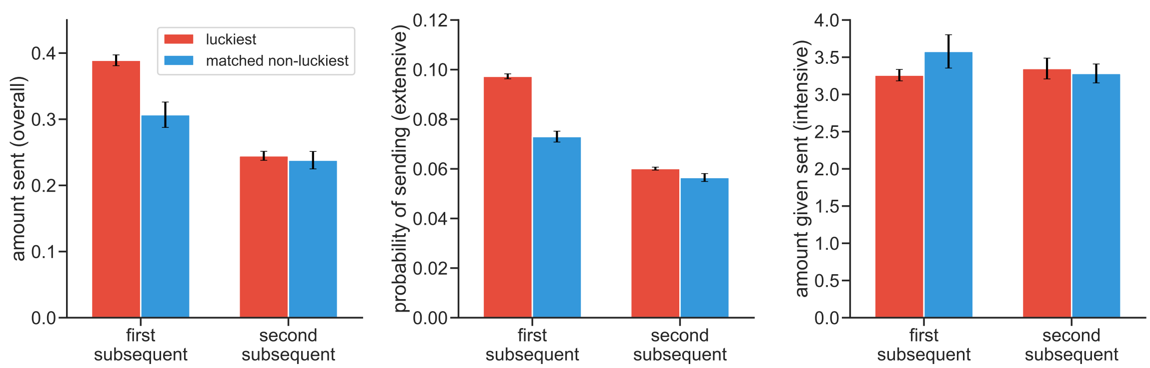

Figure 6 Comparisons between luckiest and non-luckiest draw recipients for the unconditional amount that a user sends ((left), the probability of sending (middle), and the conditional amount that a user sends (right). Error bars are the 95% CIs.

As shown in the left panel of Figure 6, the cash amount sent in the first subsequent red packet increases by 0.080 CNY from non-luckiest to luckiest draw recipients, an effect that is significant

[9] We conduct one-to-many matching (Stuart 2010).

at the 1% level. This result suggests that being the luckiest draw recipient alone promotes the gift contagion. By contrast, for the ***second*** subsequent red packet, we find a much smaller increase and the effect is no longer significant ($p > 0.1$).[10] We also decompose the overall effect into the extensive and intensive margins.[11] For both the first and second subsequent red packets, we find significant differences for the extensive margins ($p < 0.01$), although the difference for the first subsequent red packets is much larger. For the intensive margin, the effect of luckiest draw recipients is smaller than non-luckiest draw recipients for the first subsequent ($p = 0.013$) but not for the second subsequent red packet ($p > 0.1$).

Our results suggest the existence of a group norm whereby the luckiest draw recipients should send the first subsequent red packet. This norm can facilitate coordination among group members to maintain a chain of red packets (Feldman 1984, Seinen and Schram 2006, Gächter et al. 2013). Moreover, we find that the strength of such a group norm is contingent on the discrepancy between the amounts received by the luckiest draw recipient and the amounts received by other recipients (*Appendix D.2*), suggesting that the fairness concern plays a role in influencing the strength of the luckiest draw effect (Bolton and Ockenfels 2000, 2006). In addition to the group norm, gifts may pressure recipients into signaling their own virtue, especially for luckiest-draw recipients. However, since users endogenously decide whether they want to receive a red packet, they can avoid social pressure by not clicking on an offered packet. In addition, the upper limit of a red packet's cash amount is not very large – 200 CNY (roughly 30 USD) and the average cash amount for luckiest-draw recipients in our setting is 1.16 CNY. Therefore, we suspect that social pressure or reputational concerns do not play an important role in our setting.

5.4. Social contagion and social network

In this section, we apply social network analysis to understand how the group network structure affects the strength of our observed gift contagion. Since group members may or may not be private contacts ("friends"), we construct a relationship network among group members, with each edge indicating that two group members are contacts.

First, we examine how individual network positions affects gift contagion. Specifically,we focus on the clustering coefficient and degree. The clustering coefficient of user i in group g (Holland and Leinhardt 1971, Watts and Strogatz 1998), or the extent to which a user's friends are connected, is defined below:

[10] There is no significant difference for the third and subsequent red packets.

[11] Note that the definitions here are slightly different: (1) overall: the amount sent in the kth subsequent red packet; (2) extensive margin: whether the recipient sent the kth subsequent red packet; and (3) intensive margin: the amount sent conditional on being the user who sends the kth subsequent red packet.

$$\text{clustering coefficient}(i,g) = \frac{\sum_{j \in N_i^g} \sum_{k \in N_i^g, k \neq j} \mathbb{1}[k \in N_j^g]}{|N_i^g|(|N_i^g| - 1)}, \tag{2}$$

where N_i^g is the set of a user i's in-group friends in group g. The value of the clustering coefficient ranges from $[0,1]$; 0 indicates that none of i's friends are connected and 1 indicates that all of i's friends are connected in a group. Moreover, we use the normalized degree in our analysis: $\frac{\text{degree}(i,g)}{\text{No. of group members}}$, with a range of $[0,1]$.[12]

Table 5 reports the regression results adding the clustering coefficient, the normalized degree, and their interaction terms with the amount received as independent variables. We summarize the results below:

Result 5 (Individual network position on gift contagion)

(a) The overall effect of gift contagion is smaller for group members with a higher clustering coefficient.

(b) The normalized degree does not significantly impact the overall effect of gift contagion.

Support. *As shown in Columns (1) and (2) of Table 5, the interaction term between "Amount received" and "Clustering coefficient" is negative and significant at the 1% level (10 minutes:* -0.2918*,* $p < 0.01$*; 24 hours:* -0.7596*,* $p < 0.01$*), and the clustering coefficient itself is also negative and significant (10 minutes:* -0.1237*,* $p < 0.05$*; 24 hours:* -0.4350*,* $p < 0.01$*). The coefficient for normalized degree is positive and significant at the 1% level (10 minutes:* 1.0236*,* $p < 0.01$*; 24 hours:* 2.3044*,* $p < 0.01$*), although its interaction term with "Amount received" is not significant.*

By Result 5(a), we reject the null hypothesis in favor of Hypothesis 5(a). This finding is consistent with prior studies (Aral and Walker 2012, Ugander et al. 2012). Moreover, as shown in Columns (3)-(6), the interaction terms for the extensive and intensive margins are also negative and significant.[13] For the normalized degree, we do not find a salient interaction effect, and thus we fail to reject the null hypothesis in favor of Hypothesis 5(b).[14]

Next, we examine the effect of the group-level network structure on our observed gift contagion. We use *the average normalized degree*, or *network density* to measure the degree to which a network is tightly connected (Newman et al. 2006):

$$\text{average normalized degree}(g) = \frac{\sum_{i \in G} |N_i^g|}{|G| \cdot (|G| - 1)}. \tag{3}$$

G denotes the set of group g's members. The average normalized degree ranges from [0, 1]. We present results of the regression with average normalized degree and the interaction term in Table 6.

[12] Compared to the (unnormalized) degree, normalized degree considers the effect of group size.

[13] The only exception is the intensive margin result for 10 minutes.

[14] We also examine the impact of centrality, in particular, the eigenvector centrality, which is widely used in the literature of networks (Marsden 2002, Jackson 2010). However, no significant overall effect for the interaction term is found (Table A.13).

Table 5 Effect of individual in-group degree and clustering coefficient on gift contagion

	Overall		Extensive		Intensive	
	10 min	24 h	10 min	24 h	10 min	24 h
	(1)	(2)	(3)	(4)	(5)	(6)
Amount received	0.3456***	0.6748***	0.0084***	0.0088***	0.1261	0.4101
	(0.0858)	(0.2084)	(0.0004)	(0.0005)	(0.3030)	(0.5835)
Amount received × normalized degree	0.0674	0.1839	-0.0051***	-0.0053***	0.3049	0.2794
	(0.0910)	(0.2058)	(0.0004)	(0.0004)	(0.3515)	(0.6398)
Amount received × clustering coefficient	-0.2918***	-0.7596***	-0.0028***	-0.0029***	-0.3899	-1.0140**
	(0.0742)	(0.1594)	(0.0004)	(0.0004)	(0.2492)	(0.4404)
Normalized degree	1.0236***	2.3044***	0.0656***	0.0905***	3.8504***	6.7114***
	(0.0710)	(0.1586)	(0.0012)	(0.0014)	(0.3725)	(0.6468)
Clustering coefficient	-0.1237**	-0.4350***	-0.0438***	-0.0636***	1.6890***	2.1104***
	(0.0519)	(0.1101)	(0.0010)	(0.0012)	(0.2706)	(0.4650)
Group size	Y	Y	Y	Y	Y	Y
Stratum fixed effect	Y	Y	Y	Y	Y	Y
No. of observations	7,266,446	7,266,446	7,266,446	7,266,446	1,060,746	1,370,741
Adjusted R^2	0.0400	0.0403	0.0260	0.0308	0.1524	0.1102

Note: The dependent variable (DV) for Columns (1) and (2) is the amount sent within the respective timeframe. It is coded as zero for those who do not send red packets. The DV in Columns (3) and (4) is the dummy variable for sending red packets. The DV in Columns (5) and (6) is the amount conditioning on sending red packets. Marginal effects are reported. Standard errors clustered at the group and user level are in parentheses. *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.

Table 6 Effect of average normalized degree in groups

	Overall		Extensive		Intensive	
	10 min	24 h	10 min	24 h	10 min	24 h
	(1)	(2)	(3)	(4)	(5)	(6)
Amount received	0.2165***	0.4092***	0.0062***	0.0062***	0.0144	0.1839
	(0.0578)	(0.1305)	(0.0003)	(0.0003)	(0.2024)	(0.3737)
Amount received × avg normalized degree	-0.0902	-0.3313	-0.0046***	-0.0045***	-0.0121	-0.5867
	(0.0868)	(0.2035)	(0.0004)	(0.0004)	(0.2983)	(0.5848)
Avg normalized degree	0.8661***	1.7084***	0.0184***	0.0192***	4.7967***	7.1958***
	(0.0806)	(0.1819)	(0.0019)	(0.0022)	(0.4218)	(0.7421)
Group size	Y	Y	Y	Y	Y	Y
Stratum fixed effect	Y	Y	Y	Y	Y	Y
No. of observations	7,266,446	7,266,446	7,266,446	7,266,446	1,060,746	1,370,741
Adjusted R^2	0.0397	0.0399	0.0239	0.0272	0.1523	0.1100

Note: The dependent variable (DV) for Columns (1) and (2) is the amount sent within the respective timeframe. It is coded as zero for those who do not send red packets. The DV in Columns (3) and (4) is the dummy variable for sending red packets. The DV in Columns (5) and (6) is the amount conditioning on sending red packets. Marginal effects are reported. Standard errors clustered at the group and user level are in parentheses. *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.

We find that although there is no significant overall impact of group network structure on gift contagion, the interaction effect between the amount received and the average normalized degree is negative and significant for the extensive margin. In Columns (3) and (4) of Table 6, the interaction term for "Amount received avg normalized degree" is negative and significant (10 minutes: 0.0046, $p < 0.01$; 24 hours: 0.0045, $p < 0.01$), although there is no significant interaction effect for overall effects or intensive margins. We also examine the impact of overall clustering (Jackson 2010) and find similar results. The detailed analyses are reported in *Appendix D.2*.

Finally, we examine the impact of receiving gifts on network dynamics. We change the dependent variable in Eq. (1) to the number of within-group edges added by a user after the user receives a red packet. Figure 7 presents the results, where the x-axis indicates different time intervals and the y-axis represents the marginal effect of the amount received (in CNY) on the number of new friends added by the recipient within the group. On average, receiving 100 CNY encourages the recipient to add 0.055 friends within the group in the subsequent seven days ($p < 0.01$). Although this appears to be a small effect, it reflects how in-group gifts can foster in-group interactions through establishing new connections. In sum, our findings suggest that in-groups gifts not only promote gift contagion, but can also encourage within-group interaction and strengthen group solidarity.

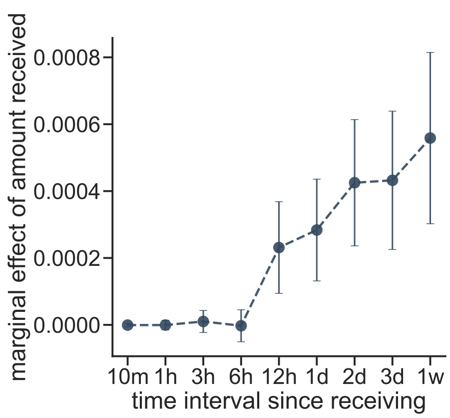

Figure 7 The marginal effect on the within-group edges added by the recipient within the group. Error bars are the 95% CIs.

6. Discussion

Taking advantage of the random assignment of red packet amounts to gift recipients, we leverage a natural experiment to quantify the strength of gift contagion within online groups. We document the presence of gift contagion and further find that the overall effect is driven primarily by the extensive margin, i.e., receiving red packets encourages more users to send packets. The degree of gift contagion varies across different time periods and various groups. Moreover, we find evidence of a group norm whereby the luckiest draw recipients are expected to take the lead in sending the first subsequent red packet. Regarding the moderating effect of in-group social networks, we find that the higher a user's clustering coefficient is, the less susceptible she is to gift contagion. Additionally, there is a significantly negative interaction effect for the extensive margin between the amount received and how tightly knit a group network is. Overall, our results, especially the analyses for the extensive and intensive margins, deepen our understanding of the social phenomenon of gift contagion.

Our study has important managerial implications. First, online group chats facilitate communication and coordination, but the virtual format may pose challenges to establishing group solidarity. Our results show that receiving larger amounts not only promotes the recipient to send more gifts subsequently, but also encourages the recipient to add more friends within the group. These results offer insights into how one might utilize online gift giving to foster social bonds within both online groups and offline groups.

Moreover, because of the popularity of online gifts and online red packets across different platforms,[15] our heterogeneity analyses offer insights into how to leverage gift contagion to promote the adoption of online gifts. Because of the stronger gift contagion that occurs during festival periods, we advise that marketing campaigns be conducted during those periods. In addition, since we find that gift contagion is stronger in groups of relatives, platforms are advised to make additional efforts to improve the gift design for relatives and family members, which may further promote the adoption of online gifts through these social relationships. Finally, the finding that the strength of gift contagion varies with social network characteristics helps us understand whom the marketing campaigns should be concentrated on gift production promotion.

There are several possible future directions based on our study. First, it would be interesting to examine how receiving red packets affects other types of user behaviors, such as group communication and liking others' feeds. Second, due to data constraints, we are not able to disentangle which mechanism, such as reciprocity or fairness concern, is the main driver for our observed gift contagion. Therefore, carefully design experimental studies are needed for future work to investigate the primary mechanism. Finally, as we are analyzing online gift contagion in East Asian culture, it would be interesting to explore whether our results can be generalized to offline settings or other culture groups.

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[15] Examples of this include Pinduoduo, the largest group buying platform in China; Alipay, the largest online payment platform in China; and other Asian bank apps such as DBS Bank and OCBC Bank in Singapore.

References

Aral S, Muchnik L, Sundararajan A (2009) Distinguishing influence-based contagion from homophily-driven diffusion in dynamic networks. *Proceedings of the National Academy of Sciences of the United States of America* 106(51):21544–21549.

Aral S, Walker D (2012) Identifying influential and susceptible members of social networks. *Science* 337:337–341.

Athey S, Imbens GW (2017) The econometrics of randomized experiments. *Handbook of Economic Field Experiments*, volume 1, 73–140 (Elsevier).

Backstrom L, Huttenlocher D, Kleinberg J, Lan X (2006) Group formation in large social networks: membership, growth, and evolution. *Proceedings of the 12th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 44–54 (ACM).

Bloom N, Liang J, Roberts J, Ying ZJ (2015) Does working from home work? evidence from a chinese experiment. *The Quarterly Journal of Economics* 130(1):165–218.

Bolton GE, Ockenfels A (2000) Erc: A theory of equity, reciprocity, and competition. *American Economic Review* 90(1):166–193.

Bolton GE, Ockenfels A (2006) Inequality aversion, efficiency, and maximin preferences in simple distribution experiments: comment. *American Economic Review* 96(5):1906–1911.

Bond RM, Fariss CJ, Jones JJ, Kramer AD, Marlow C, Settle JE, Fowler JH (2012) A 61-million-person experiment in social influence and political mobilization. *Nature* 489(7415):295.

Bott KM, Cappelen AW, Sørensen EØ, Tungodden B (2020) You've got mail: A randomized field experiment on tax evasion. *Management Science* 66(7):2801–2819.

Brynjolfsson E, Horton JJ, Ozimek A, Rock D, Sharma G, TuYe HY (2020) Covid-19 and remote work: An early look at us data. Technical report, National Bureau of Economic Research.

Cao C, Li SX, Liu TX (2020) A gift with thoughtfulness: A field experiment on work incentives. *Games and Economic Behavior* 124:17–42.

Charness G, Rabin M (2002) Understanding social preferences with simple tests. *The Quarterly Journal of Economics* 117(3):817–869.

Chen Y, Li SX (2009) Group identity and social preferences. *American Economic Review* 99(1):431–57.

Christakis NA, Fowler JH (2007) The spread of obesity in a large social network over 32 years. *New England Journal of Medicine* 357(4):370–379.

Cialdini RB, Goldstein NJ (2004) Social influence: Compliance and conformity. *Annual Review of Psychology* 55:591–621.

Efron B (1992) Bootstrap methods: Another look at the jackknife. *Breakthroughs in Statistics*, 569–593 (Springer).

Feldman DC (1984) The development and enforcement of group norms. *Academy of Management Review* 9(1):47–53.

Gächter S, Nosenzo D, Sefton M (2013) Peer effects in pro-social behavior: Social norms or social preferences? *Journal of the European Economic Association* 11(3):548–573.

Holland PW, Leinhardt S (1971) Transitivity in structural models of small groups. *Comparative Group Studies* 2(2):107–124.

Holton JA (2001) Building trust and collaboration in a virtual team. *Team Performance Management: An International Journal* 7(3/4):36–47.

Hossain T, Li KK (2014) Crowding out in the labor market: A prosocial setting is necessary. *Management Science* 60(5):1148–1160.

Imai K, King G, Stuart EA (2008) Misunderstandings between experimentalists and observationalists about causal inference. *Journal of the Royal Statistical Society: Series A* 171(2):481–502.

Imbens GW, Rubin DB (2015) *Causal Inference in Statistics, Social, and Biomedical Sciences* (Cambridge University Press).

Jackson MO (2010) *Social and Economic Networks* (Princeton University Press).

Kernan WN, Viscoli CM, Makuch RW, Brass LM, Horwitz RI (1999) Stratified randomization for clinical trials. *Journal of Clinical Epidemiology* 52(1):19–26.

Kizilcec RF, Bakshy E, Eckles D, Burke M (2018) Social influence and reciprocity in online gift giving. *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*, 126 (ACM).

Liu S, Zhang Y, Chen L, Guo L, Yu D (2015) Enterprise wechat groups: Their effect on work-life conflict and life-work enhancement. *Frontiers of Business Research in China* 9(4):516.

Liu TX, Yang J, Adamic LA, Chen Y (2014) Crowdsourcing with all-pay auctions: A field experiment on taskcn. *Management Science* 60(8):2020–2037.

Luo Y (2008) The changing chinese culture and business behavior: The perspective of intertwinement between guanxi and corruption. *International Business Review* 17(2):188–193.

Markovsky B, Lawler EJ (1994) A new theory of group solidarity 11:113–137.

Marsden PV (2002) Egocentric and sociocentric measures of network centrality. *Social Networks* 24(4):407–422.

Mauss M (2002) *The gift: The Form and Reason for Exchange in Archaic Societies* (Routledge).

McPherson M, Smith-Lovin L, Cook JM (2001) Birds of a feather: Homophily in social networks. *Annual Review of Sociology* 27(1):415–444.

Newman M, Barabasi AL, Watts DJ (2006) *The Structure and Dynamics of Networks* (Princeton University Press).

Nowak MA, Roch S (2007) Upstream reciprocity and the evolution of gratitude. *Proceedings of the Royal Society B: Biological Sciences* 274(1610):605–610.

Park N, Kee KF, Valenzuela S (2009) Being immersed in social networking environment: Facebook groups, uses and gratifications, and social outcomes. *Cyberpsychology & behavior* 12(6):729–733.

Pearl J (2009) *Causality* (Cambridge University Press).

Qiu J, Li Y, Tang J, Lu Z, Ye H, Chen B, Yang Q, Hopcroft JE (2016) The lifecycle and cascade of wechat social messaging groups. *Proceedings of the 25th International Conference on World Wide Web*, 311–320 (ACM).

Seinen I, Schram A (2006) Social status and group norms: Indirect reciprocity in a repeated helping experiment. *European Economic Review* 50(3):581–602.

Shalizi CR, Thomas AC (2011) Homophily and contagion are generically confounded in observational social network studies. *Sociological Methods & Research* 40(2):211–239.

Stuart EA (2010) Matching methods for causal inference: A review and a look forward. *Statistical Science* 25(1):1.

Tajfel H, Turner JC, Austin WG, Worchel S (1979) An integrative theory of intergroup conflict. *Organizational Identity: A Reader* 56–65.

Ugander J, Backstrom L, Marlow C, Kleinberg J (2012) Structural diversity in social contagion. *Proceedings of the National Academy of Sciences* 109(16):5962–5966.

Veinott ES, Olson J, Olson GM, Fu X (1999) Video helps remote work: Speakers who need to negotiate common ground benefit from seeing each other. *Proceedings of the SIGCHI conference on Human Factors in Computing Systems*, 302–309.

Wang CL, Siu NY, Barnes BR (2008) The significance of trust and renqing in the long-term orientation of chinese business-to-business relationships. *Industrial Marketing Management* 37(7):819–824.

Watts DJ, Strogatz SH (1998) Collective dynamics of ‘small-world’ networks. *Nature* 393(6684):440.

Wheeler L (1966) Toward a theory of behavioral contagion. *Psychological Review* 73(2):179.

Yamagishi T, Cook KS (1993) Generalized exchange and social dilemmas. *Social Psychology Quarterly* 235–248.

Yuan Y, Altenburger K, Kooti F (2021) Causal network motifs: Identifying heterogeneous spillover effects in A/B tests. *Proceedings of the Web Conference 2021*, 3359–3370.