The Spread of Virtual Gifting in Live Streaming: The Case of Twitch

Ji Eun Kim[1], Seura Ha[1], Sangmi Kim[1, 2], Libby Hemphill[1]
[1]School of Information, University of Michigan
[2]School of Education and Human Development, University of Miami
jieunkim@umich.edu, seura@umich.edu, sangmik@umich.edu, libbyh@umich.edu

Abstract

This paper examines how gifting spreads among viewers on Twitch, one of the largest live streaming platforms worldwide. On Twitch, users can purchase gift subscriptions for other viewers and often opt for community gifting, in which subscriptions are distributed to randomly selected viewers. Leveraging this random distribution as a natural experiment, we investigate the conditions under which gift recipients pay it forward to others. Our findings show that receiving a gift significantly increases the likelihood to pay it forward. This positive effect is amplified in single-recipient gifting events (i.e., one subscription is given to one individual per event) compared to mass distributions involving multiple recipients. Conversely, receiving a gift from a frequent gifter can attenuate the willingness to pay it forward. Finally, anonymous gifting has no significant influence on the spread of gifting. This research contributes to the literature on the spread of online prosocial behavior by providing robust empirical evidence and offers actionable insights for platform designers seeking to promote and sustain prosocial interactions in online communities.

Introduction

Gifting is a fundamental component of human society, studied extensively across diverse contexts and disciplines. In the digital age, this practice has evolved alongside information and communication technologies. Modern gifting and donation systems, which incorporate social media features, enable users to exchange gifts seamlessly, transcending temporal and geographical constraints. Moreover, these systems provide a rich data environment for researchers to investigate online gifting and donation patterns at scale. Understanding how people exchange gifts and make donations online is crucial for sustaining large-scale, active gifting systems, including crowdfunding platforms (Sisco and Weber 2019), live streaming services (Chaudhry, Wang, and Ouyang 2024), and gift exchange systems within social media (Kizilcec et al. 2018) and online gaming (Bisberg et al. 2022).

This paper investigates the spread of gifting in live streaming, with a specific focus on Twitch. Live streaming has become a global phenomenon in online entertainment, facilitating novel forms of user engagement through real-time communication. We selected Twitch as our research site because its massive global viewership and data accessibility provide an ideal environment for the systematic observation of user interactions at scale.

Viewer engagement on Twitch is primarily categorized into three modalities: commenting, donating, and gifting. First, viewers can use the integrated chat interface to post text messages and emotes for real-time communication with the streamer and other viewers. As a zero-cost activity, commenting is the most basic form of user engagement. Second, viewers may provide financial support with streamers in various ways, such as subscribing to channels, purchasing memberships, or sending virtual currency donations. While access to live content and chat is generally free, viewers often provide monetary rewards as a form of appreciation for the streamer's content. A prominent method of donation involves "Bits," the platform's virtual currency; these are purchased at an approximate rate of 100 Bits per USD. Viewers can post messages accompanied by a specific quantity of Bits they wish to donate. Although Bits are intended for donations to streamers, Twitch also enables gift subscriptions, allowing viewers to purchase channel memberships for others. Recipients of these gifts can unlock several premium affordances, such as access to channel-specific emotes and an ad-free viewing experience. For the remainder of this paper, we define "gift" specifically as a gift subscription given by one viewer to another in the chat room, whereas "donation" refers to any monetary transfer from a viewer to a streamer. Gifters may target specific individuals or authorize the platform to distribute subscriptions randomly among non-subscribers in the chat room (see Figure 1). Our study specifically focuses on community gifting where recipients are randomly selected by the platform. Additionally, the platform provides an option for anonymous gifting.

Gifting on Twitch represents a unique form of digital altruism that generates significant positive externalities: it provides recipients with premium access at no personal expense while simultaneously supporting the streamer's financial sustainability. While practitioners strive to design features that promote such behaviors (Grüning et al. 2024; Harvey, Golightly, and Smith 2014), they often face significant challenges because users frequently perceive a diminished obligation to contribute in large-scale, anony-

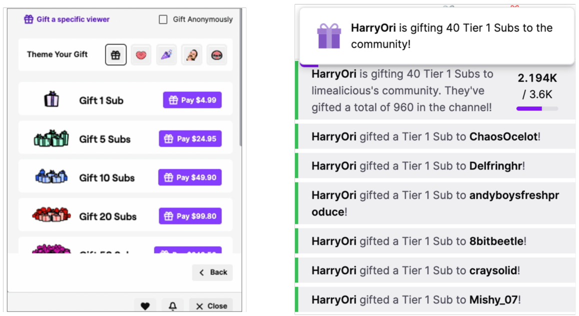

Figure 1: The Twitch gifting interface allows users to target specific individuals or authorize the platform to distribute gift subscriptions to randomly selected individuals in the chat room (Left). The system-generated announcement reveals the gifter and the recipients, noting that the gifter gave 40 gift subscriptions to the community. Additionally, the message displays the cumulative number of subscriptions gifted by the gifter to the channel, which is 960 in this example (Right). Images were retrieved from the Twitch website (Twitch 2024a,b).

mous online spaces. This challenge is exacerbated by a paucity of empirical benchmarks regarding how positive interactions scale in digital environments. Unlike antisocial behaviors, which have been extensively documented, the mechanisms that drive prosocial contagion remain relatively under-researched (Dörr et al. 2025), particularly in environments where prosocial behavior incurs personal economic costs. By delineating the conditions that catalyze the pay-it-forward mechanism, we aim to provide a timely and essential framework for implementing effective interventions that can foster sustainable prosociality.

To identify the drivers of behavioral contagion in virtual gifting, we analyze a large-scale dataset of 8,068 Twitch streams. Leveraging the platform's algorithmic distribution of gift subscriptions as a natural experiment, we employ mixed-effects logistic regression to estimate the causal impact of gift-receiving on subsequent prosocial behavior. Our results show that gift recipients are significantly more likely to pay it forward compared to non-recipients. This effect is amplified when the gifting event has a single recipient (i.e., one subscription is given to one individual). Conversely, receiving a gift from a frequent gifter dampens the impulse to reciprocate. This study contributes to the literature on online prosociality by providing empirical evidence for generalized reciprocity in digital environments. We also offer actionable insights for platform designers seeking to foster prosocial behavior within online communities. Specifically, we suggest design strategies such as modulating the level of individualized attention directed toward beneficiaries and the social visibility of gifting activities.

Related Work

Gifting and Contagion of Prosocial Behavior

Gifting is a foundational form of prosocial behavior, defined as "any action that benefits others, often at a personal cost to the actor" (Thielmann, Spadaro, and Balliet 2020). Because voluntary gifting entails a material or opportunity cost for the giver, extensive research has investigated its underlying psychological and social motivations. These drivers include relational maintenance and bond formation (Ruth, Otnes, and Brunel 1999; Sherry Jr 1983); symbolic communication used to signal social, economic, or educational status (Camerer 1988; Schwartz 1967); and identity signaling or self-representation (Batson and Powell 2003). Furthermore, gifting is often driven by hedonic and eudaimonic values, where the act of giving generates rewards such as pleasure, self-fulfillment, and improved well-being (Anik et al. 2009; Lai et al. 2020; Wolfinbarger and Yale 1993).

While the motivations of givers have been extensively documented, the reactions of gift recipients have received relatively less scholarly attention (Lampinen et al. 2013). However, a deeper understanding of these reactions is essential for elucidating the underlying mechanisms of prosocial contagion. Prior research suggests that beneficiaries are inclined toward either direct reciprocity (repaying the original giver) or generalized reciprocity (paying it forward to others) (Skågeby 2010; Tsvetkova and Macy 2014). These subsequent prosocial acts are primarily mediated by two distinct emotional responses: indebtedness and gratitude (Peng, Nelissen, and Zeelenberg 2018; Schaumberg and Flynn 2009). Specifically, feelings of indebtedness may compel recipients to reciprocate to alleviate the psychological discomfort or anxiety associated with an unfulfilled social obligation (Nahum-Shani, Bamberger, and Bacharach 2011). On the other hand, gratitude has been shown to broaden prosocial tendencies, fostering a desire to pay it forward to the community (Bartlett and DeSteno 2006; Nowak and Roch 2007).

Generalized Reciprocity in Online Communities

While the theoretical foundations of prosocial behavior were established within the context of offline communities, recent scholarship has expanded to encompass digital environments. Online platforms provide unique sociotechnical settings that facilitate the solicitation, acquisition, and public observation of gift exchanges through integrated interaction features (Bisberg et al. 2022; Kwon et al. 2017). Some scholars argue that virtual gifting lacks the emotional intimacy and physical effort of offline exchanges, which can lower a gift's perceived value (Kwon et al. 2017; Shmargad and Watts 2016). However, digital affordances such as real-time messaging, commenting, and automated distribution tools enable the seamless solicitation of support and the rapid spread of prosocial behavior.

While these features lower the barriers to engaging in prosocial behavior, researchers have noted that individuals often perceive a diminished obligation to contribute in expansive online environments compared to smaller, cohesive offline groups (Tsvetkova and Macy 2015). In digital spaces, prosociality often diffuses through generalized reciprocity, which involves paying the benefit forward to the community rather than to the original benefactor (Lampinen et al. 2013). However, the structural characteristics of many online platforms, including weak social cohesion, pervasive anonymity, and the difficulty of sanctioning free-riders, allow recipients to bypass these informal obligations without cost (Dubreuil 2008). Consequently, significant uncertainty remains regarding the spread of prosociality in digital contexts, underscoring the need to investigate the specific mechanisms and environmental conditions that either catalyze or inhibit the propagation of prosocial behavior.

Gifting in Live Streaming

Live streaming provides a large-scale, dynamic environment for observing social patterns and behavioral contagion within interpersonal interactions among users. To date, researchers have primarily focused on viewer-to-streamer donations. One research trajectory examines the conditions that facilitate donations. For instance, viewers who actively comment and recommend streams to other users are more likely to donate to streamers (Yu et al. 2018). Another research indicates that viewers donate to streamers for a variety of reasons: to reward entertaining or educational content, to express affinity for a streamer's personality, to facilitate direct interaction, or to support streamers dedicated to social causes (Wohn, Freeman, and McLaughlin 2018). Other studies emphasize the role of streamer characteristics in driving greater financial support from viewers. Specifically, streamer traits such as perceived trustworthiness and attractiveness foster parasocial emotional attachment, which significantly mediates donation decisions (Li and Peng 2021). Furthermore, recent work suggests that streamer gender and the presence of active moderation interact to influence engagement and monetization (Wolff and Shen 2024). Notably, the positive impact of moderation on donation volume appears significantly stronger for female streamers.

While existing scholarship focuses on viewer-to-streamer donations, empirical research on viewer-to-viewer gifting remains sparse. Addressing this gap is critical to understanding the gifting dynamics that underpin community growth and long-term user retention. Although Chaudhry, Wang, and Ouyang (2024) observed that viewer-to-viewer gifting triggers generalized reciprocity, their work does not delineate the conditions or mechanisms that catalyze the diffusion of gifting.

Research Questions

Based on the literature review, we identified several gaps warranting further investigation. While prior research has primarily focused on the conditions facilitating viewer-to-streamer donations, the dynamics governing the spread of gifting among viewers remain underexplored. Furthermore, while the existence of behavioral contagion has been noted in the context of community gifting on Twitch (Chaudhry, Wang, and Ouyang 2024), the moderating influence of specific gift attributes on recipient behavior has yet to be systematically examined. To address this, our analysis incorporates a set of gift-related variables. In the following paragraphs, we elaborate on the theoretical significance of these factors and present our research questions.

To our knowledge, the only empirical investigation into peer-to-peer gifting contagion in live streaming focused on Twitch music streams, which represent a small fraction of the platform's overall traffic (Chaudhry, Wang, and Ouyang 2024; Twitch 2025). While Twitch has expanded into various non-gaming categories, the platform remains historically gaming-centric. Given that video game streams constitute the vast majority of Twitch content, it is essential to examine whether generalized reciprocity persists across these dominant content types. We therefore formulate the following research question:

- **RQ1**: Do gift recipients pay it forward by gifting subscriptions to others?

Gifting is frequently conceptualized as a strategic activity designed to cultivate social capital, build reputations, or signal status (Berman and Silver 2022). Consequently, most donors prefer public recognition; for example, research on the GoFundMe platform reports that only approximately 20% of contributions in its dataset were made anonymously (Sisco and Weber 2019). Because anonymous gifting precludes the accumulation of social capital or the public advertisement of prosociality, it is often viewed as purely altruistic (Siem and Stürmer 2018; Tsang and Martin 2019). Previous research suggests that when recipients perceive support as unconditional and genuinely motivated, they experience heightened gratitude, which serves as a psychological catalyst for direct or generalized reciprocity (Ma, Tunney, and Ferguson 2014). It is therefore plausible that gifts from anonymous gifters amplify recipient gratitude by removing the expectation of a social return and strengthen the impulse to pay it forward. We thus propose the following question:

- **RQ2**: How does gifter anonymity influence the likelihood to pay it forward?

A critical factor in prosocial exchange is whether a gift is directed toward a single individual or whether multiple gifts are distributed across a group. On Twitch, gifters can authorize the platform to randomly select recipients, in either case of gifting a single subscription to one viewer or triggering a mass distribution to multiple viewers simultaneously—an event informally called a "sub bomb." Individuals who are the sole beneficiaries are more likely to reciprocate than beneficiaries who receive support as part of a group (Kolyesnikova and Dodd 2008). This is because they perceive a higher degree of individualized attention, which amplifies gratitude and social obligation to reciprocate. Also, gifts perceived as exclusive are often assigned a higher subjective value, making the recipients more inclined to reciprocate (Tsang 2021). Conversely, in sub bomb scenarios, the pressure to reciprocate may be subject to diffusion of responsibility, as recipients can blend into the crowd and feel less personally accountable for paying the benefit forward (Tsvetkova and Macy 2015). To explore this dynamic on Twitch, we ask:

- **RQ3**: How does the number of recipients in a gifting event (receiving a gift as the sole recipient versus being part of a sub bomb event) influence the likelihood to pay it forward?

Finally, we examine whether a gifter's prior gifting history influences the recipient's likelihood to pay it forward. As Twitch explicitly signals a user's standing by displaying their cumulative gifting history during gift announcements (see Figure 1), this community-level social cue serves as a proxy for status, reflecting a gifter's long-term financial commitment to the channel. Through these real-time notifications, viewers can distinguish between frequent gifters (those with a high volume of prior contributions) and infrequent gifters (those with minimal prior gifting activity). Previous research suggests that individuals often imitate the prosocial actions of high-status figures to align themselves with a higher social rank (Kumru and Vesterlund 2010). This dynamic is also observed in Twitch chat rooms; viewers often mimic the commenting behavior of influential users like moderators, adopting similar patterns of spamming, questioning, and emote usage (Seering, Kraut, and Dabbish 2017). Conversely, average users may refrain from emulating high-status actors if they feel overshadowed or perceive an inability to compete within the established hierarchy. In live streaming contexts, prior research suggests that average viewers may feel their smaller contributions are insignificant when compared to high-status whales, leading to a decrease in donation activity (Luo et al. 2024). Given these competing predictions, we investigate:

- **RQ4**: How does a gifter's gifting history (frequent gifter versus infrequent gifter) influence the likelihood to pay it forward?

Data and Methods

Data

We used the Twitch API[1] to collect user metadata, stream metadata, and chat logs. Our initial collection comprised a random sample of 18,657 English-language streams broadcast during the first two weeks of September 2022. Consistent with prior findings that viewership on Twitch follows a power-law distribution (Deng et al. 2015), our raw dataset revealed significant skewness: 18% of streams recorded no chat activity, while only 55% exceeded a threshold of 50 chat messages. As our analysis focuses on interpersonal gifting dynamics, we excluded low-activity streams to ensure sufficient interaction intensity. The resulting dataset consists of 8,068 streams, each meeting the inclusion criteria of at least 10 unique users and a message volume between 50 and 10,000. This resulted in a final dataset of 956,328 unique users and 11,272,948 messages (see Table 1 for descriptive statistics). It should be noted that the API does not capture lurkers (i.e., viewers who watch the stream without participating in the chat); thus, our sample is limited to chatters, which we define as viewers who posted at least one message in the chat. Within this subset, the mean number of chatters per stream is 138.91, while the median is 45. Our dataset does not contain any personally identifiable information, and results are reported only in aggregate to ensure ethical compliance.

Bot Detection. Most Twitch streamers employ a combination of human moderators and bots to manage chat interactions. While the Twitch API flags all moderator accounts, it does not distinguish between human moderators and bots. These two groups exhibit divergent behavioral patterns: human moderators engage discursively at their discretion, whereas bots typically broadcast predefined, periodic messages (e.g., scheduled event reminders). Additionally, bots generate event-driven responses, such as automated gratitude for donations. They can post multiple automated messages rapidly, often with better grammar. To ensure data integrity, we implemented a multi-stage bot identification process. First, we cross-referenced usernames against a crowd-sourced repository of known Twitch bots[2], identifying an initial set of 201 bots. We then manually audited these results to define a heuristic profile based on bot-specific characteristics (e.g., the "bot" substring in usernames, presence across multiple concurrent streams). Applying these criteria to the remaining moderator accounts, we identified additional bots, resulting in a final count of 717 unique bots.

User type	Number of users	Number of messages
Chatter	916,139 (95.80%)	9,020,657 (80.02%)
Moderator	33,591 (3.51%)	1,498,147 (13.29%)
Streamer	5,881 (0.61%)	116,091 (1.03%)
Bot	717 (0.07%)	638,053 (5.66%)
Total	956,328 (100%)	11,272,948 (100%)

Table 1: Dataset overview.

Descriptive Statistics. Of the 8,068 streams analyzed, 47.15% (3,804) contained at least one gifting event. As illustrated in Figure 1, an automated announcement is broadcast in the chat interface immediately following a gift transaction. This notification details the gifter's cumulative number of gifts given to the channel and the number of gift subscriptions provided in the current event. Our dataset identifies 65,732 total gift subscriptions distributed across 15,653 discrete gifting events. While 10.44% (6,863) were directed to specific recipients, the vast majority (87.17%; 57,301) were distributed randomly to non-subscribing viewers; the remaining 2.39% (1,568) originated from anonymous gifters. We distinguish between single-recipient gifting (one subscription given to one person) and multiple-recipient gifting (multiple subscriptions distributed among multiple recipients simultaneously in a single event), accounting for 9.29% (6,106) and 90.71% (59,626) of the total number of gift subscriptions, respectively. The dataset includes 11,898 unique gifters and 64,691 unique recipients. Among streams featuring gifting activity, the median number of subscriptions provided is 7.

Natural Experiment Design

The Twitch gifting interface provides a unique opportunity to study behavioral contagion through a natural experiment. On Twitch, gifters may either target specific individuals or allow the platform to distribute gift subscriptions to viewers chosen at random. In the latter case, an algorithmic pro-

[1]https://dev.twitch.tv/docs/api/

[2]https://twitchbots.info/

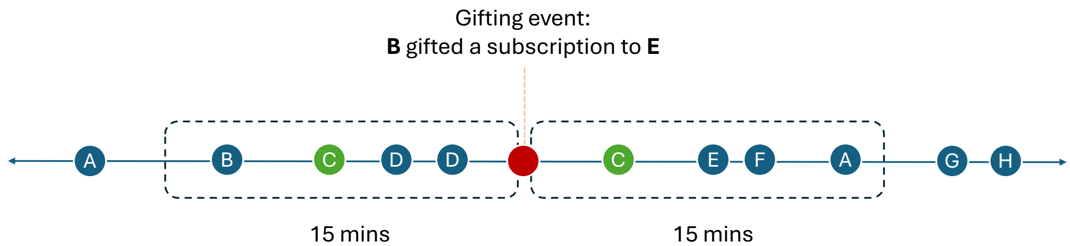

Figure 2: Identification of treatment and control groups. Blue and green nodes represent messages from non-subscribing and subscribing viewers, respectively; letters within nodes indicate specific chatters. The red node denotes a platform-generated system message regarding the focal gifting event. In this example, user E is the treated subject (recipient), while users A, D, and F serve as the control group. The control group consists of non-subscribers active in the chat within a $\pm$15-minute temporal window around the gifting event. This design facilitates a within-stream, within-event comparison, controlling for stream-specific context. These localized pairs were aggregated across 1,808 streams to form the final analytical dataset.

Variable	**Treatment** Mean (SD)	**Control** Mean (SD)	t-statistic	p-value	Cohen's d
Number of comments	3.840 (10.55)	3.617 (10.03)	1.640	0.101	0.022
Mean comment length	2.812 (4.12)	3.085 (4.12)	-5.139	$< .001$	-0.066
User tenure (in years)	4.732 (3.10)	3.772 (3.05)	23.955	$< .001$	0.312
Proportion of toxic commenters	0.002 (0.05)	0.003 (0.05)	-0.725	0.469	-0.009
Proportion of donors who donated to streamers	0.005 (0.07)	0.005 (0.07)	-0.079	0.937	-0.001
N	6,130	255,943			

Table 2: Balance table. Results are based on Welch's t-test to account for unequal variances and group sizes.

cess allocates gifts according to the following priority order: non-subscribing viewers, followers, and moderators, while systematically excluding trolls (Twitch 2024). We leverage this algorithmic distribution to examine the causal influence of gift-receiving on a recipient's subsequent behavior. Because these gifts are randomly distributed via an external algorithm in most cases rather than deliberate interpersonal selection, they approximate a random treatment assignment. Our analysis omits targeted gifting in which a gifter manually designates a specific recipient. Within this framework, recipients of randomly distributed gifts constitute the *treatment group*, while non-recipients who are otherwise comparable serve as the *control group*. By "comparable," we mean that the control users can serve as a counterfactual representing what might have happened to the treated users if they had not been randomly selected to receive gifts. To ensure a valid counterfactual, we selected control users from the same *gifting event* context, thereby accounting for temporal and environmental confounders specific to a given stream.

Figure 2 illustrates the identification of treated and control users within a sample gifting event. In this example, user E is assigned to the treatment group upon receiving a gift subscription from user B. To construct the control group, we employed a 30-minute observation window spanning 15 minutes before and after the event to identify non-recipients who posted at least one chat message in the chat, excluding the gifter (B). Since treated users were all non-subscribers before the gifting event, we restricted the control group to users who were not current subscribers at the time of the event to ensure comparability. Consequently, non-subscribing users A, D, and F were selected as the counterfactual. Note that user C was excluded from the analysis because the user was already a subscriber at the time of the gifting event.

While prior research has conceptualized community gifting on Twitch as an exogenous shock, concerns remain regarding potential endogeneity arising from the platform's algorithm for selecting random recipients (Chaudhry, Wang, and Ouyang 2024). To mitigate these concerns, Chaudhry, Wang, and Ouyang (2024) restricted their sample by excluding bots and users who had already subscribed before the gifting event. Adopting a similar strategy, we restricted our analysis to non-subscribing viewers and excluded streamers, moderators, and bots. This filtering process yielded a final dataset of 4,127 gifting events across 1,808 streams. The resulting analytical sample comprises 6,130 treated users and 255,943 control users.

We conducted balance tests to assess whether the treatment and control groups were statistically comparable prior to the gifting event. We evaluated several pre-treatment covariates, including the number of comments, mean comment length, user tenure, and the proportions of toxic commenters and donors. All variables in Table 2 represent aggregated user-level statistics within a stream prior to the gifting event. The number of comments was defined as the total count of comments posted by a user in a stream before the gifting event, while mean comment length was calculated by tokenizing messages via whitespace. User tenure denotes the interval between the user's account creation and the stream timestamp, represented in years. We used the Perspective API[3] to identify toxic commenters. For each user, we computed a mean toxicity score as the average toxicity score across all messages they posted. A user was classified as toxic if this mean score was at least 0.7, consistent with established guidelines for social science research.[4] Finally, the proportion of donors is the share of users in each group who had previously donated to the streamer.

Table 2 indicates that while three covariates are well-balanced, statistically significant differences exist in mean comment length and user tenure. Although the Cohen's d effect size for comment length is negligible, the disparity in user tenure is more pronounced. Although Twitch describes the community gifting mechanism as random, this imbalance suggests potential deviations from perfect randomness. This may stem from undisclosed algorithmic weighting (e.g., prioritizing long-standing community members) or from our exclusion of lurkers. Since our sample is restricted to chatters, this filtering may have disproportionately omitted less-tenured users from the treatment group, thereby contributing to the imbalance in tenure. The inherent rarity of gifting events also creates a substantial imbalance in group size (N_T = 6,130; N_C = 255,943), which can amplify baseline variances. To account for these imbalances, we include both mean comment length and user tenure as control variables in our models. We further confirmed the robustness of our results using propensity score matching to construct well-balanced groups, with findings remaining consistent (see Appendix).

Identification Strategy

We employed a mixed-effects logistic regression framework, incorporating a random intercept for each stream to account for unobserved stream-level heterogeneity. This approach treats stream-specific factors that may systematically influence user behavior (e.g., community norms, streamer characteristics, audience size) as random effects. In addition, we utilized clustered standard errors at the stream level to ensure robust inference.

Our outcome variable is binary, indicating whether a user becomes a gifter in any stream within the dataset following a gifting event. Our models include several key predictors. The *Gift-receiving* variable indicates whether a user received a gift (1) or not (0). The *Anonymous gifting* variable represents whether the gift was from an anonymous gifter (1) or not (0). The *Single-recipient gifting* variable is an indicator of whether the gift was given to a single recipient (1) or was part of a sub bomb event (0). Based on a user's cumulative gifting history, we categorized users as either infrequent gifters (low-volume gifters) and frequent gifters (high-volume gifters). An *infrequent gifter* is defined as a gifter who falls below the 20th percentile of all gifters in the dataset, while a *frequent gifter* is someone above the 80th percentile. We specify four models to answer our research questions. These models evaluate the baseline effect of gift-receiving on pay-it-forward behavior and include interaction terms to analyze how specific gift attributes moderate the contagion of gifting.

Model 1 includes our primary predictor, *Gift-receiving*, in addition to *Mean comment length* and *User tenure* as user-level covariates. We include a random intercept $u_{j[i]}$ for stream j to which user i belongs. The model is specified as follows:

$$\begin{aligned}\mathrm{logit}(\Pr[PayItForward_i = 1]) = \beta_0 \\ + \beta_1 \cdot GiftReceiving_i \\ + \beta_2 \cdot CommentLength_i + \beta_3 \cdot UserTenure_i \\ + u_{j[i]}\end{aligned}$$

In this specification, $PayItForward_i$ is a binary indicator of whether user i engaged in pay-it-forward behavior. Our coefficient of interest, β_1, captures the effect of receiving a gift on the likelihood of paying it forward.

Model 2 incorporates the *Anonymous gifting* variable and its interaction term with *Gift-receiving*. The coefficient β_4 represents the main effect of the *Anonymous gifting* variable. The coefficient β_5 for the interaction term *Gift-receiving* $\times$ *Anonymous gifting* indicates how the effect of receiving a gift changes when the gift comes from an anonymous gifter, compared to receiving a gift from an identified gifter. The model is specified as follows:

$$\begin{aligned}\mathrm{logit}(\Pr[PayItForward_i = 1]) = \beta_0 \\ + \beta_1 \cdot GiftReceiving_i \\ + \beta_2 \cdot CommentLength_i + \beta_3 \cdot UserTenure_i \\ + \beta_4 \cdot AnonymousGifting_i \\ + \beta_5 \cdot GiftReceiving_i \cdot AnonymousGifting_i \\ + u_{j[i]}\end{aligned}$$

For a treated user i, $AnonymousGifting_i$ is a binary indicator equal to 1 if the gift was from an anonymous gifter; for a control user i, $AnonymousGifting_i$ is a binary indicator equal to 1 if the associated gifting event was initiated by an anonymous gifter.

Model 3 includes the *Single-recipient gifting* variable and its interaction with *Gift-receiving* to examine the effect of receiving a gift on paying it forward when the gift is given to a single recipient rather than as part of a sub bomb event. The model is specified as follows:

$$\begin{aligned}\mathrm{logit}(\Pr[PayItForward_i = 1]) = \beta_0 \\ + \beta_1 \cdot GiftReceiving_i \\ + \beta_2 \cdot CommentLength_i + \beta_3 \cdot UserTenure_i \\ + \beta_6 \cdot SingleRecipient_i \\ + \beta_7 \cdot GiftReceiving_i \cdot SingleRecipient_i \\ + u_{j[i]}\end{aligned}$$

In this specification, the variable $SingleRecipient_i$ takes the value of 1 if the gift was given to a single recipient in the associated event, and 0 otherwise.

[3]https://perspectiveapi.com/

[4]https://developers.perspectiveapi.com/s/about-the-api-score

Finally, Model 4 includes the *Infrequent Gifter* and *Frequent Gifter* variables, in addition to their respective interactions with *Gift-receiving*. The coefficients for these interaction terms identify how the effect of receiving a gift varies by the gifter's gifting history. The model is specified as follows:

$$
\begin{aligned}
\text{logit}(\Pr[PayItForward_i = 1]) = \beta_0 \\
+ \beta_1 \cdot GiftReceiving_i \\
+ \beta_2 \cdot CommentLength_i + \beta_3 \cdot UserTenure_i \\
+ \beta_8 \cdot InfrequentGifter_i + \beta_9 \cdot FrequentGifter_i \\
+ \beta_{10} \cdot GiftReceiving_i \cdot InfrequentGifter_i \\
+ \beta_{11} \cdot GiftReceiving_i \cdot FrequentGifter_i \\
+ u_{j[i]}
\end{aligned}
$$

$InfrequentGifter_i$ and $FrequentGifter_i$ are binary indicators denoting whether the gifter—associated with the gift for treated users or the gifting event for control users—was classified as an infrequent or frequent gifter, respectively.

Results

Table 3 presents the results from four model specifications, each including a random intercept to account for unobserved heterogeneity in baseline user behavior across different streams. Across all four models, the likelihood ratio test results confirmed that the mixed-effects specification provided a significantly superior fit, justifying the inclusion of stream-level random effects.

Model 1 shows that **gift recipients are significantly more likely to engage in future gifting compared to non-recipients** (b = 1.018, $p < 0.001$). This finding confirms the existence of a behavioral contagion effect, or a virtuous cycle of prosociality among viewers. The corresponding odds ratio (OR = 2.77) indicates that the odds of a recipient paying it forward are 2.77 times higher than those of non-recipients. In contrast, the intercept ($b = -5.925$, $p < 0.001$) indicates a very low baseline probability of future gifting among non-recipients.

In Model 2, our results reveal that **gifter anonymity does not exert a statistically significant influence on the likelihood of subsequent gifting** for either non-recipients (b = 0.154, p = 0.334) or recipients ($b = -0.055$, p = 0.911).

In Model 3, we examined whether receiving a gift as the sole beneficiary of a single-recipient event influences the likelihood of paying it forward. The interaction term (*Gift-receiving* $\times$ *Single-recipient gifting*) is positive and statistically significant (b = 0.550, $p < 0.05$), indicating that **the positive effect is significantly amplified in a single-recipient gifting event compared to a sub bomb event**. The calculated odds ratio (OR = 1.73) suggests that for recipients, the odds of becoming a gifter are 73% higher when receiving a gift from a single-recipient gifting event than when receiving a gift as part of a sub bomb.

Model 4 indicates that **gifts from infrequent gifters do not significantly influence future gifting behavior** for either non-recipients ($b = -0.118$, p = 0.271) or recipients (b = 0.277, p = 0.451). However, a distinct pattern emerges regarding frequent gifters. While their gifting does not impact non-recipients (b = 0.076, p = 0.389), it significantly dampens the reciprocity of recipients ($b = -0.565$, $p < 0.05$). The interaction term (*Gift-receiving* $\times$ *Frequent gifter*) yields an odds ratio of 0.57, indicating that **the pay-it-forward boost is significantly attenuated when the gift originates from a frequent gifter**. In other words, while receiving a gift generally increases the odds of reciprocity, this boost is reduced by approximately 43% when the gifter is a high-volume gifter.

Discussion

Main Findings

Understanding the spread of prosocial behavior is essential for cultivating sustainable and positive digital ecosystems. This study provides causal evidence for the spread of gifting on Twitch, identifying the specific conditions that catalyze this behavioral contagion. Gift recipients are more likely to pay it forward than non-recipients, indicating that merely observing gifting behavior is not sufficient to trigger gifting. This result aligns with the work of Tsvetkova and Macy (2014), suggesting that while observing prosociality may set a social norm, receiving a benefit is a far more potent driver of paying it forward than mere observation. Moreover, while previous research identified similar patterns within the niche context of Twitch music streams (Chaudhry, Wang, and Ouyang 2024), our findings demonstrate that this effect is robust across genres. By confirming these dynamics in video game streams, we establish the generalizability of gift contagion as a platform-wide social phenomenon rather than a genre-specific subculture.

We also estimated how specific gift attributes moderate the spread of gifting. First, our analysis reveals that anonymous gifting does not significantly contribute to the spread of gifting among Twitch viewers. One possible explanation is that anonymity may dilute the gifter's social presence, which weakens the interpersonal link required to trigger a reciprocal response.

Our findings indicate that Twitch viewers are significantly more likely to pay it forward after receiving a gift as the sole beneficiary of a gifting event. Although the monetary value of a subscription is identical whether it is gifted in a single-recipient gifting event or as part of a sub bomb, the perceived social value appears to be higher when the recipient is the sole beneficiary and receives individualized attention, rather than one of many recipients of mass-distributed gifts. This aligns with previous findings that gifts perceived as intentional and personalized elicit a greater sense of gratitude (Peng, Nelissen, and Zeelenberg 2018), which in turn leads to a tendency to reciprocate. Alternatively, the observed effect may be driven by the lowered barriers to behavioral mimicry because reciprocating a single gift is financially less demanding than replicating a mass sub bomb. Thus, being the sole recipient of a gifting event not only fosters deeper personal gratitude but also provide a more imitable and financially accessible pathway for paying it forward. Furthermore, when a gift is given to a single individual, it

	Model 1	Model 2	Model 3	Model 4
Intercept	−5.925***	−5.932***	−5.904***	−5.926***
	(0.076)	(0.076)	(0.078)	(0.079)
Gift-receiving	1.018***	1.021***	0.925***	1.103***
	(0.108)	(0.110)	(0.119)	(0.125)
Anonymous gifting		0.154		
		(0.159)		
Gift-receiving × Anonymous gifting		−0.055		
		(0.491)		
Single-recipient gifting			−0.111	
			(0.086)	
Gift-receiving × Single-recipient gifting			0.550*	
			(0.264)	
Infrequent gifter				−0.118
				(0.107)
Gift-receiving × Infrequent gifter				0.277
				(0.367)
Frequent gifter				0.076
				(0.088)
Gift-receiving × Frequent gifter				−0.565*
				(0.286)
Mean comment length	0.084***	0.084***	0.085***	0.085***
	(0.022)	(0.023)	(0.022)	(0.023)
User tenure	0.036	0.036	0.036	0.035
	(0.029)	(0.029)	(0.029)	(0.029)
Number of observations	262,073	262,073	262,073	262,073
AIC	15,251.62	15,254.70	15,250.99	15,253.05
BIC	15,304.01	15,328.03	15,324.32	15,347.34

Table 3: Mixed-effects logistic regression results. AIC and BIC refer to the Akaike information criterion and Bayesian information criterion, respectively. $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

minimizes the diffusion of responsibility that often occurs in group settings; the recipient cannot hide in the crowd and thus feels a heightened obligation to reciprocate.

Finally, while recipients are largely uninfluenced by gifts from infrequent gifters, gifts from frequent gifters dampen the contagion of gifting. This pattern is likely driven by diffusion of responsibility (Tsvetkova and Macy 2015) because recipients may perceive frequent gifters as the designated contributors of the community. If a gifter is known for high-volume, frequent contributions, a recipient may assume that the community's needs are already met, thereby reducing their own perceived obligation to contribute.

Implications

This study offers several theoretical and practical contributions, advancing the literature on online prosociality while providing evidence-based recommendations for platform designers. First, we shift the analytical focus from streamer-viewer interactions and parasocial relationships toward viewer-viewer interactions. Our work also adopts a robust causal inference framework to study online prosocial behavior. Establishing causal inference is challenging outside of laboratory settings. By leveraging Twitch's community gifting feature, we identified a natural experiment setting where gift-receiving occurs largely by chance. This approach, combined with highly granular log data, allowed us to make meaningful comparisons between gift recipients and non-recipients and provide a robust causal account of gift contagion.

Another contribution of this research is a shift in focus toward recipients' reactions, a dimension of prosocial exchange that remains underexplored relative to givers' motivations. By incorporating a diverse set of gift attributes into our model, we quantified how the specific characteristics of a gift systematically moderate the spread of gifting. These findings can help researchers investigating prosociality and reciprocity in other digital contexts. In addition, our findings underscore the necessity of accounting for platform-specific affordances when studying online prosociality because such features create a social environment fundamentally different from offline settings.

This research offers useful insights for the design of live streaming platforms and other prosocial digital economies. Given that receiving a gift as the sole beneficiary of a gifting event serves as a potent catalyst for the spread of gifting, visual cues or personalized notifications that highlight a recipient as a unique beneficiary could amplify the sense of gratitude, thereby sustaining the chain of gifting more effectively. Furthermore, our results suggest a complex trade-off regarding the visibility of frequent gifters. While the presence of frequent gifters may inadvertently discourage recipients from reciprocating, simply obscuring their contributions is likely counterproductive. Such an approach risks undermining the reputation-based incentives that motivate frequent gifters to contribute in the first place. Ultimately, the challenge for platform designers lies in engineering an environment that preserves the motivational advantages of reputation systems for frequent contributors while simultaneously preventing the demotivation of average users.

Limitations and Future Work

This study is subject to several limitations. First, the Twitch API provides limited metadata regarding streamer characteristics and video content. Future research could integrate streamer demographics or real-time content analysis to provide a more nuanced understanding of how stream-specific features influence gifting behavior. For example, future studies might categorize streams by content genre or stream size to examine whether the treatment effect exhibits heterogeneity across different broadcast contexts. Although we could not directly account for streamer-specific or content-related variables, we mitigated their potential confounding influence by employing mixed-effects models and adopting a tight temporal window for our natural experiment. Our design ensures that both treatment and control groups were exposed to identical stream content and environmental stimuli at the moment of the gifting event.

Second, our dataset is restricted to chatters, as the Twitch API only permits the identification of users who post at least one chat message. Although lurkers comprise the majority of the audience (Wohn and Freeman 2020), they are unobservable in our dataset due to this constraint; consequently, we could not estimate the treatment effect for lurkers. Furthermore, the lack of longitudinal panel data and the relatively short observation window limit our ability to assess the long-term downstream effects of gifting. Future research analyzing longitudinal datasets could further explore the long-term impact of gifting on community lifecycle and user retention.

Finally, the generalizability of our findings is limited by the unique sociotechnical affordances of live streaming. The primary driver of community gifting on Twitch is less rooted in dyadic relationship maintenance due to the randomized and anonymous nature of the distribution. Consequently, gifters have a minimal expectation of direct reciprocity or feedback from recipients. However, gifters may still accrue recognition and reputation within the channel, as their contributions are publicly broadcast via automated notifications. These dynamics diverge significantly from gift exchanges on social media platforms, which typically prioritize the reinforcement of existing ties among friends and family. Future research should examine how varying platform-specific features and social architectures influence the diffusion and motivation of virtual gifting.

Conclusion

This study investigates the dynamics of generalized reciprocity in Twitch live streaming communities, specifically examining whether gifting behavior is contagious. We also identified the conditions that catalyze or inhibit the spread of gifting. Our findings reveal that receiving a gift subscription significantly increases the likelihood to pay it forward. This positive effect is stronger in single-recipient gifting events (i.e., one subscription is given to one individual per event). However, receiving a gift from a frequent gifter appears to dampen reciprocity. Anonymous gifting does not significantly influence the willingness to pay it forward.

References

Anik, L.; Aknin, L. B.; Norton, M. I.; and Dunn, E. W. 2009. Feeling Good About Giving: The Benefits (and Costs) of Self-Interested Charitable Behavior.

Bartlett, M. Y.; and DeSteno, D. 2006. Gratitude and Prosocial Behavior: Helping When It Costs You. *Psychological Science*, 17(4): 319–325.

Batson, C. D.; and Powell, A. A. 2003. Altruism and Prosocial Behavior. In *Handbook of Psychology: Volume 5: Personality and Social Psychology*. John Wiley & Sons, Inc., Hoboken, New Jersey.

Berman, J. Z.; and Silver, I. 2022. Prosocial behavior and reputation: When does doing good lead to looking good? *Current Opinion in Psychology*, 43: 102–107.

Bisberg, A. J.; Jiang, J.; Zeng, Y.; Chen, E.; and Ferrara, E. 2022. The Gift that Keeps on Giving: Generosity is Contagious in Multiplayer Online Games. *Proceedings of the ACM on Human-Computer Interaction*, 6(CSCW2): 1–22.

Camerer, C. 1988. Gifts as Economic Signals and Social Symbols. *American Journal of Sociology*, 94: S180–S214.

Chaudhry, A.; Wang, Y.; and Ouyang, E. 2024. Community Gifting and Recipients Engagement with Peers and Influencers: Evidence from Natural Experiments on Twitch. *Journal of Interactive Marketing*, 1–17.

Deng, J.; Cuadrado, F.; Tyson, G.; and Uhlig, S. 2015. Behind the game: Exploring the twitch streaming platform. In *2015 International Workshop on Network and Systems Support for Games (NetGames)*, 1–6. IEEE.

Dörr, T.; Nagpal, T.; Watts, D.; and Bail, C. 2025. A research agenda for encouraging prosocial behaviour on social media. *Nature Human Behaviour*, 9(3): 441–449.

Dubreuil, B. 2008. Strong Reciprocity and the Emergence of Large-Scale Societies. *Philosophy of the Social Sciences*, 38(2): 192–210.

Grüning, D. J.; Kamin, J.; Panizza, F.; Katsaros, M.; and Lorenz-Spreen, P. 2024. A framework for promoting online prosocial behavior via digital interventions. *Communications Psychology*, 2(1): 6.

Harvey, J.; Golightly, D.; and Smith, A. 2014. HCI as a means to prosociality in the economy. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 2955–2964.

Kizilcec, R. F.; Bakshy, E.; Eckles, D.; and Burke, M. 2018. Social Influence and Reciprocity in Online Gift Giving. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*, 1–11.

Kolyesnikova, N.; and Dodd, T. H. 2008. Effects of Winery Visitor Group Size on Gratitude and Obligation. *Journal of Travel Research*, 47(1): 104–112.

Kumru, C. S.; and Vesterlund, L. 2010. The effect of status on charitable giving. *Journal of Public Economic Theory*, 12(4): 709–735.

Kwon, H.; Koleva, B.; Schnädelbach, H.; and Benford, S. 2017. "It's Not Yet A Gift": Understanding Digital Gifting. In *Proceedings of the 2017 ACM Conference on Computer Supported Cooperative Work and Social Computing*, 2372–2384.

Lai, W.; Yang, Z.; Mao, Y.; Zhang, Q.; Chen, H.; and Ma, J. 2020. When Do Good Deeds Lead to Good Feelings? Eudaimonic Orientation Moderates the Happiness Benefits of Prosocial Behavior. *International Journal of Environmental Research and Public Health*, 17(11): 4053.

Lampinen, A.; Lehtinen, V.; Cheshire, C.; and Suhonen, E. 2013. Indebtedness and reciprocity in local online exchange. In *Proceedings of the 2013 conference on Computer supported cooperative work*, 661–672.

Li, Y.; and Peng, Y. 2021. What drives gift-giving intention in live streaming? The perspectives of emotional attachment and flow experience. *International Journal of Human-Computer Interaction*, 37(14): 1317–1329.

Luo, L.; Hanyi, S.; Zheng, Y.; and Yuan, Y. 2024. To Gift or Not: Understanding Gifting Behavior on Live Streaming Platforms from the Perspective of Social Influence and Herding. *International Journal of Human-Computer Interaction*, 1–18.

Ma, L. K.; Tunney, R. J.; and Ferguson, E. 2014. Gratefully Received, Gratefully Repaid: The Role of Perceived Fairness in Cooperative Interactions. *PLOS One*, 9(12): e114976.

Nahum-Shani, I.; Bamberger, P. A.; and Bacharach, S. B. 2011. Social Support and Employee Well-Being: The Conditioning Effect of Perceived Patterns of Supportive Exchange. *Journal of Health and Social Behavior*, 52(1): 123–139.

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

Peng, C.; Nelissen, R. M.; and Zeelenberg, M. 2018. Reconsidering the roles of gratitude and indebtedness in social exchange. *Cognition and Emotion*, 32(4): 760–772.

Ruth, J. A.; Otnes, C. C.; and Brunel, F. F. 1999. Gift Receipt and the Reformulation of Interpersonal Relationships. *Journal of Consumer Research*, 25(4): 385–402.

Schaumberg, R.; and Flynn, F. J. 2009. Differentiating between grateful and indebted reactions to receiving help. In *Altruism and Prosocial Behavior in Groups*, 105–132. Emerald Group Publishing Limited.

Schwartz, B. 1967. The Social Psychology of the Gift. *American Journal of Sociology*, 73(1): 1–11.

Seering, J.; Kraut, R.; and Dabbish, L. 2017. Shaping Pro and Anti-Social Behavior on Twitch Through Moderation and Example-Setting. In *Proceedings of the 2017 ACM Conference on Computer Supported Cooperative Work and Social Computing*, 111–125.

Sherry Jr, J. F. 1983. Gift Giving in Anthropological Perspective. *Journal of Consumer Research*, 10(2): 157–168.

Shmargad, Y.; and Watts, J. K. 2016. When Online Visibility Deters Social Interaction: The Case of Digital Gifts. *Journal of Interactive Marketing*, 36(1): 1–14.

Siem, B.; and Stürmer, S. 2018. Attribution of Egoistic Versus Altruistic Motives to Acts of Helping. *Social Psychology*.

Sisco, M. R.; and Weber, E. U. 2019. Examining charitable giving in real-world online donations. *Nature Communications*, 10(1): 3968.

Skågeby, J. 2010. Gift-giving as a conceptual framework: framing social behavior in online networks. *Journal of Information Technology*, 25(2): 170–177.

Thielmann, I.; Spadaro, G.; and Balliet, D. 2020. Structure, Identity, and Solidarity: A Comparative Field Study of Generalized and Direct Exchange. *Psychological Bulletin*, 146(1): 30–90.

Tsang, J.-A. 2021. (Un)special Favors: Gratitude for Group-Based Benefits. *The Journal of Positive Psychology*, 16(1): 27–37.

Tsang, J.-A.; and Martin, S. R. 2019. Four experiments on the relational dynamics and prosocial consequences of gratitude. *The Journal of Positive Psychology*, 14(2): 188–205.

Tsvetkova, M.; and Macy, M. 2015. The Contagion of Prosocial Behavior and the Emergence of Voluntary-Contribution Communities. In *Social Phenomena: From Data Analysis to Models*, 117–134. Springer.

Tsvetkova, M.; and Macy, M. W. 2014. The Social Contagion of Generosity. *PLOS One*, 9(2): e87275.

Twitch. 2024. Purchasing Gift Subscriptions. https://help.twitch.tv/s/article/gift-subscriptions?language=en_US. Accessed: 2024-11-16.

Twitch. 2025. Twitch Recap 2024. https://www.twitch.tv/annual-recap. Accessed: 2025-04-29.

Wohn, D. Y.; and Freeman, G. 2020. Audience Management Practices of Live Streamers on Twitch. In *Proceedings of the 2020 ACM International Conference on Interactive Media Experiences*, 106–116.

Wohn, D. Y.; Freeman, G.; and McLaughlin, C. 2018. Explaining Viewers' Emotional, Instrumental, and Financial

Support Provision for Live Streamers. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*, 1–13.

Wolff, G. H.; and Shen, C. 2024. Audience size, moderator activity, gender, and content diversity: Exploring user participation and financial commitment on Twitch. tv. *New Media & Society*, 26(2): 859–881.

Wolfinbarger, M. F.; and Yale, L. J. 1993. Three Motivations for Interpersonal Gift Giving: Experiental, Obligated and Practical Motivations. *Advances in Consumer Research*, 20(1).

Yu, E.; Jung, C.; Kim, H.; and Jung, J. 2018. Impact of viewer engagement on gift-giving in live video streaming. *Telematics and Informatics*, 35(5): 1450–1460.

Paper Checklist

1. For most authors...
   (a) Would answering this research question advance science without violating social contracts, such as violating privacy norms, perpetuating unfair profiling, exacerbating the socio-economic divide, or implying disrespect to societies or cultures? Yes
   (b) Do your main claims in the abstract and introduction accurately reflect the paper's contributions and scope? Yes
   (c) Do you clarify how the proposed methodological approach is appropriate for the claims made? Yes
   (d) Do you clarify what are possible artifacts in the data used, given population-specific distributions? Yes
   (e) Did you describe the limitations of your work? Yes, see the Discussion section.
   (f) Did you discuss any potential negative societal impacts of your work? NA, we described how we protected the identities of Twitch users. This study uses observational data, and therefore we did not conduct an intervention or administer any treatment that could potentially harm the Twitch users included in the study.
   (g) Did you discuss any potential misuse of your work? NA, the topic of this research is the spread of prosocial behavior.
   (h) Did you describe steps taken to prevent or mitigate potential negative outcomes of the research, such as data and model documentation, data anonymization, responsible release, access control, and the reproducibility of findings? Yes, see the Data and Methods section.
   (i) Have you read the ethics review guidelines and ensured that your paper conforms to them? Yes
2. Additionally, if your study involves hypotheses testing...
   (a) Did you clearly state the assumptions underlying all theoretical results? Yes
   (b) Have you provided justifications for all theoretical results? Yes
   (c) Did you discuss competing hypotheses or theories that might challenge or complement your theoretical results? Yes
   (d) Have you considered alternative mechanisms or explanations that might account for the same outcomes observed in your study? Yes
   (e) Did you address potential biases or limitations in your theoretical framework? Yes
   (f) Have you related your theoretical results to the existing literature in social science? Yes
   (g) Did you discuss the implications of your theoretical results for policy, practice, or further research in the social science domain? Yes, see the Discussion section.
3. Additionally, if you are including theoretical proofs...
   (a) Did you state the full set of assumptions of all theoretical results? NA
   (b) Did you include complete proofs of all theoretical results? NA
4. Additionally, if you ran machine learning experiments...
   (a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? NA
   (b) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)? NA
   (c) Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)? NA
   (d) Did you include the total amount of compute and the type of resources used (e.g., type of GPUs, internal cluster, or cloud provider)? NA
   (e) Do you justify how the proposed evaluation is sufficient and appropriate to the claims made? NA
   (f) Do you discuss what is "the cost" of misclassification and fault (in)tolerance? NA
5. Additionally, if you are using existing assets (e.g., code, data, models) or curating/releasing new assets, **without compromising anonymity**...
   (a) If your work uses existing assets, did you cite the creators? Yes, we have included the links to the Twitch and Perspective APIs in the manuscript.
   (b) Did you mention the license of the assets? Yes, they are publicly available.
   (c) Did you include any new assets in the supplemental material or as a URL? NA
   (d) Did you discuss whether and how consent was obtained from people whose data you're using/curating? Yes, we mentioned that we collected publicly accessible streams through the official Twitch API and did not disclose the identities of any individuals or streams in the paper.
   (e) Did you discuss whether the data you are using/curating contains personally identifiable information or offensive content? Yes, our dataset does not contain sensitive information.
   (f) If you are curating or releasing new datasets, did you discuss how you intend to make your datasets FAIR? NA

(g) If you are curating or releasing new datasets, did you create a Datasheet for the Dataset? NA

6. Additionally, if you used crowdsourcing or conducted research with human subjects, **without compromising anonymity**...

(a) Did you include the full text of instructions given to participants and screenshots? NA

(b) Did you describe any potential participant risks, with mentions of Institutional Review Board (IRB) approvals? NA

(c) Did you include the estimated hourly wage paid to participants and the total amount spent on participant compensation? NA

(d) Did you discuss how data is stored, shared, and deidentified? NA

Appendix (Robustness Checks)

To address the covariate imbalances reported in the main text (Table 2), we employed propensity score matching. This method confirms that our results are replicated within a matched dataset. Our goal was to ensure that the spread of gifting is driven by gift-receiving rather than baseline differences in user engagement or tenure.

We estimated the probability of treatment (receiving a gift) using a LightGBM model trained on several observed covariates, including gifting event ID, number of comments, mean comment length, user tenure, toxicity level, and donation behavior. Using the resulting propensity scores, we performed 1:10 nearest-neighbor matching, pairing each treated user with ten statistically similar control users. This matching procedure significantly improved covariate balance across groups (see Table 4 for the post-matching balance table). Our analysis of this balanced dataset (Table 5) confirms that the key findings remain statistically significant and directionally consistent with the results in Table 3.

Variable	**Treatment** Mean (SD)	**Control** Mean (SD)	t-statistic	p-value	Cohen's d
Number of comments	3.840 (10.56)	4.061 (10.98)	−1.560	0.119	−0.021
Mean comment length	2.812 (4.12)	2.781 (4.11)	0.559	0.576	0.007
User tenure (in years)	4.732 (3.10)	4.746 (3.01)	−0.329	0.742	−0.004
Proportion of toxic commenters	0.002 (0.05)	0.002 (0.05)	0.297	0.767	0.004
Proportion of donors who donated to streamers	0.005 (0.07)	0.006 (0.07)	−0.303	0.762	−0.004
N	6,130	61,300			

Table 4: Balance table for the matched dataset obtained through propensity score matching.

	Model 1	**Model 2**	**Model 3**	**Model 4**
Intercept	−9.452***	−9.489***	−9.431***	−9.800***
	(0.461)	(0.448)	(0.447)	(0.453)
Gift-receiving	1.259***	1.221***	1.038***	1.540***
	(0.189)	(0.192)	(0.199)	(0.227)
Anonymous gifting		−0.387		
		(1.083)		
Gift-receiving × Anonymous gifting		1.081		
		(1.175)		
Single-recipient gifting			−2.010***	
			(0.456)	
Gift-receiving × Single-recipient gifting			2.161***	
			(0.545)	
Infrequent gifter				−2.483***
				(0.538)
Gift-receiving × Infrequent gifter				1.812**
				(0.691)
Frequent gifter				0.829**
				(0.313)
Gift-receiving × Frequent gifter				−1.388***
				(0.417)
Number of observations	67,430	67,430	67,430	67,430
AIC	2,337.64	2,340.00	2,316.71	2,300.83
BIC	2,364.99	2,385.59	2,362.31	2,364.66

Table 5: Mixed-effects logistic regression results using the matched dataset obtained through propensity score matching. $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.