Losing Face but Winning Fame: Social Comparison and Streamer Performance in Livestreaming Platforms

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Abstract

Digital platforms are increasingly deploying competitive features to drive user engagement and monetization. This work investigates the impact of social comparison, in the form of player knockout (PK) events, on streamer performance in livestreaming platforms. The PK events create a public, competitive situation wherein streamers perform acts in real-time and compete for viewer support through virtual gifting. Meanwhile, streamers face a central trade-off on whether to join PK: potential risks like negative self-evaluation, public humiliation, and viewer disillusionment versus possible benefits like increased visibility, fans, and earnings. Analyzing granular data from a leading livestreaming platform, we report two empirical studies. In Study 1, we employ Double Machine Learning (DML) and find that, on average, streamers participating in PK events increase total gifting by over 300%, viewer engagement duration by over 70%, and significantly boost streamers' follower growth. In Study 2, we leverage the platform's randomly matched PK events to analyze how competition structure affects streamer outcomes. Interestingly, our results show that when facing with bigger opponents (streamers with relatively more followers), although streamers are more likely to 'lose' in PK, they still benefit substantially from increased gifting and follower growth. Specifically, competing against either bigger opponents or those in the same content category increases both total gifting and cross-streamer follower attraction for the focal streamer. Our further heterogeneity analysis reveals two optimal PK configurations: small streamers benefit most from competing against bigger, same-category opponents, while big streamers gain most from competing against bigger peers in different categories, in terms of gifting and follower dynamics. Our study adds to the social comparison theory by examining social comparison in a public, real-time, and multi-party setting, and extends the social exchange theory by conceptualizing and measuring two distinct types of social exchanges, namely, reputational social exchange (reflected by cross-streamer follower migration) alongside traditional monetary social exchange (reflected by gifting). Our findings also provide actionable insights for platforms operators and streamers on designing and refining competitive strategies for enhancing user engagement and monetization.

Keywords: Social Comparison, Social Exchange, Player Knockout, Streamer Performance, User Engagement, Livestreaming, Platform Monetization

1 INTRODUCTION

Digital platforms rely on user engagement to sustain operations, power growth, and enable monetization (Bapna et al., 2004). Livestreaming platforms, such as Twitch and TikTok, exemplify this engagement-driven business model and have experienced remarkable expansion. Over one-fourth of the Internet users watch livestreaming weekly, and this massive user base is fueling the livestreaming market's projected growth from $99.82 billion in 2025 to $345.13 billion by 2030 (Kumar, 2025). The extant literature has explored a range of strategies in driving user engagement, such as the integration of social network features (Huang et al., 2017), the introduction of ephemeral content (Lehrer et al., 2023), the use of gamification (Liu et al., 2017), and the deployment of social bots to stimulate interaction (Gao et al., 2025).

A novel and increasingly prominent design for user engagement is the introduction of platform-mediated, interactive, public competitions, for example, Twitch Rivals and TikTok Live Competitions[1] that pit streamers against one another in real time and boost user engagement with heightened competitiveness. As social comparison theory suggests that individuals are driven by a desire to secure or maintain a superior position (Garcia et al., 2013), we consider that streamer competitions function as public arenas for social comparisons, prompting streamers to evaluate themselves relative to their opponents. In livestreaming platforms, social comparisons are further intensified by direct competition with peers and the presence of a live audience, both of which amplify competitive pressure (Garcia et al., 2013; Malhotra, 2010).

Meanwhile, the outcomes of social comparison in livestreaming are generally determined by the total monetary value of virtual gifts streamers receive from viewers; the streamer with the lower amount loses. Although the extant research has focused on financial performance (Kim et al., 2018; Yao et al., 2024), an equally important yet under-studied streamer outcome in prior literature is the dynamics of follower acquisition and attrition. Specifically, social comparisons in livestreaming expose competing streamers to each other's followers, during which streamers can

[1] Twitch Rivals, Link: https://www.twitchrivals.com/; TikTok Live Competitions, Link: https://www.tiktok.com/discover/tiktok-live-competition

attract followers directly from their opponents. Such follower exchanges are inherently reputational because a growing follower base increases a streamer's visibility, builds popularity, and creates greater opportunities for sustained engagement and future monetization (Zhao et al., 2021). Thus, drawing on social exchange theory, which posits that individuals engage in interactions as exchanges involving anticipated benefits and costs (Cropanzano and Mitchell, 2005), we conceptualize that streamer social comparisons facilitate two types of social exchanges: monetary exchanges (streamers receiving virtual gifts from viewers) and reputational exchanges (streamers attracting followers from competitors).

In this work, we aim to understand how social comparisons, in the format of player knockout (PK) events, influence streamer performance in livestreaming platforms. Note that although social comparisons in public competitions might help enhance user engagement for the livestreaming platforms, yet streamers participating in these events face a challenging trade-off between potential rewards and significant risks. On one hand, winning these competitions means public victories validating a streamer's superiority, enhancing their status, boosting morale, and generating tangible benefits such as increased followers and gifts. On the other hand, losing may result in negative self-evaluation, public humiliation, viewer disillusionment, and follower loss.

Additionally, the structure of social comparisons might also play a role in streamer performance. Factors such as the relative follower size discrepancy and the degree of content category alignment can potentially influence the streamers' monetary and reputational social exchange outcomes. For example, a streamer with fewer followers facing a high-profile opponent with a substantially larger follower base may experience intensified pressure and lower odds of winning, whereas competitions between streamers of similar content categories may enable more opportunities for follower cannibalization. Bearing the above in mind, we seek to empirically answer the following research questions:

– What are the impacts of participating in public social comparison (i.e., PK events) on streamers' performance? – How do social comparison structures, namely, the streamers' follower-size comparison and content-category alignment, influence their performance?

To answer our research questions, we collaborate with a leading online livestreaming platform in Asia (hereafter referred to as *the partner platform*). We focus on a popular public competition in the partner platform, known as player knockout (PK) events, which enable streamers to compete against each other in head-to-head, public contests, and the winning streamer is determined by the total value of gifts received from viewers during the event. Analyzing proprietary data from the partner platform, we report two empirical studies.

In Study 1, we analyze a dataset of 272,977 livestreaming sessions and employ Double Machine Learning (DML) to estimate the effects of PK participation on streamer performance. The results show that participating in PK events significantly enhances streamer performance, with more than a 300% increase in total gifting, significant improvement in average viewer watch time, and new follower acquisition. These results indicate that, overall, PK events can be an effective platform design for boosting monetization and engagement.

In Study 2, we leverage a quasi-experimental design, focusing on the platform-randomized PK event pairings. We examine how different social comparison structures, specifically the focal-opponent follower size comparison and content category alignment, affect streamer outcomes. Our findings reveal that, small streamers (i.e., streamers with relatively fewer followers) face a higher risk of "losing" when paired against bigger opponents in PK; however, they still benefit substantially through increased viewer gifting and follower acquisition. Also, streamers competing against an opponent from the same content category experienced increases in both total gifting and follower exchange. Further, our heterogeneity analysis identifies two configurations that optimize focal streamers' benefits: small streamers achieve the greatest gains when competing against bigger opponents within the same category, whereas big streamers benefit most from facing similarly prominent peers in different categories, with respect to both gifting and follower growth.

This work makes several contributions to the related literature. First, we extend social comparison theory from previously asynchronous, private scenarios (Kankanhalli et al., 2005; Krasnova et al., 2015; Liu et al., 2017) into public, interactive, multi-party competitions. In the livestreaming PK events, public visibility, audience involvement, and outcome immediacy could likely intensify streamers' competitive behaviours, such as risk-aversion (or risk-taking), aggressive engagement (e.g., asking for gifts), or emotional appeals to attract audience support, which in turn influence performance outcomes. Additionally, beyond prior focus on individual responses to social comparisons (Li et al., 2021; Shi et al., 2025), we systematically investigate different comparison structures, like upward comparisons (a streamer competes against a stronger opponent) and content category alignment (the similarity in the type of content streamers produce), influencing viewer gifting and follower acquisition outcomes. Second, this work adds to social exchange theory (Cropanzano and Mitchell, 2005; Homans, 1958) by investigating the trade-offs streamers face (i.e., potential risks and benefits) in public social comparisons, and also distinguishing and empirically examining two types of exchanges: monetary and reputational. Prior work has mostly focused on relational norms in social exchanges, such as reciprocity, tie formation, and symbolic recognition (Qiu and Kumar, 2017; Song et al., 2019; Ye et al., 2018). We demonstrate that platform-mediated social comparison also introduces social exchanges of streamers with immediate monetary and reputational consequences. Third, we advance the prior research on platform monetization, particularly, Pay-What-You-Want (PWYW) in the form of virtual gifting in livestreaming. Prior research has explored various antecedents for streamer and platform monetization, such as perception of kindness, audience size, and social influences (Jung et al., 2014; Lu et al., 2021; Yao et al., 2024). Our study evidences social comparison features can be an effective strategy for streamer and platform monetization. Also, streamer monetization happens in tandem with their follower changes, which in turn influence streamers' future monetization potential.

Our results also offer actionable practical implications for platform operators and streamers. For streamers, particularly those with small follower bases, actively initiating PK matchups against bigger or same-category streamers can serve as an effective growth strategy. This approach of competing with a more popular opponent risks potential loss in competition but with large benefits, such as improving exposure, increasing gifting and enhancing viewer following. For digital platforms, social comparison features can be powerful designs to boost both user engagement and streamers' financial performance as well as follower attraction.

2 THEORETICAL FOUNDATION & RELATED LITERATURE

2.1 Social Comparison Theory

Social comparison theory posits that individuals are inherently motivated to compare with others and minimize perceived discrepancies between themselves and others (Festinger, 1954). This fundamental psychological process drives competitive behaviors aimed at reducing perceived discrepancies and preserving (or enhancing) one's perceived superiority (Garcia et al., 2013; Tauer and Harackiewicz, 1999). Prior research on social comparison theory has identified two main directions of social comparisons. One is upward comparison, where individuals compare themselves to superior others, often fueling the desire to compete and outperform (Malhotra, 2010; Tesser, 1988); and the other is downward comparison, which can also elicit competitive responses, especially when those performing worse are seen as potential threats to one's current advantage (Garcia and Miller, 2007; Graf et al., 2012; Solnick and Hemenway, 1998).

Information Systems (IS) scholars have employed social comparison theory in various contexts for understanding user behaviors, such as group interactions in the adoption of collaborative technologies (Kan et al., 2012), negative emotions like envy on social networking sites (Krasnova et al., 2015), and the motivational appeal of competitive features in gamified systems (Liu et al., 2017). The extant literature has largely focused on how comparison affects individuals' own behaviors or emotional states in asynchronous and private contexts (e.g., academic work, online dating). For example, Li et al. (2021) found that peer performance information motivates men more than women in competitive learning, due to men's stronger social comparison orientation. Similarly, Shi et al. (2025) showed that popularity feedback in online dating prompts strategic adaptations, especially among men, who adjust their date-seeking behavior per comparison-based information.

Note that prior studies have primarily considered social comparison as an internal process of self-evaluation versus others (Li et al., 2021; Liu et al., 2017; Shi et al., 2025), our work aims to extend social comparison theory to the context of livestreaming, particularly PK events. PK events pair streamers in public, time-limited contests, wherein streamers perform live to compete for viewer support through virtual gifting. The PK outcome is determined by the total value of gifts each streamer receives from viewers. This process is different from traditional social comparison because PK events externalize social comparisons into a public setting where outcomes hinge on both streamers' actions and collective viewer responses. Further, directions of social comparisons may also influence streamer outcomes. For instance, when a small streamer (i.e., with relatively fewer followers) competes against a more popular one, he/she faces an upward comparison, which can motivate the viewing followers to rally behind him/her. Conversely, a popular streamer facing a lesser-known rival engages in a downward comparison, where the need to defend his/her superior status from a potential threat can motivate his/her own fanbase. We thus delve into the comparison structure of PK events and aim to understand how variations, such as opponent's follower size, content alignment, influence streamer outcomes.

2.2 Social Exchange Theory

Social exchange theory posits that human interactions function as transactions with expected rewards and costs (Homans, 1958). Related literature distinguishes between economic exchanges, which are explicit and transactional, and social exchanges, which involve unspecified future obligations and are capable of evolving into social relationships (Blau, 1964; Cropanzano and Mitchell, 2005). For instance, the exchange process can generate positive or negative emotions that become associated with the relationship or group, thereby strengthening or weakening social bonds (Lawler, 2001). Similarly, research on reciprocity shows that indirect or generalized exchanges, where repayment is not direct or immediate, are helpful for trust building in relationships (Molm et al., 2007).

Social exchange theory can help explain a range of individual behaviors in online contexts. Some studies used social exchange theory to understand the motivations behind knowledge sharing in online communities, in which individuals weigh the expected benefits of reciprocity and enhanced reputation against the costs of contribution (Beck et al., 2014; Bock et al., 2005;

Kankanhalli et al., 2005; Qiu and Kumar, 2017). Another body of work draws on social exchange theory to conceptualize reciprocity behavior in online barter markets (Ye et al., 2018), health communities (Liu et al., 2022), and the formation of social ties among content providers (Song et al., 2019). Meanwhile, extant research has employed social exchange theory to explain online gifting phenomenon (Kim et al., 2018; Lin et al., 2021; Yao et al., 2024). For example, Kim et al. (2018) grounds on social exchange theory to model gifting on social networks, showing that a user's gifting decision is based on a function of expected benefits and costs.

However, previous studies have mostly examined social exchanges involving the direct transfer of tangible resources, such as monetary transactions or virtual gifts. In this work, we consider that livestreaming PK events facilitates two distinct forms of social exchanges. The first is the established *monetary social exchange* wherein viewers send virtual gifts to streamers as a means of relationship building and support. The second, and novel, form is *reputational social exchange*, an indirect exchange in which streamers leverage PK events to gain exposure and attract followers from their competitors' audiences. In this process, some followers of one streamer may begin following the other, and vice versa, creating reciprocal audience flows. Hereby, our study contributes to the social exchange theory by conceptualizing two distinct types of social exchange, and examining how social comparison in PK events influences both monetary (virtual gifting) and reputational social exchange (cross-streamer follower attraction) outcomes in livestreaming.

2.3 Monetization in Livestreaming

In addition to monetization approaches such as advertisements and membership fees (Zhao et al., 2025), most livestreaming platforms rely on a PWYW model, commonly referred to as virtual gifting, as a primary mechanism for streamers to generate revenue. This work is thus also related to the research stream on PWYW (Feldhaus et al., 2019; Gneezy et al., 2010). In our setting, viewers can voluntarily purchase and send virtual gifts to streamers during livestreaming, choosing the monetary amount they wish to spend. This closely resembles PWYW, wherein consumers determine how much to pay without a fixed price (Lu et al., 2021; Yao et al., 2024). Prior research on PWYW has been mostly situated in offline scenarios such as restaurants, theaters, and museums (Jung et al., 2014; Kim et al., 2009). Other studies extend PWYW to online contexts. For instance, Elberse and Bergsman (2008) explored PWYW behavior in Radiohead's album release, and Chen et al. (2017) as well as Spann et al. (2017) analyzed its implementation in software sales and open-access academic publishing, respectively.

Some recent studies examined PWYW in the context of livestreaming, considering various antecedents of PWYW behavior such as streamers' audience size (Lu et al., 2021), emotional reciprocity between streamers and viewers (Lin et al., 2021), and viewer tenure (Ma et al., 2022). Meanwhile, Yao et al. (2024) showed that PWYW in livestreaming not only influences streamer emotions but also affects peer viewer behaviors, sometimes crowding out contributions from others. Our study adds to this body of work by investigating PK events as a novel platform design element that influences PWYW behavior. Additionally, though prior work has primarily focused on the immediate economic outcomes, such as payment amounts, transaction volumes, and short-term revenue generation in PWYW, we extend this line of inquiry by further examining how PK's competition structures influence not only viewer gifting behaviors in PWYW but also the concurrent changes in streamer reputation in terms of follower gains and losses.

3 DATA & METHODOLOGY

3.1 Study Context

Our research context is situated in a prominent online livestreaming platform in Asia (*the partner platform*). The partner platform operates at a large scale, with hundreds of millions of monthly active users, and functions as a two-sided market, facilitating livestreaming interactions for streamers and their audiences. Livestreaming content on the partner platform encompasses a diverse range of genres, including entertainment, gaming, cooking, lifestyle, and more. During livestreaming sessions, streamers engage with viewers through real-time chat, comments, and virtual gifts. These virtual gifts, which can be converted into real currency, provide streamers with a source of financial support. The partner platform retains a commission fee during the conversion process. This voluntary payment approach, where viewers offer monetary contributions to streamers at their discretion, aligns with the PWYW model (Kim et al., 2018; Lu et al., 2021; Yao et al., 2024).

Our study focuses on the social comparison feature of the livestreaming platform, known as player knockout (PK) events, a brief interactive function in which streamers engage in real-time performance-based contests during livestreaming sessions. In a typical PK event, within 5 to 10 minutes, two streamers appear on a split screen and perform activities, such as singing, dancing, or playing games, to stimulate viewer engagement and gift contributions.[2] Viewers can actively participate in the PK events by sending virtual gifts to support their preferred streamer, directly influencing the contests' outcome. At the end of the PK event, the streamer with the highest gifting amount "wins", and the losing party undergoes a figurative punishment like performing an activity, for instance, singing a song chosen by the winner.

The PK events on the partner platform occur in two ways: *Invited PK*, where one streamer invites another, and *Random PK*, which is the platform's term for its algorithmic matching system. In *Invited PK* events, a streamer selects a specific opponent, contingent on the opponent's acceptance. In *Random PK* events, all streamers who click the Random PK button within a short time window are pooled together. The platform then assigns PK pairs using a proprietary algorithm that resembles a stratified matching process, where streamers are randomly matched up based on shared characteristics. The user interface (UI) of the PK events remains consistent across the formation approaches. Figure 1 presents a screenshot of the UI during a PK event on a typical livestreaming platform.

We empirically investigate both invited and random PK events, conducting two studies. In Study 1, we analyze the effects of this social comparison feature on streamers' performance by comparing livestreaming sessions that include PK events to those that do not. In Study 2, we focus on random PK events, leveraging variation in social comparison structures, and explore how focal-opponent follower size comparison, as well as their content category alignment, influence the

[2] PK events can involve more than two streamers. We focus on two-streamer PK events in this study as they are the most common format on the platform.

focal streamer's performance.

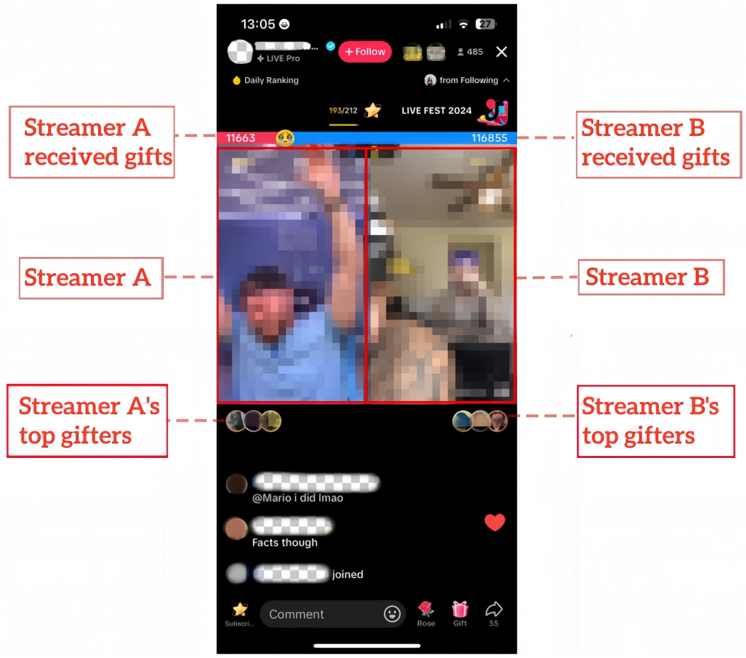

Figure 1: Screenshot of the User Interface (UI) During a PK Event in Livestreaming

3.2 Data and Measures

We obtain proprietary data from the partner platform. For the two studies in our empirical examination, we describe the dataset and variables for each study separately below.

3.2.1 Dataset for Study 1: With vs. Without PK

For Study 1, we retrieve data at the livestreaming session level, focusing on each active streamer's first session of the day, with each session containing no more than one PK event.[3] Our observation window spans between January 1 and February 1, 2023. To achieve computational feasibility and maintain representativeness, we randomly sample 20% of the sessions, resulting in a final dataset of 272,977 livestreaming sessions.

The independent variable of Study 1 is *with PK*, a binary indicator representing whether a livestreaming session includes a PK event. The dependent variables of Study 1 include several key

[3] We define active streamers as those who had received virtual gifts at least once before the observed livestreaming session.

metrics, including *streamer revenue*, measured by the total value of gifts that a streamer received during a livestreaming session; *viewer engagement*, captured by the average viewing duration per viewer during a livestreaming session; *audience growth*, indicated by the number of new followers and net follower gains; *fan commitment*, measured by the number of new loyal fans who joined the streamer's fan group; *audience interactions*, captured by the number of follower connections formed between viewers during the session; and *audience churn*, measured by the number of existing followers lost. All dependent variables are log-transformed to correct for distributional skewness and to enable percentage-based interpretation of regression estimates. Under this specification, regression coefficients can be recalculated to the percentage change in the outcome variable associated with a unit change in the predictor.

Additionally, our dataset also includes observations on streamer characteristics, such as gender, age category, content category, region, city level, community type, influencer account, streamer tenure, follower count, loyal fan count, and following count. It also contains stream device usage data, including device type, app version, and device price range. Furthermore, we account for prior viewer engagement, measured over the 10 days preceding the observed livestreaming session. These engagement metrics include cumulative livestreaming duration, total comments, likes, unique commenters, voice comments, shares, and the number of unique users who shared content during livestreaming sessions. Finally, we incorporate historical revenue data, captured as the total value of gifts received during the same 10-day period prior to the session. All continuous control variables are log-transformed to reduce skewness, whereas categorical control variables are encoded using dummy indicators.

Table 1 presents the variables and descriptions for Study 1,[4] and we report the descriptive statistics of these variables in Table 2.[5]

[4] All continuous variables are transformed using $\log(x+1)$ to address right-skewed distributions and reduce the influence of extreme values.

[5] Note that all continuous variables referenced above were desensitized by the partner platform for data sensitivity reasons. Specifically, each variable was multiplied by a constant scaling factor. Such data desensitization procedure does not compromise the validity of our analyses. We report further details in Appendix D.

Table 1: Variable Descriptions for Study 1: With vs. Without PK

Variables	**Descriptions**
Independent Variables:	
with PK	Indicates whether this live session has a PK (Player Knockout) event (0 = no PK event, 1 = has PK event)
Dependent Variables:	
Total Gifting (log)	Logarithm of the total value of gifts received during a live session.
Avg Play Duration per Viewer (Log)	Logarithm of the average play duration per viewer during a live session.
New Follower Gain (Log)	Logarithm of the number of new followers a streamer gains during a live session.
Existing Follower Loss (Log)	Logarithm of the number of existing followers a streamer loses during a live session.
Net Follower Gain (Log)	Logarithm of the net change in the number of followers during a live session (Note: Since the net change in followers may include negative values, we applied a minimum-shift transformation before taking the logarithm.)
Viewer-to-viewer Follower Gain (Log)	Logarithm of the number of times viewers follow other viewers during a live session.
New Loyal Fan Gain (Log)	Logarithm of the number of new members joining a streamer's fan group (loyal fans) during a live session. On the platform, joining a fan group is a formal action indicating elevated loyalty, often accompanied by privileges such as badges, exclusive interactions.
Control Variables:	
Gender	Gender of the streamer (0 = Male; 1 = Female).
Age Category	Age category of the streamer (3 = 18–23; 4 = 24–30; 5 = 31–40; 6 = 41–49; 7 = 50+).
Streamer Content Category	Content Category of streamer (1 = Influencer; 2 = E-commerce; 3 = Show; 4 = Game).
Region	Region of the streamer (0 = Unknown; 1 = Northern; 2 = Southern).
City Level	Tier of the streamer's city (0 = Unknown; 1 = First-tier; 2 = New first-tier; 3 = Second-tier; 4 = Third-tier; 5 = Fourth-tier; 6 = Fifth-tier).
Device Type	Type of device used (1 = Android; 2 = iOS).
App Version	App version used (0 = Unknown; 1 = Lite; 2 = Express; 3 = Regular).
Device Price Range	Device price range (0 = Budget; 1 = Mid-range; 2 = High-end; 3 = Premium).
Community Type	Community classification (0 = Unknown; 1 = Urban; 2 = Foreign; 3 = Rural; 4 = Township).
Influencer Account	Indicates if the streamer is a verified influencer (0 = No; 1 = Yes).
Tenure Days (Log)	Logarithm of the number of days since registration (streamer's tenure).
Follower Count (Log)	Logarithm of the total follower count before the observation session.
Following Count (Log)	Logarithm of the number of users followed by the streamer prior to the observation session.
Loyal Fan Count (Log)	Logarithm of the count of loyal fans (from the fan group) before the observation session.
Historical Total Gifting (Log)	Logarithm of the total value of gifts received in live sessions during the 10 days preceding the observation session.
Historical Play Duration (Log)	Logarithm of the total play duration in live sessions during the 10 days preceding the observation session.
Historical Play Count (Log)	Logarithm of the total number of views in live sessions during the 10 days preceding the observation session.
Historical Viewer Count (Log)	Logarithm of the total viewer count in live sessions during the 10 days preceding the observation session.
Historical Like Count (Log)	Logarithm of the total like count in live sessions during the 10 days preceding the observation session.
Historical Like Users (Log)	Logarithm of the total number of unique users who liked content in live sessions during the 10 days preceding the observation session.
Historical Comment Count (Log)	Logarithm of the total comment count in live sessions during the 10 days preceding the observation session.
Historical Commenters (Log)	Logarithm of the total number of unique commenters in live sessions during the 10 days preceding the observation session.
Historical Voice Comments (Log)	Logarithm of the total voice comment count in live sessions during the 10 days preceding the observation session.
Historical Voice Commenters (Log)	Logarithm of the total number of unique voice commenters in live sessions during the 10 days preceding the observation session.
Historical Shares (Log)	Logarithm of the total share count in live sessions during the 10 days preceding the observation session.
Historical Share Users (Log)	Logarithm of the total number of unique users who shared content in live sessions during the 10 days preceding the observation session.

Table 2: Summary Statistics for Study 1: With vs. Without PK

	Obs	Mean	SD	Min	Max
Independent Variables:					
with PK	272 977	0.04	0.19	0.00	1.00
Dependent Variables:					
Total Gifting (Log)	272 977	3.42	4.08	0.00	20.47
Avg Play Duration per Viewer (Log)	272 977	14.64	3.00	0.00	20.36
New Follower Gain (Log)	272 977	2.98	3.37	0.00	15.47
Existing Follower Loss (Log)	272 977	2.28	3.00	0.00	14.03
Net Follower Gain (Log)	272 977	13.13	0.04	0.00	15.40
Viewer-to-viewer Follower Gain (Log)	272 977	1.20	2.41	0.00	15.33
New Loyal Fan Gain (Log)	272 977	0.77	1.93	0.00	13.55
Control Variables:					
Gender	272 977	0.50	0.49	0.00	1.00
Age Category	272 977	5.49	1.17	3.00	7.00
Streamer Content Category	272 977	2.94	0.26	1.00	4.00
Region	272 977	1.15	0.37	0.00	2.00
City Level	272 977	4.58	1.41	0.00	6.00

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	Obs	Mean	SD	Min	Max
Device Type	272 977	1.21	0.41	1.00	2.00
App Version	272 977	1.69	1.49	0.00	3.00
Device Price Range	272 977	2.66	0.73	0.00	3.00
Community Type	272 977	2.36	1.25	0.00	4.00
Influencer Account	272 977	0.00	0.03	0.00	1.00
Tenure Days (Log)	272 977	11.96	0.47	8.59	12.93
Follower Count (Log)	272 977	12.95	1.99	0.00	22.35
Following Count (Log)	272 977	10.85	1.92	0.00	13.14
Loyal Fan Count (Log)	272 977	8.54	2.43	0.00	19.29
Historical Total Gifting (Log)	272 977	7.63	4.47	0.00	25.10
Historical Play Duration (Log)	272 977	21.99	6.14	0.00	34.76
Historical Play Count (Log)	272 977	12.22	3.89	0.00	24.21
Historical Viewer Count (Log)	272 977	11.88	3.80	0.00	23.61
Historical Like Count (Log)	272 977	11.23	4.19	0.00	23.90
Historical Like Users (Log)	272 977	8.20	3.03	0.00	19.10
Historical Comment Count (Log)	272 977	8.94	3.53	0.00	20.68
Historical Commenters (Log)	272 977	7.85	3.14	0.00	18.85
Historical Voice Comments (Log)	272 977	2.70	3.93	0.00	14.50
Historical Voice Commenters (Log)	272 977	2.30	3.34	0.00	12.51
Historical Shares (Log)	272 977	4.32	3.70	0.00	18.43
Historical Share Users (Log)	272 977	4.13	3.51	0.00	16.65

3.2.2 Dataset for Study 2: Within Random PK

For Study 2, we retrieve data on livestreaming sessions with random PK events to examine the relationship between the structure of social comparisons, specifically, variations in the pairing of focal-opponent streamers' follower size and content category, and streamer performance. Our observation window spans from January 1, 2022, to September 1, 2024. The data is at the livestreaming session level, with each session containing exactly one random PK event involving a pair of streamers. For each pair, the structure of social comparison is perspective-dependent. That is, when two streamers—Streamer A and Streamer B—compete, the interpretation of the follower size comparison depends on which streamer is designated as the focal one. For example, if Streamer A has fewer followers than Streamer B, then from Streamer A's perspective, the focal streamer competes against an opponent with a larger follower base. Conversely, from Streamer B's perspective, the focal streamer faces an opponent with a smaller follower base. To ensure non-duplication, we randomly select one streamer from each PK pair and designate him/her as the focal streamer.

We analyze PK events from the focal streamer's perspective, focusing on their outcomes rather than those of their opponents. Additionally, our analysis also includes only active streamers, defined as those who had received virtual gifts at least once before the observed livestreaming session. Further, to avoid streamer learning effects, we include only the first PK event of each streamer in our sample. Our final dataset for Study 2 comprises 174,781 focal streamers' random PK livestreaming sessions.

We focus on three key independent variables in Study 2. The first variable, *vs. Big Follower Opponent*, indicates whether the opponent streamer's follower size is greater than the focal streamer's follower size. This variable allows us to examine how the opponent's follower base size influences the outcomes of the focal streamer's livestreaming session. The second variable, *vs. Same Category Opponent*, captures whether the focal streamer and the opponent belong to the same livestreaming content category. This variable helps us assess how the opponent's content category influences the focal streamer's livestreaming session outcomes. The third variable, *Big Follower Focal*, is a binary indicator denoting whether the focal streamer is classified as a "Big" streamer (1 = focal streamer's follower size $\geq$ 10,000; 0 = follower size < 10,000).[6] We use this variable to explore whether the focal streamer's own follower size moderates the effects of focal-opponent follower size comparison and content category alignment on their own livestreaming outcomes.

The dependent variables in Study 2 include metrics related to streamer performance and audience engagement. Specifically, we incorporate *Focal Win*, a binary indicator of whether the focal streamer won the PK session (excluding ties), to capture the competitive outcome of the event. And we measure the total gifting value and the average value of gifts sent per viewer in a livestreaming session, representing monetary social exchanges between streamers and viewers. Next, we capture the number of new followers gained, the number of existing followers lost, and the net change in followers, reflecting follower base size fluctuations. Additionally, we examine the number of the opponent's followers gained by the focal streamer and the number of the focal streamer's followers gained by the opponent, as indicators for reputational social exchange between competing streamers. All dependent variables are log-transformed to correct for distributional skewness and to enable percentage-based interpretation of regression estimates. Under this specification, regression coefficients can be recalculated to the percentage change in the outcome

[6] The 10,000-follower threshold aligns with the classification used by our industry partner, which designates streamers with fewer than 10,000 followers as small streamers.

variable associated with a unit change in the predictor.

In terms of control variables, we include information on streamer characteristics, such as gender, age category, content category, region, city level, community type, streamer tenure, follower count, loyal fan count, and following count, to account for potential systematic differences in streamer profiles that could influence performance. For instance, gender and age group may correlate with audience preferences and engagement, while content category and community type may reflect different viewer motivations and expectations. Also, streamer tenure, follower count, loyal fan count, and following count are included to control for the effects of streamer popularity and prior viewer engagement on current performance. We further control for stream device usage data, including device type, app version, and device price range. Different device types and app versions can impact the user experience, and the device price range may reflect socioeconomic factors that influence viewer behavior and engagement. Moreover, we account for prior viewer engagement, which includes cumulative livestreaming duration, total comments, likes, unique commenters, voice comments, shares, and the number of unique users who shared content during the 10 days preceding the session. These variables are included to capture the baseline level of historical viewer activity and content interaction, which may influence the current performance. Finally, we control for historical revenue, measured by the total value of gifts received during the same 10-day period prior to the session, to account for the potential carryover effects of the past performance on current outcomes. All continuous control variables are log-transformed to reduce skewness, whereas categorical control variables are encoded using dummy indicators.

Table 3 presents the list of variables and their descriptions for Study 2,[7] and Table 4 shows the descriptive statistics of these variables.[8]

[7] All continuous variables are transformed using $\log(x+1)$ to address right-skewed distributions and reduce the influence of extreme values. Control variables are all included in those presented in Table 1 and are omitted here to conserve space.

[8] Note that all continuous variables referenced above were desensitized by the partner platform for data sensitivity reasons. Specifically, each variable was multiplied by a constant scaling factor. Such data desensitization procedure does not compromise the validity of our analyses. We report further details in Appendix D.

Table 3: Variable Descriptions for Study 2: Within Random PK

Variables	**Descriptions**
Independent Variables:	
vs.Big Follower Opponent	Indicates whether the opponent streamer's follower size is greater than the focal streamer's follower size (1 = opponent streamer's follower size $\geq$ focal streamer's follower size ; 0 = opponent streamer's follower size $<$ focal streamer's follower size).
vs.Same Category Opponent	Indicates if the focal and opponent streamers belong to the same content category (0 = no; 1 = yes).
Big Follower Focal	Indicates whether the focal streamer is classified as a Big streamer (1 = focal streamer's follower size $\geq$ 10,000; 0 = focal streamer's follower size $<$ 10,000).
Dependent Variables:	
Focal Win	Indicates whether the focal streamer won the PK session against the opponent. (1 = win; 0 = loss; 2 = draw; we exclude draw events for analysis of this variable.).
Total Gifting (Log)	Logarithm of the total value of gifts received during a live session.
Avg Gifting per Viewer (Log)	Logarithm of the average gifts sent per viewer during a live session.
Opponent Follower Attraction (Log)	Logarithm of the number of followers who originally followed the opponent but started following the focal streamer during the same PK session. This captures the focal streamer's ability to attract the opponent's followers.
Focal Follower Attraction (Log)	Logarithm of the number of followers who originally followed the focal streamer but started following the opponent during the same PK session. This reflects the opponent's ability to attract the focal streamer's followers.
New Follower Gain (Log)	Logarithm of the number of new followers gained by the focal streamer during the session.
Existing Follower Loss (Log)	Logarithm of the number of existing followers lost by the focal streamer during the session.
Net Follower Gain (Log)	Logarithm of the net change in the number of followers for the focal streamer during the session. (Note: Since the net change in followers may include negative values, we applied a minimum-shift transformation before taking the logarithm.)

Table 4: Summary Statistics for Study 2: Within Random PK

	Obs	**Mean**	**SD**	**Min**	**Max**
Independent Variables:					
vs.Big Follower Opponent	174 781	0.50	0.50	0.00	1.00
vs.Same Category Opponent	174 781	0.34	0.47	0.00	1.00
Big Follower Focal	174 781	0.15	0.36	0.00	1.00
Dependent Variables:					
Focal Win	174 781	1.346	0.81	0.00	2.00
Total Gifting (Log)	174 781	2.92	4.07	0.00	16.57
Average Gifting per Viewer (Log)	174 781	1.04	1.80	0.00	12.90
Opponent Follower Attraction (Log)	174 781	0.04	0.46	0.00	10.13
Focal Follower Attraction (Log)	174 781	0.04	0.46	0.00	9.43
New Follower Gain (Log)	174 781	1.00	2.18	0.00	12.72
Existing Follower Loss (Log)	174 781	0.83	1.96	0.00	12.26
Net Follower Gain (Log)	174 781	11.03	0.03	0.00	12.61
Opponent Follower Attraction (Relative)	174 781	0.00	0.00	0.00	0.17
Focal Follower Attraction (Relative)	174 781	0.00	0.00	0.00	0.33
Net Follower Gain (Relative)	174 781	0.00	0.05	-0.25	14.00
New Follower Gain (Relative)	174 781	0.00	0.05	0.00	14.25
Existing Follower Loss (Relative)	174 781	0.00	0.00	0.00	1.00
Control Variables:					
Gender	174 781	0.50	0.50	0.00	1.00
Age Category	174 781	5.23	1.37	3.00	7.00
Streamer Content Category	174 781	3.00	0.16	1.00	4.00
Region	174 781	1.28	0.45	0.00	2.00
City Level	174 781	4.46	1.49	0.00	6.00
Device Type	174 781	1.30	0.46	1.00	2.00
App Version	174 781	1.16	1.46	0.00	3.00
Device Price Range	174 781	2.53	0.84	0.00	3.00
Community Type	174 781	2.32	1.27	0.00	4.00
Tenure Days (Log)	174 781	11.78	0.84	4.62	12.97
Follower Count (Log)	174 781	11.98	1.97	0.00	20.85
Follow Count (Log)	174 781	10.68	1.98	0.00	13.13
Loyal Fan Count (Log)	174 781	6.30	3.58	0.00	17.29
Historical Total Gifting (Log)	174 781	7.33	5.39	0.00	19.92
Historical Play Duration (Log)	174 781	19.99	7.25	0.00	32.84
Historical Play Count (Log)	174 781	11.00	4.38	0.00	22.21
Historical Viewer Count (Log)	174 781	10.74	4.30	0.00	21.69
Historical Like Count (Log)	174 781	10.09	4.68	0.00	21.29
Historical Like Users (Log)	174 781	7.26	3.41	0.00	15.86
Historical Comment Count (Log)	174 781	8.06	3.99	0.00	18.78
Historical Commenters (Log)	174 781	6.99	3.46	0.00	16.07
Historical Voice Comments (Log)	174 781	2.19	3.52	0.00	15.10
Historical Voice Commenters (Log)	174 781	1.86	2.96	0.00	13.49
Historical Shares (Log)	174 781	3.31	3.52	0.00	16.94
Historical Share Users (Log)	174 781	3.15	3.34	0.00	16.52

3.3 Identification Strategies

3.3.1 Study 1: With vs. Without PK

In Study 1, we seek to estimate the impact of with (vs. without) PK events on streamers' performance. In doing so, it's important to address the potential endogeneity issues, which may arise from omitted variable bias. For example, unobserved factors such as latent streamer characteristics, production quality, or pre-existing audience loyalty could influence both streamers' likelihood of participating in PK events and the resulting outcomes. Hereby, we employ Double Machine Learning (DML) methods that utilize machine learning algorithms to estimate the relationships between the treatment variables (independent variables) and the outcomes while debiasing the influences of confounders (Chernozhukov et al., 2018; Ye et al., 2023). The DML approach is particularly suitable for our context, given the high-dimensional control variables in our dataset.

Specifically, we employ partially linear regression (PLR) to estimate the effect of PK event participation on streaming outcomes while controlling for high-dimensional covariates, as specified in Equations (1) and (2):

$$Y = D\theta_0 + g_0(X) + \zeta, \quad E[\zeta|D, X] = 0, \tag{1}$$

$$D = m_0(X) + V, \quad E[V|X] = 0, \tag{2}$$

where Y is the outcome variables of interest, D is a binary indicator for PK event participation, and X is a set of high-dimensional control variables.[9] The function $g_0(X)$ captures potential nonlinear effects of the control variables, and the function $m_0(X)$ represents the conditional expectation of treatment assignment given the covariates, while ζ and V represent stochastic error terms.

[9] Control variables are selected based on contextual understanding and consultations with the partner platform, as discussed in Section 3.2.1, to account for key streamer-specific and historical factors influencing participating, engagement, and gifting outcomes. We have attempted to include as many relevant controls as possible, based on both theoretical considerations and empirical feasibility.

To estimate θ_0, we apply the DML procedure, which consists of three steps. In the first step, estimating nuisance functions, we estimate the conditional expectations of Y and D given X, known as the nuisance functions: $l(X) = E[Y|X]$, $m_0(X) = E[D|X]$. These functions are estimated using machine learning methods to flexibly capture nonlinear relationships. In the second step, residualization (orthogonalization), we construct residualized versions of Y and D: $\tilde{Y} = Y - \hat{l}(X)$, $\tilde{D} = D - \hat{m}_0(X)$. This orthogonalization step ensures that the estimation of θ_0 is robust to potential confounding by X. In the third step, to estimate the treatment effect, we substitute these residualized variables to obtain $\tilde{Y} = \theta_0\tilde{D} + \zeta$, where $E[\zeta\tilde{D}] = 0$. Under this orthogonality condition, we estimate θ_0 using ordinary least squares (OLS): $\hat{\theta}_0 = (E[\tilde{D}^2])^{-1}E[\tilde{D}\tilde{Y}]$.

To estimate the nuisance functions $\hat{l}(X)$ and $\hat{m}_0(X)$, we use five different machine learning models: Least absolute shrinkage and selection operator (LASSO), random forests, regression trees, boosted trees, and neural networks, which allow us to flexibly capture the relationships between the control variables and both the outcome and treatment assignment. By leveraging cross-fitting, we aim to ensure that the estimations remain asymptotically unbiased. In addition, we perform several robustness checks to validate our findings. These include applying fixed effects (FE) regressions and matching-based approaches. Specifically, we performed propensity score matching (PSM) using a generalized linear model (GLM) estimator with varying nearest-neighbor ratios (1:1, 1:2, and 1:10), and coarsened exact matching (CEM), followed by OLS estimations. We also examine the sensitivity of our results to variations in the number of cross-fitting folds used in the DML procedure.

3.3.2 Study 2: Social Comparison Structure Within Random PK

In Study 2, we investigate how variations in the social comparison structure within random PK events influence the performance of focal streamers. Given the platform's feature that randomly matches streamers for PK events, we exploit this quasi-experimental setting to identify the effects of streamers competing against different types of opponents on their own performances.

Specifically, we focus on two key dimensions of social comparison structure: The comparison in follower base size between the focal streamer and their randomly assigned opponent, and whether the focal streamer belongs to the same content category as their randomly assigned opponent.

Before proceeding with analyses, we first assess the validity of the random assignment of streamers within random PK events through randomization checks. Specifically, we test whether streamer characteristics (such as gender, age category, content category, region, city level, follower count, and streamer tenure), device usage data (such as device type, app version, and device price range) and behavioral characteristics (such as historical viewer engagement—including total comments, likes, shares, and unique commenters), are balanced between the focal streamers and their corresponding opponents. The results indicate no systematic differences in these characteristics across the focal streamers and their opponents in random PK events, providing evidence of successful random assignments. We report the results of the randomization checks in Appendix A.

We then employ ordinary least squares (OLS) regressions to examine the effects of focal-opponent follower size comparison and content category alignment on the focal streamer's performance, following Equations (3) and (4):

$$Y_i = \beta_0 + \beta_1 \text{vs.Big Follower Opponent}_i + \gamma X_i + \varepsilon_i \tag{3}$$

$$Y_i = \beta_0 + \beta_1 \text{vs.Same Category Opponent}_i + \gamma X_i + \varepsilon_i \tag{4}$$

where Y_i represents the outcome variables of interest at the livestreaming session level. The independent variables, vs.Big Follower Opponent$_i$, indicates whether the opponent streamer's follower size is greater than the focal streamer's follower size (1 = yes ; 0 = no), and vs.Big Follower Opponent$_i$, indicates whether the opponent streamer belongs to the same content category as the focal streamer (1 = same category; 0 = different categories). The vector X_i includes the set of control variables. We also use robust standard errors clustered at the streamer level in our regressions to account for any correlation in error terms within streamer observations.

Next, we further explore the possible moderating effects of the focal streamer's follower base size, estimating Equations (5) and (6):

$$\begin{aligned} Y_i = \beta_0 + \beta_1 \text{ vs.Big Follower Opponent}_i + \beta_2 \text{ Big Follower Focal}_i \\ + \beta_3 \left(\text{vs.Big Follower Opponent}_i \times \text{Big Follower Focal}_i\right) + \gamma X_i + \varepsilon_i \end{aligned} \tag{5}$$

$$\begin{aligned} Y_i = \beta_0 + \beta_1 \text{ vs.Same Category Opponent}_i + \beta_2 \text{ Big Follower Focal}_i \\ + \beta_3 \left(\text{vs.Same Category Opponent}_i \times \text{Big Follower Focal}_i\right) + \gamma X_i + \varepsilon_i \end{aligned} \tag{6}$$

here Big Follower Focal$_i$, indicates whether the focal streamer is classified as a "Big" streamer (1 = focal streamer's follower size $\geq$ 10,000; 0 = focal streamer's follower size $<$ 10,000). Also, all estimations in Equations (3) through (6) include year, month, and day indicators. We also employ a continuous measure for the focal streamer's follower size as the moderator in Appendix C.

4 RESULTS

4.1 Study 1: With vs. Without PK

In Study 1, we estimate Equation (1) to examine the impact of participating in PK events on streamer revenue and follower growth. Table 5 presents the results of the Double Machine Learning (DML) estimates. Our analysis reveals robust and consistent evidence that PK events significantly enhance multiple performance metrics of streaming, especially the monetary social exchanges between viewers and streamers. Specifically, PK events significantly increase streamer revenue (measured by total gifting), viewer engagement (measured by average play duration), audience growth (measured by new follower gains and net follower gains), fan commitment (measured by new loyal fan gain), and audience interactions (measured by viewer-to-viewer follower gains).

Our results show that participating in PK events is beneficial to streamers and the livestreaming platform in terms of monetization and user engagement. The consistent estimates across different machine learning methods such as LASSO, random forest, regression trees, boosted trees, and neural networks demonstrate the robustness of our findings, suggesting that our results are not sensitive to model specifications.[10]

Here, we interpret the effect sizes per the lower-bound coefficients across estimation approaches. The estimated total gifting increases by at least 323.34% ($e^{1.443} - 1 = 323.34\%$, $p < 0.001$) and the average play duration increases by at least 69.72% ($e^{0.529} - 1 = 69.72\%$, $p < 0.001$). PK events also generate lower bound increases of 65.53% in new followers ($e^{0.504} - 1 = 65.53\%$, $p < 0.001$), 70.92% in viewer-to-viewer interactions ($e^{0.536} - 1 = 70.92\%$, $p < 0.001$), and 16.88% in loyal fan acquisition ($e^{0.156} - 1 = 16.88\%$, $p < 0.001$). Although PK events are also associated with elevated existing follower loss, the overall net follower growth appears modestly positive across most models ($e^{0.001} - 1 = 0.10\%$, $p < 0.01$), indicating overall positives for streamers participating in PK events in livestreaming.

Table 5: The Effects of PK Event Participation on Streamer Performance

	(1) Total Gifting (log)	(2) Avg Play Duration per Viewer (log)	(3) New Follower Gain (log)	(4) Viewer-to-Viewer Follower Gain (log)	(5) New Loyal Fan Gain (log)	(6) Existing Follower Loss (log)	(7) Net Follower Gain (log)
LASSO	1.514***	0.594***	0.682***	0.536***	0.184***	0.547***	0.00003
	(0.037)	(0.012)	(0.028)	(0.026)	(0.020)	(0.024)	(0.0003)
Random Forest	1.556***	0.590***	0.655***	0.548***	0.186***	0.546***	0.001+
	(0.037)	(0.012)	(0.027)	(0.024)	(0.019)	(0.024)	(0.000)
Regression Trees	1.443***	0.535***	0.504***	0.582***	0.156***	0.527***	0.001*
	(0.037)	(0.013)	(0.027)	(0.025)	(0.019)	(0.024)	(0.000)
Boosted Trees	1.478***	0.529***	0.761***	0.551***	0.237***	0.599***	0.128***
	(0.036)	(0.014)	(0.026)	(0.024)	(0.018)	(0.023)	(0.004)
Neural Network	1.531***	0.693***	0.830***	0.556***	0.250***	0.637***	0.002*
	(0.036)	(0.013)	(0.027)	(0.024)	(0.019)	(0.024)	(0.001)
Obs	272,977	272,977	272,977	272,977	272,977	272,977	272,977

Notes: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

4.2 Study 2: Social Comparison Structure Within Random PK

4.2.1 Focal-Opponent Follower Size Comparison and Content Category Alignment

According to the social comparison framework proposed by Garcia et al. (2013), individuals are more likely to engage in competitive behavior when they perceive their counterparts as similar in ability or performance. Such similarity increases the salience of comparison concerns, thereby

[10] In addition, we conduct several robustness checks using fixed effects models and various matching methods to validate our findings and report the results in Appendix B.

intensifying the drive to outperform the rival (Goethals and Darley, 1977; Kilduff et al., 2010). Additionally, the direction of social comparison, whether upward (comparing to more popular others) or downward (comparing to less popular others), can influence competition outcomes and follower responses. Building on this framework, we examine how the social comparison structure embedded in PK matchups, specifically the follower size comparison and content category alignment between paired streamers, affects the performance of streamers and the behaviors of their viewers.

In Study 2, we investigate how the social comparison structure within random PK events influences focal streamers' outcomes, focusing on both gifting performance and follower dynamics. Gifting performance, representing monetary social exchange, is measured by total gifting and average gifting per viewer. Follower dynamics encompass two aspects: (1) cross-streamer follower exchange, representing reputational social exchange, measured by the number of opponent's followers attracted by the focal streamer and the number of the focal streamer's followers attracted by the opponent; and (2) focal streamer's own follower change, including new followers gained, existing followers lost, and net follower change.

We begin by estimating Equation (3) to examine the impact of follower size comparison on focal streamers' performance during random PK events. Table 6 presents the regression results, including focal streamers' likelihood of winning and their gifting outcomes. The analysis reveals that competing against streamers with a larger follower base significantly decreases the focal streamer's probability of winning the PK session by 5.54% ($e^{-0.057} - 1 = -5.54\%$, $p < 0.001$). In other words, streamers are less likely to win when competing against a bigger opponent. However, despite the reduced likelihood of winning, focal streamers earn significantly more in terms of both total gifting and average gifting per viewer. Specifically, when facing a bigger opponent, focal streamers experience a 35.93% increase in total gifting ($e^{0.307} - 1 = 35.93\%$, $p < 0.001$) and a 12.19% increase in average gifting per viewer ($e^{0.115} - 1 = 12.19\%$, $p < 0.001$).

We then assess how follower size comparison affects follower dynamics of the focal streamers. Table 7 presents the estimation results. In Panel A, we find that competing against

Table 6: The Impact of Follower Size Comparison on Gifting

	Focal Win	Total Gifting (Log)	Avg Gifting per Viewer (Log)
vs. Big Follower Opponent	-0.057***	0.307***	0.115***
	(0.004)	(0.018)	(0.008)
Obs	76,260	174,781	174,781
Effect Size (%)	-5.54***	35.93***	12.19***
F-test	12.60373***	889.700***	532.265***
Controls:	Yes	Yes	Yes

Notes: Focal Win column excludes tie cases (draws), and analysis is restricted to sessions with a clear win or loss. Significance levels: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

streamers with a larger follower base significantly increases the cross-streamer follower exchange. Specifically, when facing a bigger opponent, the number of the opponent's followers attracted by the focal streamer increases by 4.50% ($e^{0.044} - 1 = 4.50\%$, $p < 0.001$), while the number of the focal streamer's followers attracted by the opponent rises by 1.92% ($e^{0.019} - 1 = 1.92\%$, $p < 0.001$). These results show that competing against a bigger opponent will benefit focal streamers in terms of the reputational social exchange.

In terms of focal streamer's own follower change shown in Panel B, new follower acquisition increases by 11.63% ($e^{0.110} - 1 = 11.63\%$, $p < 0.001$), existing follower loss rises by 9.20% ($e^{0.088} - 1 = 9.20\%$, $p < 0.001$), and the net change in followers shows an increase of 0.05% ($e^{0.0005} - 1 = 0.05\%$, $p < 0.001$). Taken together, these findings indicate that although facing a bigger opponent accelerates focal streamers' follower gains and losses, it ultimately results in a significant and positive net impact on the focal streamer's follower base. While the net effect size appears modest, it could be economically significant given the low barrier and repeatable nature of PK participation.

Next, we turn to Equation (4) to evaluate the relationship between streamer content category alignment and focal streamers' performance. Table 8 presents the estimation results for focal streamers' winning probability and gifting outcomes. The analysis indicates that competing against an opponent from the same content category does not significantly influence the likelihood of winning for focal streamers. This is to be expected given that there is no theoretical foundation for higher or lower winning probability when competing with opponents from the same category.

Table 7: The Impact of Follower Size Comparison on Follower Dynamics

Panel A: Follower Attraction

	Opponent Follower Attraction (Log)	Focal Follower Attraction (Log)
vs. Big Follower Opponent	0.044***	0.019***
	(0.003)	(0.003)
Obs	174,781	174,781
Effect Size(%)	4.50***	1.92***
F-test	48.157***	56.888***
Controls:	Yes	Yes

Panel B: Follower Gains and Losses

	New Follower Gain (Log)	Existing Follower Loss (Log)	Net Follower Gain (Log)
vs. Big Follower Opponent	0.110***	0.088***	0.0005***
	(0.010)	(0.009)	(0.0001)
Obs	174,781	174,781	174,781
Effect Size(%)	11.63***	9.20***	0.05***
F-test	534.302***	701.594***	42.884***
Controls:	Yes	Yes	Yes

Notes: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

However, it does lead to a substantial increase in viewer gifting. Specifically, when competing against an opponent from the same category, focal streamers experience a 6.40% increase in both total gifting and average gifting per viewer ($e^{0.062} - 1 = 6.40\%$, $p < 0.001$).

Table 8: The Impact of Content Category Alignment on Gifting

	Focal Win	Total Gifting (Log)	Avg Gifting per Viewer (Log)
vs. Same Category Opponent	-0.004	0.062***	0.062***
	(0.004)	(0.019)	(0.009)
Obs	76,260	174,781	174,781
Effect Size (%)	-0.40	6.40***	6.40***
F-test	14.774***	884.817***	530.282***
Controls:	Yes	Yes	Yes

Notes: Focal Win column excludes tie cases (draws), and analysis is restricted to sessions with a clear win or loss. Significance levels: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Meanwhile, we also investigate whether content category alignment affects follower dynamics. As shown in Panel A of Table 9, we find that competition within the same content category significantly increases cross-streamer follower exchange. Specifically, when facing a same content category opponent, the number of the opponent's followers attracted by the focal streamer increases by 1.41% ($e^{0.014} - 1 = 1.41\%$, $p < 0.001$), while the number of the focal streamer's followers attracted by the opponent rises by 1.51% ($e^{0.015} - 1 = 1.51\%$, $p < 0.001$). These results show that competing against a same-category opponent will also benefit focal streamers in terms of the reputational social exchange.[11]

Focusing only on focal streamer's own follower change, the results in Panel B show that new follower acquisition decreases by 5.07% ($e^{-0.052} - 1 = -5.07\%$, $p < 0.001$), existing follower loss decreases by 4.40% ($e^{-0.045} - 1 = -4.40\%$, $p < 0.001$). The net change in followers, however, is statistically insignificant. Taken together, these findings suggest that although competition within the same content category decreases follower gains and losses, it does not result in a significant change in the net size of a streamer's follower base.

Table 9: The Impact of Content Category Alignment on Follower Dynamics

Panel A: Follower Attraction

	Opponent Follower Attraction (Log)	Focal Follower Attraction (Log)
vs. Same Category Opponent	0.014***	0.015***
	(0.003)	(0.003)
Obs	174,781	174,781
Effect Size(%)	1.41***	1.51***
F-test	44.409***	56.609***
Controls:	Yes	Yes

Panel B: Follower Gains and Losses

	New Follower Gain (Log)	Existing Follower Loss (Log)	Net Follower Gain (Log)
vs. Same Category Opponent	-0.052***	-0.045***	-0.00009
	(0.010)	(0.009)	(0.00015)
Obs	174,781	174,781	174,781
Effect Size(%)	-5.07***	-4.40***	-0.009
F-test	532.960***	700.428***	42.805***
Controls:	Yes	Yes	Yes

Notes: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Taken together, these results underscore the impact of social comparison structure on two types of social exchanges with focal streamers during PK events. Importantly, we find that competing against opponents with a relatively larger follower base or the same content category significantly enhances both monetary social exchange (reflected in increased viewer gifting), and reputational social exchange (reflected in heightened cross-streamer follower exchange).

[11] The relatively same effect sizes of competing with same-category opponents on the exchanges of followers further provide the evidence of the randomization design in our Study 2.

4.2.2 Heterogeneity Analysis by Focal Streamer Follower Size

In this section, we further examine how the focal streamer's own follower size moderates the impact of social comparison structure on their performance. Specifically, we investigate whether the impact of competing against bigger opponents or same-category opponents varies based on the focal streamer's follower size. Prior literature also suggests that audience sizes could play an important role in streamers' behaviors in the livestreaming context (Lin et al., 2021; Lu et al., 2021). After categorizing focal streamers' follower size as "big" (those with more than 10,000 followers) or "small" (otherwise), we estimate Equations (5) and (6), with results presented in Tables 10, 12, 13 and 15.[12]

In Table 10, the main effect of *vs. Big Follower Opponent* ($\hat{\beta}_1 = 0.321$, $p < 0.001$) suggests that, ceteris paribus, streamers receive significantly more total gifting when matched against an opponent with a larger follower base, and being a big focal streamer also significantly increases total gifting ($\hat{\beta}_2 = 0.377$, $p < 0.001$). However, the interaction term of *vs. Big Follower Opponent* and *Big Follower Focal* is significant and negative for the total gifting outcome ($\hat{\beta}_3 = -0.126$, $p < 0.05$), indicating that the positive effect of competing against a bigger opponent is attenuated for focal streamers with a large follower base.

Table 10: Heterogeneity Analysis with Follower Size Comparison on Gifting

	Total Gifting (Log)	Avg Gifting per Viewer (Log)
vs.Big Follower Opponent	0.321***	0.115***
	(0.019)	(0.009)
Big Follower Focal	0.377***	0.072**
	(0.069)	(0.028)
vs.Big Follower Opponent * Big Follower Focal	-0.126*	-0.006
	(0.062)	(0.029)
Obs	174,781	174,781
F-test	871.438***	520.576***
Controls:	Yes	Yes

Notes: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

We then use Table 11 to present predicted average outcomes from Table 10 across the four combinations of *vs. Big Follower Opponent* and *Big Follower Focal*. Taking the case where focal

[12] This cutoff of 10,000 followers was determined by the partner platform based on internal streamer segmentation practice. We also report robustness checks using continuous focal follower size in Appendix C.

Table 11: Predicted Total Gifting by Focal and Opponent Follower Size

	Opponent – Smaller	Opponent – Bigger
Focal – Small	2.71	3.03
	[2.54, 2.87]	*[2.86, 3.19]*
Focal – Big	3.08	3.28
	[2.88, 3.29]	*[3.06, 3.49]*

Notes: (a) Cell values represent the predicted average total gifting (log) and associated 95%-confidence intervals. (b) All pairwise comparisons between the four groups are statistically significant ($p < 0.001$).

streamers have small follower bases and are matched with a smaller opponent as the baseline (predicted log total gifting: 2.71, 95%-CI: [2.54, 2.87]), we find that small focal streamers benefit from competing against a bigger opponent (bigger than focal streamer), as total gifting increases to 3.03, 95%-CI: [2.86, 3.19]. Similarly, big focal streamers consistently receive higher total gifting than small ones. When competing against a smaller opponent, the predicted total gifting is 3.08, 95%-CI: [2.88, 3.29], and when matched with a bigger opponent, this increases further to 3.28, 95%-CI: [3.06, 3.49]. Although the underlying regression includes a negative interaction term suggesting diminishing marginal returns when both the focal streamer is a big streamer and the opponent has a larger follower base, the highest predicted gifting still occurs in this configuration. Thus, the most profitable PK matchup, in terms of total gifting, is between a big focal streamer and a bigger opponent.

Meanwhile, we also examine how focal streamers' own follower size moderates the influence of social comparison on follower dynamics. As shown in Panel A of Table 12, facing a bigger opponent significantly increases both opponent follower attraction ($\hat{\beta}_1 = 0.029$, $p < 0.001$) and focal follower attraction ($\hat{\beta}_1 = 0.016$, $p < 0.001$). The main effect of being a big focal streamer is also positive for focal follower attraction ($\hat{\beta}_2 = 0.028$, $p < 0.001$), indicating that more popular streamers tend to provide more potential follower attraction for the opponents. Notably, the significantly positive interaction term between *vs. Big Follower Opponent* and *Big Follower Focal* on opponent follower attraction ($\hat{\beta}_3 = 0.110$, $p < 0.001$) suggests that this effect is especially pronounced when the focal streamer is a big streamer.

Table 12: Heterogeneity Analysis with Follower Size Comparison on Follower Dynamics

Panel A: Follower Attraction

	Opponent Follower Attraction (Log)	Focal Follower Attraction (Log)
vs. Big Follower Opponent	0.029***	0.016***
	(0.002)	(0.002)
Big Follower Focal	-0.006	0.028***
	(0.006)	(0.007)
vs. Big Follower Opponent Big Follower Focal	0.110***	0.017
	(0.014)	(0.013)
Obs	174,781	174,781
F-test	50.620***	56.307***
Controls:	Yes	Yes

Panel B: Follower Gains and Losses

	New Follower Gain (Log)	Existing Follower Loss (Log)	Net Follower Gain (Log)
vs. Big Follower Opponent	0.092***	0.091***	0.0001
	(0.010)	(0.009)	(0.0001)
Big Follower Focal	0.057+	0.391***	-0.001+
	(0.032)	(0.029)	(0.000)
vs. Big Follower Opponent Big Follower Focal	0.119**	-0.050	0.002**
	(0.040)	(0.037)	(0.001)
Obs	174,781	174,781	174,781
F-test	522.864***	693.484***	42.215***
Controls:	Yes	Yes	Yes

Notes: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Focusing only on focal streamer's own follower change, the results in Panel B of Table 12 show that competing against a bigger opponent increases both new follower gain ($\hat{\beta}_1 = 0.092$, $p < 0.001$) and existing follower loss ($\hat{\beta}_1 = 0.091$, $p < 0.001$), but results in no significant change in net follower gain. In terms of focal follower size, big focal streamers experience higher levels of both new follower acquisition ($\hat{\beta}_2 = 0.057$, $p < 0.1$) and existing follower loss ($\hat{\beta}_2 = 0.391$, $p < 0.001$). Importantly, the interaction effects show that big focal streamers benefit more when facing a bigger opponent: the interaction term is significantly positive for new follower gain ($\hat{\beta}_3 = 0.119$, $p < 0.01$) and net follower gain ($\hat{\beta}_3 = 0.002$, $p < 0.01$), while not significant for existing follower loss.

The heterogeneity results suggest that competing against a bigger opponent is beneficial for both small and big focal streamers in terms of attracting more followers, but the effects are more pronounced for the big focal streamers. This aligns with the findings on gifting, suggesting the best

PK configuration in terms of net follower gain is still a big focal streamer competing against a bigger opponent.

Next, looking at Table 13, consistent with our earlier findings, competing against an opponent in the same content category is positive and significant ($\hat{\beta}_1 = 0.152$, $p < 0.001$), and the main effect of being a big focal streamer is also significant and positive ($\hat{\beta}_2 = 1.985$, $p < 0.001$). Meanwhile, the interaction term of *vs. Same Category Opponent* and *Big Follower Focal* is significant and negative for the total gifting outcome ($\hat{\beta}_3 = -0.379$, $p < 0.001$), suggesting that the positive effect of competing with opponents in the same content category is actually weaker for focal streamers with large follower bases.

Table 13: Heterogeneity Analysis with Content Category Alignment on Gifting

	Total Gifting (Log)	Avg Gifting per Viewer (Log)
vs.Same Category Opponent	0.152***	0.087***
	(0.020)	(0.009)
Big Follower Focal	1.985***	0.400**
	(0.054)	(0.022)
vs.Same Category Opponent * Big Follower Focal	-0.379***	-0.115***
	(0.060)	(0.028)
Obs	174,781	174,781
F-test	867.127***	518.721***
Controls:	Yes	Yes

Notes: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 14: Predicted Total Gifting by Focal Follower Size and Opponent Category Alignment

	Opponent – Same Cat.	Opponent – Different Cat.
Focal – Small	2.74	2.59
	[2.61, 2.87]	*[2.47, 2.71]*
Focal – Big	4.35	4.57
	[4.18, 4.52]	*[4.42, 4.73]*

Notes: (a) Cell values represent the predicted average total gifting (log) and associated 95%-confidence intervals. (b) All pairwise comparisons between the four groups are statistically significant ($p < 0.001$).

Table 14 illustrates the average predicted values based on the regression coefficients from Table 13. Using the scenario where the focal streamer is small and the opponent is from a different content category as the baseline (predicted log total gifting: 2.59, 95%-CI: [2.47, 2.71]), we find that category similarity leads to a modest but statistically significant increase in total gifting for small focal streamers, rising to 2.74, 95%-CI: [2.61, 2.87] when the opponent is from the same content category. For big focal streamers, total gifting levels are substantially higher overall. However, the predicted gifting is significantly lower when facing a same-category opponent (4.35, 95%-CI: [4.18, 4.52]) compared to a different-category opponent (4.57, 95%-CI: [4.42, 4.73]). This suggests that, unlike small focal streamers, big focal streamers do not benefit from category similarity in terms of total gifting. Thus, the best PK configuration for big focal streamers, in terms of total gifting, is competing against an opponent from a different content category; the best PK configuration for small focal streamers is competing against an opponent from the same content category.

We further explore whether the impact of content category alignment on follower dynamics during Random PK differs by the focal streamer's follower size. As shown in Panel A of Table 15, competing against an opponent from the same content category significantly increases both opponent follower attraction ($\hat{\beta}_1 = 0.008$, $p < 0.001$) and focal follower attraction ($\hat{\beta}_1 = 0.005$, $p < 0.01$), indicating the intensified cross-streamer follower exchange when content overlap exists. The main effects of being a big focal streamer are also positive and significant for opponent follower attraction ($\hat{\beta}_2 = 0.074$, $p < 0.001$) and focal follower attraction ($\hat{\beta}_2 = 0.082$, $p < 0.001$). Moreover, the interaction terms between *vs. Same Category Opponent* and *Big Follower Focal* are significantly positive for both opponent follower attraction ($\hat{\beta}_3 = 0.051$, $p < 0.001$) and focal follower attraction ($\hat{\beta}_3 = 0.071$, $p < 0.001$). This means that big focal streamers tend to exchange a greater number of followers from their same-category opponents.

Panel B of Table 15 focuses on focal streamers' own follower change. The main effect of competing against a same-category opponent is statistically insignificant for both new follower gain and follower loss, and marginally negative for net follower gain. Meanwhile, the main effects of being a big focal streamers are significantly positive for new follower gain ($\hat{\beta}_2 = 1.163$, $p < 0.001$), existing follower loss ($\hat{\beta}_2 = 1.745$, $p < 0.001$), but not net follower gain ($\hat{\beta}_2 = 0.001$, $p < 0.1$). Notably, the interaction term between *vs. Same Category Opponent* and *Big Follower Focal* is significantly negative for new follower gain ($\hat{\beta}_3 = -0.112$, $p < 0.01$) and follower loss

Table 15: Heterogeneity Analysis with Content Category Alignment on Follower Dynamics

Panel A: Follower Attraction

	Opponent Follower Attraction (Log)	Focal Follower Attraction (Log)
vs. Same Category Opponent	0.008***	0.005**
	(0.002)	(0.002)
Big Follower Focal	0.074***	0.082***
	(0.006)	(0.007)
vs. Same Category Opponent * Big Follower Focal	0.051***	0.071***
	(0.012)	(0.012)
Obs	174,781	174,781
F-test	47.494***	61.662***
Controls:	Yes	Yes

Panel B: Follower Gains and Losses

	New Follower Gain (Log)	Existing Follower Loss (Log)	Net Follower Gain (Log)
vs. Same Category Opponent	-0.004	-0.003	-0.0001*
	(0.010)	(0.008)	(0.000)
Big Follower Focal	1.163***	1.745***	0.001+
	(0.030)	(0.029)	(0.001)
vs. Same Category Opponent * Big Follower Focal	-0.112**	-0.201***	0.001
	(0.040)	(0.039)	(0.001)
Obs	174,781	174,781	174,781
F-test	539.304***	694.061***	12.420***
Controls:	Yes	Yes	Yes

Notes: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

($\hat{\beta}_3 = -0.201, p < 0.001$), but insignificant for net follower gain. These results, which are different from the moderation effects on cross-streamer follower exchange, suggest that competing against same-category opponents for big focal streamers does not significantly increase their own follower base, and may even lead to a slight decrease in new follower acquisition. This finding indicates that while category alignment enhances cross-streamer follower exchange, it does not necessarily translate into net follower gains for the focal streamers with large follower bases.

In summary, our findings indicate that while competing against a bigger opponent reduces the likelihood of winning, it significantly boosts both viewer gifting (representing monetary social exchange) and cross-streamer follower exchange (representing reputational social exchange), as well as net follower gains for the focal streamer. In contrast, facing opponents from the same content category does not significantly impact the chances of winning. However, it does result in notable increases in viewer gifting and follower exchange across streamers. Heterogeneity analysis reveals two optimal configurations: In terms of gifting and follower dynamics, small streamers benefit most from competing against bigger, same-category opponents, while big streamers gain most from competing against bigger peers in different categories.

5 DISCUSSIONS

5.1 Key Findings

This study investigates how platform-mediated competition affects streamer performance on livestreaming platforms, focusing on PK events and using two studies. In the first study, our results show that PK events lead to significant increases in total gifting, substantial improvements in viewer engagement duration, new follower growth, and fan commitment. In the second study, we examine how different social comparison structures within randomly matched PK events influence the focal streamers' gifting and follower dynamics. We find that despite having a lower probability of winning, streamers competing against opponents with larger follower bases receive significantly more gifts relative to their own baseline than their opponents do relative to theirs. Similarly, competing against an opponent from the same content category also boosts gifting. This competition also induces a reputational social exchange between streamers (reflected by cross-streamer follower exchange). Facing a bigger or same-category opponent results in notable increases in follower exchange across streamers. Additionally, facing a bigger opponent leads to a net positive follower gain, as streamers attract more followers from their opponent's audience than they lose. Moreover, our heterogeneity analyses show that small streamers gain the most financially and in followers when challenging bigger, same-category opponents, providing a clear motivation for their participation despite the high risk of losing. Conversely, big streamers benefit most from competing against bigger peers from different content categories.

5.2 Implications to Research

Our work offers several implications to research. First, we advance social comparison theory by adapting it to a livestreaming context where comparison is not only public but also competitively structured and monetized. Prior work has typically examined social comparison in asynchronous and private settings (Krasnova et al., 2015; Liu et al., 2017; Shi et al., 2025). Our research examines how social comparison is externalized and enacted in real time through PK events, where outcomes are determined by collective audience behavior. We demonstrate that social comparison structures, such as upward comparison (a small streamer facing a larger opponent) and lateral comparison within the same content category, significantly influence following and gifting behaviors. Also, our work complements a recent study by Gu et al. (2024), which examines how firms cooperatively mix big and small influencers (streamers) in livestream selling; whereas this work investigates streamers competing with each other in content livestreaming.

Second, our work contributes to social exchange theory by demonstrating how a platform-mediated competitive design influences social exchange outcomes. Social exchange theory has been widely used to understand incentives for knowledge sharing (Kankanhalli et al., 2005; Qiu and Kumar, 2017) and reciprocity in online settings (Ye et al., 2018), and its application in livestreaming has largely focused on gifting as a monetary social exchange (Kim et al., 2018; Yao et al., 2024). We show that platform-induced social comparison not only intensifies this established monetary social exchange but also activates a novel, concurrent form of reputational social exchange between the competing streamers. Based on social exchange theory, we seek to answer a seemingly behavioral puzzle: Why do small streamers enter into social comparisons they are likely to lose? Our findings reveal that even when small streamers lose the PK events, they often benefit reputationally and financially due to social exchanges among streamers and viewers.

Third, we advance the body of work on digital platform monetization, particularly, in the form of PWYW. Prior research has largely focused on immediate economic drivers of gifting behavior, such as perceived kindness, audience size, or social pressure (Chen et al., 2017; Kim et al., 2009; Lu et al., 2021; Yao et al., 2024). In contrast, our study stresses the reputational implications that occur alongside monetary exchanges. Specifically, we demonstrate that social comparison structures embedded in PK events not only influence short-term gifting behavior but also shape audience migration patterns (i.e., follower gains and losses), which affect a streamer's future earning potential. Our findings also extend the work by Milstein et al. (2022) in the context of software development, whichs show that rivalry can both enhance and impair performance depending on individual capabilities and the perceived risk of status loss. Translating this insight to the context of digital platforms, our findings suggest that even when the risk of 'losing' is high, as in cases where smaller streamers face much larger opponents, PK events can still yield positive reputational outcomes due to audience-side behavior.

5.3 Implications to Practice

Our results provide actionable implications for digital platform operators and content creators. Platforms without real-time competitive features can consider implementing PK-style social comparison as an effective way to drive user engagement and monetization. For platforms already offering PK functionality, operators can optimize their matching algorithms to pair smaller streamers with larger competitors more frequently. This seemingly unbalanced approach actually benefits both parties, as smaller creators gain exposure to new audiences, whereas larger creators can demonstrate their dominance and potentially attract supporters from their opponents' communities. In addition, platforms can implement incentive mechanisms, such as social nudges or targeted financial rewards, to encourage big streamers to participate in PK events with smaller peers, thereby promoting a more inclusive and balanced creator ecosystem. For streamers, particularly those with small follower bases, actively seeking PK matchups against bigger, categorically aligned competitors presents a promising strategy. Meanwhile, for big streamers, the advantageous strategy appears to be competing against similarly bigger peers from different content categories, which is effective at maximizing immediate monetization and tapping into distinct viewer pools.

5.4 Limitations and Future Research

This work has several potential limitations, which also point to fruitful directions for future research. First, we acknowledge possible selections in Study 1, as streamers voluntarily choose to participate in PK events. It's possible that the participating streamers possess unobserved characteristics that influence both their decision to compete and their performance outcomes. Future research can address this by manipulating eligibility in participating in PK events through randomized field experiments. Second, our investigations focus on the financial and follower dynamics within the first PK event for each streamer. Future research can explore the longer-term effects of repeated participation. It is possible that the benefits of competition diminish over time, or that repeated losses could have a cumulative negative impact on a streamer's motivation and community. Third, though we focused on the streamers and streamer-side outcomes, it would be useful to also understand viewer-side perspectives in future research. Extending this line of thinking, examining streamer–viewer interactions during PK events can be another promising direction for future exploration.

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Online Appendices

A RANDOMIZATION CHECKS

As shown in Table A1, we conduct two-tailed t-tests for continuous variables and Chi-squared tests for categorical variables for Study 2, and find no statistically significant differences in observable covariates between focal streamers and opponent streamers.

Table A1: Randomization Checks

Variables	**P-value**
Gender	0.996
Age Category	0.539
Streamer Content Category	0.169
Region	0.953
City Level	0.449
Device Type	0.404
App Version	0.741
Device Price Range	0.277
Community Type	0.469
Tenure Days (Log)	0.644
Follower Count (Log)	0.558
Following Count (Log)	0.923
Loyal Fan Count (Log)	0.943
Historical Total Gifting (Log)	0.710
Historical Play Duration (Log)	0.838
Historical Play Count (Log)	0.631
Historical Viewer Count (Log)	0.607
Historical Like Count (Log)	0.891
Historical Like Users (Log)	0.762
Historical Comment Count (Log)	0.658
Historical Commenters (Log)	0.551
Historical Voice Comments (Log)	0.943
Historical Voice Commenters (Log)	0.955
Historical Shares (Log)	0.913
Historical Share Users (Log)	0.997

B ROBUSTNESS CHECKS FOR PK VS. NON-PK ANALYSIS

To ensure the robustness of our findings for Study 1, we employ multiple complementary methods that reinforce and validate the estimated effects of PK event participation obtained from our primary DML analysis. These approaches provide additional evidence for the consistency of our results across different modeling frameworks.

B.1 Fixed-Effects Models

As a first step in validating the robustness of our DML-based findings, we estimate a two-way fixed-effects model that includes streamer fixed effects and date fixed effects. The streamer fixed effects account for unobserved, time-invariant heterogeneity across streamers (e.g., baseline popularity, content style), while the date fixed effects absorb platform-wide shocks or trends common to all streamers on a given day. This specification enables us to exploit within-streamer variation over time and control for contemporaneous confounding at the platform level. Table B1 reports the results, which confirm that the estimated effects remain consistent under this alternative modeling strategy.

Table B1: Effects of PK Event Participation on Streamer Performance (FE)

	(1) Total Gifting (log)	(2) Avg Play Duration per Viewer (log)	(3) New Follower Gain (log)	(4) Viewer-to-Viewer Follower Gain (log)	(5) New Loyal Fan Gain (log)	(6) Existing Follower Loss (log)	(7) Net Follower Gain(log)
with PK	1.685***	0.792***	0.987***	0.530***	0.315***	0.736***	0.001***
	(0.041)	(0.022)	(0.030)	(0.027)	(0.021)	(0.028)	(0.000)
Obs	272,977	272,977	272,977	272,977	272,977	272,977	272,977
Controls:	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Streamer FE:	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date FE:	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

B.2 Propensity Score and Coarsened Exact Matching with OLS

To further validate our findings, we implement propensity score matching (PSM) and coarsened exact matching (CEM), followed by ordinary least squares (OLS) regression on the matched samples. These matching techniques aim to mitigate potential biases due to covariate imbalances between PK and non-PK sessions by constructing more comparable treatment and control groups, thereby improving the credibility of the estimated treatment effects.

For PSM, we estimate propensity scores using a generalized linear model (GLM) and implement nearest-neighbor matching with three different matching ratios (1:1, 1:2, and 1:10), allowing us to examine the robustness of our estimates across varying levels of matching granularity. Additionally, we employ CEM, which groups observations into strata with similar covariate profiles prior to matching, thereby ensuring better balance on key covariates.

Table B2: Effects of PK Event Participation on Streamer Performance (PSM, ratio = 1)

	(1) Total Gifting (log)	(2) Avg Play Duration per Viewer (log)	(3) New Follower Gain (log)	(4) Viewer-to-Viewer Follower Gain (log)	(5) New Loyal Fan Gain (log)	(6) Existing Follower Loss(log)	(7) Net Follower Gain(log)
with PK	1.518***	0.632***	0.702***	0.507***	0.192***	0.559***	0.0002
	(0.054)	(0.029)	(0.040)	(0.037)	(0.028)	(0.034)	(0.0005)
Obs	20,624	20,624	20,624	20,624	20,624	20,624	20,624
F-test	282.685***	66.286***	282.614***	189.137***	181.106***	383.142***	67.761***
Controls:	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table B3: Effects of PK Event Participation on Streamer Performance (PSM, ratio = 2)

	(1) Total Gifting (log)	(2) Avg Play Duration per Viewer (log)	(3) New Follower Gain (log)	(4) Viewer-to-Viewer Follower Gain (log)	(5) New Loyal Fan Gain (log)	(6) Existing Follower Loss (log)	(7) Net Follower Gain(log)
with PK	1.491***	0.619***	0.690***	0.483***	0.186***	0.548***	0.0001
	(0.047)	(0.022)	(0.035)	(0.033)	(0.025)	(0.030)	(0.0005)
Obs	30,936	30,936	30,936	30,936	30,936	30,936	30,936
F-test	399.832***	82.719***	435.574***	268.243***	276.331***	574.452***	115.974***
Controls:	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table B4: Effects of PK Event Participation on Streamer Performance (PSM, ratio = 10)

	(1) Total Gifting (log)	(2) Avg Play Duration per Viewer (log)	(3) New Follower Gain (log)	(4) Viewer-to-Viewer Follower Gain (log)	(5) New Loyal Fan Gain (log)	(6) Existing Follower Loss (log)	(7) Net Follower Gain(log)
with PK	1.469***	0.585***	0.652***	0.511***	0.177***	0.522***	0.0002
	(0.041)	(0.015)	(0.031)	(0.029)	(0.023)	(0.027)	(0.0004)
Obs	113,432	113,432	113,432	113,432	113,432	113,432	113,432
F-test	1327.57***	235.559***	1598.782***	836.669***	975.942***	2058.429***	351.282***
Controls:	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table B5: Effects of PK Event Participation on Streamer Performance (CEM)

	(1) Total Gifting (log)	(2) Avg Play Duration per Viewer (log)	(3) New Follower Gain (log)	(4) Viewer-to-Viewer Follower Gain (log)	(5) New Loyal Fan Gain (log)	(6) Existing Follower Loss (log)	(7) Net Follower Gain(log)
with PK	1.728***	0.843***	0.962***	0.509***	0.306***	0.774***	0.012
	(0.140)	(0.096)	(0.103)	(0.091)	(0.069)	(0.090)	(0.012)
Obs	2,018	2,018	2,018	2,018	2,018	2,018	2,018
F-test	35.817***	9.472***	36.795***	28.040***	26.691***	44.197***	1.890***
Controls:	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

After matching, we estimate the average treatment effects using OLS regressions on the matched samples. The results are presented in Tables B2, B3, B4 and B5, and show consistent and robust treatment effects across different matching specifications.

Next, we conduct balance checks to ensure that the covariate distributions between treatment and control groups are comparable after matching. The results, presented in Tables B6, B7, B8, and B9, confirm that covariate balance is successfully achieved across all matched samples.

Table B6: Balance Check: PSM (ratio = 1)

Variable	**Std. Diff. Before**	**Std. Diff. After**
Propensity Score Distance	0.64	0.00
Gender	−0.02	0.00
Age Category: 3	0.02	0.00
Age Category: 4	0.01	0.00
Age Category: 5	0.00	0.00
Age Category: 6	0.00	0.00
Age Category: 7	−0.03	0.00
Streamer Content Category: 1	0.00	0.00
Streamer Content Category: 2	−0.04	0.00
Streamer Content Category: 3	0.05	0.00
Streamer Content Category: 4	0.00	0.00
Region: 0	0.00	0.00
Region: 1	−0.05	0.00
Region: 2	0.05	0.00
City Level: 0	0.00	0.00
City Level: 1	0.00	0.00
City Level: 2	−0.01	0.00
City Level: 3	−0.01	0.00
City Level: 4	−0.02	0.00
City Level: 5	−0.01	0.00
City Level: 6	0.05	−0.01
Device Type: 2	0.03	0.00
App Version: 3	−0.01	0.00
Device Price Range: 0	0.00	0.00
Device Price Range: 1	0.02	0.00
Device Price Range: 2	0.00	0.00
Device Price Range: 3	−0.03	0.00
Community Type: 0	−0.01	0.00
Community Type: 1	−0.01	0.00
Community Type: 2	0.00	0.00
Community Type: 3	0.01	0.00
Community Type: 4	0.01	0.01
Influencer Account	0.00	0.00
Follower Count (Log)	0.32	0.00
Historical Total Gifting (Log)	0.51	0.00
Historical Play Duration (Log)	0.17	−0.02
Historical Comment Count (Log)	0.37	0.00

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Variable	Std. Diff. Before	Std. Diff. After
Historical Like Count (Log)	0.34	0.00
Following Count (Log)	0.19	0.00
Loyal Fan Count (Log)	0.29	0.00
Tenure Days (Log)	0.02	−0.01
Historical Play Count (Log)	0.27	−0.01
Historical Viewer Count (Log)	0.27	−0.01
Historical Commenters (Log)	0.35	0.00
Historical Voice Comments (Log)	0.23	−0.01
Historical Voice Commenters (Log)	0.23	−0.01
Historical Like Users (Log)	0.35	0.00
Historical Shares (Log)	0.20	0.01
Historical Share Users (Log)	0.20	0.01

Table B7: Balance Check: PSM (ratio = 2)

Variable	Std. Diff. Before	Std. Diff. After
Propensity Score Distance	0.64	0.00
Gender	−0.02	0.00
Age Category: 3	0.02	0.00
Age Category: 4	0.01	0.00
Age Category: 5	0.00	0.00
Age Category: 6	0.00	0.00
Age Category: 7	−0.03	0.00
Streamer Content Category: 1	0.00	0.00
Streamer Content Category: 2	−0.04	0.00
Streamer Content Category: 3	0.05	0.00
Streamer Content Category: 4	0.00	0.00
Region: 0	0.00	0.00
Region: 1	−0.05	0.00
Region: 2	0.05	0.00
City Level: 0	0.00	0.00
City Level: 1	0.00	0.00
City Level: 2	−0.01	0.00
City Level: 3	−0.01	0.00
City Level: 4	−0.02	0.00
City Level: 5	−0.01	0.00
City Level: 6	0.05	0.00
Device Type: 2	0.03	0.00
App Version: 3	−0.01	0.00
Device Price Range: 0	0.00	0.00
Device Price Range: 1	0.02	0.00
Device Price Range: 2	0.00	0.00
Device Price Range: 3	−0.03	0.00
Community Type: 0	−0.01	0.00
Community Type: 1	−0.01	0.00
Community Type: 2	0.00	0.00
Community Type: 3	0.01	0.00
Community Type: 4	0.01	0.00
Influencer Account	0.00	0.00
Follower Count (Log)	0.32	0.00
Historical Total Gifting (Log)	0.51	0.00
Historical Play Duration (Log)	0.17	−0.02
Historical Comment Count (Log)	0.37	0.00
Historical Like Count (Log)	0.34	0.00
Following Count (Log)	0.19	0.00
Loyal Fan Count (Log)	0.29	0.00
Tenure Days (Log)	0.02	0.00
Historical Play Count (Log)	0.27	−0.01
Historical Viewer Count (Log)	0.27	−0.01
Historical Commenters (Log)	0.35	0.00
Historical Voice Comments (Log)	0.23	−0.01
Historical Voice Commenters (Log)	0.23	−0.01
Historical Like Users (Log)	0.35	0.00
Historical Shares (Log)	0.20	0.01
Historical Share Users (Log)	0.20	0.01

Table B8: Balance Check: PSM (ratio = 10)

Variable	Std. Diff. Before	Std. Diff. After
Propensity Score Distance	0.64	0.18
Gender	−0.02	−0.01
Age Category: 3	0.02	0.01
Age Category: 4	0.01	0.00
Age Category: 5	0.00	0.00
Age Category: 6	0.00	0.00
Age Category: 7	−0.03	−0.01
Streamer Content Category: 1	0.00	0.00
Streamer Content Category: 2	−0.04	0.00
Streamer Content Category: 3	0.05	0.00
Streamer Content Category: 4	0.00	0.00
Region: 0	0.00	0.00
Region: 1	−0.05	−0.01
Region: 2	0.05	0.01
City Level: 0	0.00	0.00
City Level: 1	0.00	0.00
City Level: 2	−0.01	0.00
City Level: 3	−0.01	0.00
City Level: 4	−0.02	0.00
City Level: 5	−0.01	0.00
City Level: 6	0.05	0.00
Device Type: 2	0.03	0.01
App Version: 3	−0.01	0.00
Device Price Range: 0	0.00	0.00
Device Price Range: 1	0.02	0.01
Device Price Range: 2	0.00	0.00
Device Price Range: 3	−0.03	−0.01
Community Type: 0	−0.01	0.00
Community Type: 1	−0.01	0.00
Community Type: 2	0.00	0.00
Community Type: 3	0.01	0.00
Community Type: 4	0.01	0.00
Influencer Account	0.00	0.00
Follower Count (Log)	0.32	0.06
Historical Total Gifting (Log)	0.51	0.07
Historical Play Duration (Log)	0.17	0.01
Historical Comment Count (Log)	0.37	0.04
Historical Like Count (Log)	0.34	0.04
Following Count (Log)	0.19	0.01
Loyal Fan Count (Log)	0.29	0.05
Tenure Days (Log)	0.02	−0.01
Historical Play Count (Log)	0.27	0.03
Historical Viewer Count (Log)	0.27	0.03
Historical Commenters (Log)	0.35	0.04
Historical Voice Comments (Log)	0.23	0.00
Historical Voice Commenters (Log)	0.23	0.00
Historical Like Users (Log)	0.35	0.04
Historical Shares (Log)	0.20	0.04
Historical Share Users (Log)	0.20	0.04

Table B9: Balance Check: CEM

Variable	Std. Diff. Before	Std. Diff. After
Gender	−0.02	0.00
Age Category: 3	0.02	0.00
Age Category: 4	0.01	0.00
Age Category: 5	0.00	0.00
Age Category: 6	0.00	0.00
Age Category: 7	−0.03	0.00
Streamer Content Category: 1	0.00	0.00
Streamer Content Category: 2	−0.04	0.00
Streamer Content Category: 3	0.05	0.00
Streamer Content Category: 4	0.00	0.00
Region: 0	0.00	0.00
Region: 1	−0.05	0.00
Region: 2	0.05	0.00
City Level: 0	0.00	0.00
City Level: 1	0.00	0.00
City Level: 2	−0.01	0.00

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Variable	**Std. Diff. Before**	**Std. Diff. After**
City Level: 3	−0.01	0.00
City Level: 4	−0.02	0.00
City Level: 5	−0.01	0.00
City Level: 6	0.05	0.00
Device Type: 2	0.03	0.00
App Version: 3	−0.01	0.00
Device Price Range: 0	0.00	0.00
Device Price Range: 1	0.02	0.00
Device Price Range: 2	0.00	0.00
Device Price Range: 3	−0.03	0.00
Community Type: 0	−0.01	0.00
Community Type: 1	−0.01	0.00
Community Type: 2	0.00	0.00
Community Type: 3	0.01	0.00
Community Type: 4	0.01	0.00
Influencer Account	0.00	0.00
Follower Count (Log)	0.32	0.00
Historical Total Gifting (Log)	0.51	0.00
Historical Play Duration (Log)	0.17	0.00
Historical Comment Count (Log)	0.37	0.00
Historical Like Count (Log)	0.34	0.00
Following Count (Log)	0.19	0.00
Loyal Fan Count (Log)	0.29	0.00
Tenure Days (Log)	0.02	0.00
Historical Play Count (Log)	0.27	0.00
Historical Viewer Count (Log)	0.27	0.00
Historical Commenters (Log)	0.35	0.00
Historical Voice Comments (Log)	0.23	0.00
Historical Voice Commenters (Log)	0.23	0.00
Historical Like Users (Log)	0.35	0.00
Historical Shares (Log)	0.20	0.00
Historical Share Users (Log)	0.20	0.00

B.3 Cross-Fitting Folds (n=5)

As an additional robustness check, we examine the sensitivity of our Double Machine Learning (DML) results to the choice of cross-fitting folds. While the primary analysis employed n=3 for cross-fitting, this robustness test evaluates the case with n=5. Adjusting the number of folds allows us to assess whether the partitioning of the data during cross-validation affects the results. The consistency of findings across different fold configurations, as shown in Table B10, reinforces the robustness of our conclusions.

Table B10: Effects of PK Event Participation on Streamer Performance (5 folds)

	(1) Total Gifting (log)	(2) Avg Play Duration per Viewer (log)	(3) New Follower Gain (log)	(4) Viewer-to-Viewer Follower Gain (log)	(5) New Loyal Fan Gain (log)	(6) Existing Follower Loss (log)	(7) Net Follower Gain(log)
LASSO	1.514***	0.594***	0.682***	0.537***	0.184***	0.547***	0.00003
	(0.037)	(0.012)	(0.028)	(0.026)	(0.020)	(0.024)	(0.0003)
Random Forest	1.555***	0.590***	0.657***	0.549***	0.189***	0.547***	0.0004
	(0.037)	(0.012)	(0.027)	(0.024)	(0.019)	(0.024)	(0.0003)
Regression Trees	1.440***	0.532***	0.498***	0.562***	0.152***	0.536***	0.001**
	(0.037)	(0.013)	(0.027)	(0.025)	(0.019)	(0.024)	(0.000)
Boosted Trees	1.472***	0.527***	0.761***	0.552***	0.240***	0.599***	0.129***
	(0.036)	(0.014)	(0.026)	(0.024)	(0.018)	(0.023)	(0.004)
Neural Network	1.530***	0.692***	0.828***	0.551***	0.254***	0.633***	0.001
	(0.036)	(0.013)	(0.027)	(0.024)	(0.019)	(0.024)	(0.001)
Obs	272,977	272,977	272,977	272,977	272,977	272,977	272,977

Notes: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

C ROBUSTNESS CHECKS FOR WITHIN RANDOM PK ANALYSIS

To ensure the robustness of our heterogeneous treatment effect (HTE) findings in Study 2, we replicate the analysis using the continuous follower count of focal streamers as a moderator, rather than the binary 10,000-follower threshold used in the main analysis (Section 4.2.2).

Tables C1 and C3, as well as Tables C2 and C4, report the results based on the continuous moderator specification.

Across all specifications, we find qualitatively consistent patterns with those obtained using the 10,000 threshold. Specifically, the interaction term between *vs. Big Follower Opponent* and *Big Follower Focal* remains significantly negative for total gifting, and significantly positive for net follower gain, indicating that the results are robust to the functional form of the moderator. Similarly, the interaction between *vs. Same Category Opponent* and *Big Follower Focal* remains significantly negative for total gifting and remains statistically insignificant for net follower gain.

Table C1: HTE of Follower Size Comparison Effects on Gifting (Log) (Continuous)

	Total Gifting (Log)	Avg Gifting per Viewer (Log)
vs.Big FollowerOpponent	0.309***	0.115***
	(0.018)	(0.008)
Big Follower Focal (Continuous)	0.385***	0.083***
	(0.011)	(0.005)
vs.Big Follower Opponent * Big Follower Focal (Continuous)	-0.034**	0.013**
	(0.010)	(0.005)
Obs	174,781	174,781
F-test	889.894***	532.387***
Controls:	Yes	Yes

Notes: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table C2: HTE of Follower Size Comparison on Follower Dynamics (Log) (Continuous)

Panel A: Follower Attraction

	Opponent Follower Attraction (Log)	Focal Follower Attraction (Log)
vs. Big Follower Opponent	0.044***	0.019***
	(0.003)	(0.002)
Big Follower Focal (Continuous)	0.017***	0.026***
	(0.002)	(0.002)
vs. Big Follower Opponent * Big Follower Focal (Continuous)	0.011***	-0.005*
	(0.002)	(0.002)
Obs	174,781	174,781
F-test	48.678***	56.460***
Controls:	Yes	Yes

Panel B: Follower Gains and Losses

	New Follower Gain (Log)	Existing Follower Loss (Log)	Net Follower Gain (Log)
vs. Big Follower Opponent	0.110***	0.093***	0.0004***
	(0.010)	(0.009)	(0.0001)
Big Follower Focal (Continuous)	0.167***	0.412***	-0.0002
	(0.006)	(0.006)	(0.0003)
vs. Big Follower Opponent * Big Follower Focal (Continuous)	-0.014*	-0.096***	0.001*
	(0.006)	(0.006)	(0.000)
Obs	174,781	174,781	174,781
F-test	528.341***	700.888***	42.913***
Controls:	Yes	Yes	Yes

Notes: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table C3: HTE of Content Category Comparison Effects on Gifting (Log) (Continuous)

	Total Gifting (Log)	Avg Gifting per Viewer (Log)
vs.Same Category Opponent	0.121***	0.074***
	(0.019)	(0.009)
Big Follower Focal (Continuous)	0.508***	0.100***
	(0.007)	(0.003)
vs.Same Category Opponent * Big Follower Focal (Continuous)	-0.032***	-0.010*
	(0.010)	(0.005)
Obs	174,781	174,781
F-test	1163.275***	644.935***
Controls:	Yes	Yes

Notes: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table C4: HTE of Content Category Comparison on Follower Dynamics (Log) (Continuous)

Panel A: Follower Attraction

	Opponent Follower Attraction (Log)	Focal Follower Attraction (Log)
vs. Same Category Opponent	0.017***	0.018***
	(0.002)	(0.002)
Big Follower Focal (Continuous)	0.018***	0.021***
	(0.001)	(0.001)
vs. Same Category Opponent * Big Follower Focal (Continuous)	0.014***	0.016***
	(0.002)	(0.002)
Obs	174,781	174,781
F-test	54.480***	71.588***
Controls:	Yes	Yes

Panel B: Follower Gains and Losses

	New Follower Gain (Log)	Existing Follower Loss (Log)	Net Follower Gain (Log)
vs. Same Category Opponent	-0.004	-0.008	-0.00003
	(0.010)	(0.009)	(0.0001)
Big Follower Focal (Continuous)	0.287***	0.432***	0.0002
	(0.005)	(0.004)	(0.0002)
vs. Same Category Opponent * Big Follower Focal (Continuous)	-0.006	-0.011+	0.0002
	(0.006)	(0.006)	(0.0002)
Obs	174,781	174,781	174,781
F-test	601.807***	895.070***	12.545***
Controls:	Yes	Yes	Yes

Notes: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

D DESENSITIZATION AND ITS EFFECT ON REGRESSION COEFFICIENTS

In our study, the variables are desensitized by multiplying them by a constant factor c. This section examines how such desensitization affects regression coefficients under two commonly used model specifications: a log-transformed model and a linear model without transformation.

Log-Transformed Model Consider the following model:

$$\log(Y+1) = \alpha + \beta\, T + \varepsilon,$$

where α is the intercept, β captures the effect of treatment T, and ε is the error term. Suppose the dependent variable Y is desensitized by a constant factor c, such that the observed variable becomes $Y^* = cY$. For sufficiently large values of Y, we can approximate:

$$\log(cY+1) \approx \log(cY) = \log(c) + \log(Y).$$

Substituting this into the original model yields:

$$\log(cY+1) \approx (\alpha + \log(c)) + \beta T + \varepsilon.$$

This indicates that desensitization shifts the intercept by $\log(c)$, while the slope coefficient β remains unaffected. Therefore, the interpretation of β, as the percentage change in Y associated with a one-unit increase in T, remains valid under desensitization.

Linear (Untransformed) Model Now consider a standard linear model without transformation:

$$Y = \alpha + \beta X + \varepsilon.$$

If Y is desensitized by a multiplicative factor c, we observe $Y^* = cY$. Substituting into the model gives:

$$Y^* = c(\alpha + \beta X + \varepsilon) = c\alpha + c\beta X + c\varepsilon.$$

When estimating this model via OLS, the resulting coefficients are:

$$Y^* = \alpha^* + \beta^* X + \varepsilon^*,$$

Where:

$$\alpha^* = c\alpha, \quad \beta^* = c\beta, \quad \varepsilon^* = c\varepsilon.$$

Hence, the estimated slope β^* is inflated by a factor of c, and the true coefficient can be recovered by:

$$\beta = \frac{\beta^*}{c}.$$

Summary:

- In the **log-transformed model**, desensitization by a factor c results in an intercept shift of $\log(c)$, while the slope coefficient β remains unchanged. Thus, the interpretation of β as a relative (percentage) change remains valid.

- In the **linear model**, desensitization scales both the intercept and slope by c. To recover the original effect size, the slope must be rescaled as $\beta = \beta^*/c$.