Competitive Gamification in Digital Consumption: Evidence from TikTok

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Abstract

We study competition behavior among consumers and gamification design in digital consumption. Specifically, we focus on gifting behavior in the context of livestreaming. Leveraging real-time data from TikTok and high-frequency identification methods, we causally identify competitive motives in gifting behavior, besides showing appreciation. Competitive motive reflects the incentive to climb the leaderboard by out-gifting others, whereas showing appreciation only captures gifting tendency on popular content. Furthermore, the strength of the competitive motive depends on the intensity of the competition. When a consumer's score is substantially higher or lower than that of immediate competitors, the return from competing diminishes, reducing the incentive to gift competitively. We then build and estimate a continuous-time dynamic game model of consumers' gifting behavior. Our first counterfactual result reveals that competitive and appreciation motives account for 45% and 37% of total platform revenue, respectively. Our second and third counterfactuals take incentive design approaches on the leaderboard to manage competition intensity: (1) reducing the number of rewarded top ranks from three to two intensifies the competition among top-ranked consumers, increasing total revenue by 6.5%; and (2) revising the score rule to weigh recent gifting activity more heavily intensify the competition among all consumers, yielding a 45% increase in total revenue. Our findings underscore the role of competitive motives in driving engagement in digital consumption and highlight the importance of gamification design in optimizing platform revenue.

Keywords: Gamification, competition, livestreaming, leaderboard, moment-to-moment data, high-frequency identification, continuous-time dynamic game

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1 Introduction

Competitive gamification is the use of game-design elements that promote comparison and competition, such as leaderboards, badges, and ranking systems, in non-game contexts (Deterding et al., 2011). Digital platforms increasingly adopt these tools to introduce competitive dynamics into activities that are typically driven by intrinsic interests and not inherently competitive. For instance, health apps such as Peloton and Fitbit use leaderboards to track users' fitness activity and publicly display relative standings; education platforms like Duolingo and Khan Academy incorporate peer ranking systems to provide feedback on learning progress; and livestreaming platforms including TikTok Live and Twitch use gifting leaderboards to display contributor rankings in real time and reward top contributors with rank-based badges. Despite their widespread adoption on digital platforms, whether these competitive elements meaningfully encourage user engagement remains unclear.[1]

This paper seeks to fill this gap with an empirical study of the gifting leaderboard on a leading livestreaming platform, TikTok Live. Livestreaming of events—such as live performances, interactive chats, gaming, and beauty tutorials—has become an increasingly popular form of digital content, with about one-third of internet users worldwide watching livestreams each week (Meltwater, 2025). The global livestreaming market was valued at \$88 billion in 2024 and is projected to reach \$600 billion by 2033, growing at an annual rate of 24% (Imarc, 2025). Like other livestreaming platforms, TikTok Live monetizes content primarily through consumers purchasing and sending virtual gifts during streams (Forbes, 2025). To encourage such spending, TikTok Live implements gifting leaderboards that track and display consumers' cumulative contributions in real time. These leaderboards are tied to non-monetary rewards. Specifically, top-gifter badges are dynamically awarded to the top three gifters in real time as rankings update during the stream.

We investigate the effectiveness of competitive gamification on livestreaming platforms by focusing on three key research questions. First, how does the gifting leaderboard shape consumers' gifting motives? Second, what is the economic value of the leaderboard in terms of its

[1] Existing empirical evidence is limited and mixed. Lemus and Marshall (2021) finds that the leaderboard positively affects the competition outcome on the crowdsourcing platforms. Hydari, Adjerid, and Striegel (2023) finds that the effect of leaderboard on users' workout performance is mixed on health apps.

contribution to total revenue? Third, how should the platform design the leaderboard mechanics, such as the number of rewards and performance metrics, to maximize total revenue?

Leveraging real-time data from TikTok Live, we causally identify two distinct gifting motives: competitive and appreciation. The competitive motive reflects consumers' incentives to climb the leaderboard by out-gifting others. In contrast, the appreciation motive captures consumers' tendency to gift in response to popular or engaging content, independent of leaderboard dynamics. Despite the substantial challenges of studying competitive behavior in field data, we employ a high-frequency empirical strategy to identify consumer preferences for the top leaderboard positions.[2] Specifically, we exploit unique reentry events, during which the leaderboard—constructed solely from the contributions of consumers currently active in the session—adjusts dynamically as top gifters rejoin the session, causing all lower-ranked consumers to be bumped down in real time. These exogenous, involuntary bump-downs create a natural experiment to test consumers' competitive incentives.

Building on this identification strategy, we find that following such events, top gifters immediately increase their contributions as they attempt to recover their previous ranks, indicating a strict preference for higher leaderboard positions. For instance, the gifters bumped from the top 1 position increased their gifting by 27 virtual coins—approximately 53% above their baseline gifting level—within 6 minutes of the bump-down event. In contrast, lower-ranked consumers exhibit no response, suggesting negligible utility for lower leaderboard positions. Moreover, heterogeneous analysis reveals an interesting moderating factor for the competitive motive: when a consumer's score substantially exceeds or falls behind adjacent competitors on the leaderboard, the return to compete effectively diminishes, reducing the incentive to gift competitively. Finally, we rule out alternative explanations such as herding and free-riding effects.

We build a continuous-time dynamic game model to capture consumers' gifting behavior on TikTok Live, based on developments in continuous-time dynamic game modeling (Doraszelski and Judd, 2012; Arcidiacono et al., 2016; Blevins, 2016). In this environment, each consumer makes two endogenous decisions that consumers can make: whether and how much to gift, and whether to exit the session. After entering the session, a consumer faces stochastic opportunities

[2] See Dechenaux, Kovenock, and Sheremeta (2015) for a discussion of challenges in field data on rank-based incentives.

to make decisions. Upon each opportunity, she chooses one of three actions: gifting, exiting, or doing nothing. The leaderboard updates immediately following the action-removing the score if she exits, refreshing with an increased score if she gifts, or remaining unchanged if she does nothing.

A consumer's utility from taking an action comprises two parts: an instantaneous utility, realized at the moment of gifting, and a flow utility, accrued continuously while remaining in the session until the next decision opportunity. Instantaneous utility includes both the disutility from spending and the positive utility of gifting to express appreciation for the content, which is increasing in content quality and gifting amount. The flow utility includes two component: (1) a rank-based utility that applies only when the consumers holds a top leaderboard position, and (2) a consumption value of watching the livestream itself. If the consumer exits the session, she forgoes these utilities until reentering after a random duration.

Our model flexibly accommodates a wide range of events that shape the session's evolving states, including entry, exit, re-entry, gifting, and fluctuation in content quality. The decision of a consumer to give a certain amount, exit, or do nothing is the outcome of a dynamic game. Conditional on staying, the consumer decides how much to gift by comparing the instantaneous utility of showing appreciation-net of its spending cost-against the expected utility from the continuation game, given her score. Anticipating this optimal gifting strategy on staying, the consumer decides whether to exit the session by comparing the expected utility from staying with the expected utility of exiting, accounting for the random chance of returning to the same session later. Importantly, consumers recognize that their actions affect others through the publicly visible leaderboard. For example, achieving a high score may discourage lower-ranked consumers; approaching higher-ranked competitors may spur further competition; exiting as a top gifter may encourage remaining participants to vie for the vacant top spots. Consumers are forward-looking, forming expectations about future events and strategic responses—considering not just their immediate rewards but also how their actions influence the trajectory of competition in the session over time.

To estimate the model, we employ a nested fixed-point (NFXP) algorithm combined with the Simulated Method of Moments (SMM). The estimation proceeds in two stages. In the first stage, we estimate the primitives governing entry, reentry, content quality transitions, and session termination using maximum likelihood. We also estimate the rate at which consumers receive opportunities to make gifting and exit decisions. In the second stage, we estimate the structural parameters governing consumer preferences by minimizing an SMM objective function that matches simulated moments from the model to their empirical counterparts in the data. The estimation follows the standard NFXP structure. In the inner loop, for each candidate set of structural parameters, we solve consumers' dynamic decision problems by iterating on the value function until convergence. In the outer loop, we simulate the entire environment—including consumer behavior, entry and reentry dynamics, content quality evolution, and session termination—to generate model-implied moments. We then search for the parameter vector that minimizes the distance between these simulated moments and the observed data moments. This approach allows us to recover structural primitives in a complex, dynamic environment with forward-looking, strategic consumers making interdependent decisions.

Our model estimation results reveal substantial roles for both competitive and appreciation motives in driving consumers' gifting behavior. First, consumers place significant value on achieving top leaderboard positions. The estimated utility of holding the top-one position is worth \$0.55 per minute, while the top-two and top-three positions are valued at \$0.17 per minute each. These rewards provide a strong incentive to climb the leaderboard by outgifting others. However, when the monetary cost of reaching or maintaining a top rank outweighs its utility, competitive incentives diminish, and gifting behavior is largely driven by appreciation for content. Second, we find strong evidence for appreciation-based gifting beyond competition. At the median level of content quality, consumers derive approximately \$0.71 of utility for each dollar spent on gifts. Moreover, the utility from showing appreciation is greater with higher-quality content: a one-standard-deviation increase in content quality raises the marginal utility of showing appreciation by \$0.35. This responsiveness aligns consumers' gifting activity closely with high-quality content.

We conduct a series of counterfactual analyses to unpack the economic value of the leaderboard and explore its optimal incentive design. Our first counterfactual is an income decomposition exercise that isolates the contributions of the two key gifting motives—competition and appreciation—to creator income. Specifically, we sequentially remove each motive by first shutting down the rank-based utility (to remove the competitive motive) and then eliminating the instantaneous utility from appreciation. We find that the competitive motive accounts for 45% of total gifting income, while the appreciation motive accounts for 37%. This finding highlights the central role of competitive gamification tools, such as leaderboards, in generating creator and platform revenue. The second and third counterfactuals take an incentive design approach to optimize the leaderboard's effectiveness in maximizing revenue. The second counterfactual examines the optimal reward rule-how many top-ranked consumers should be rewarded. We find that rewarding only the top two gifters (instead of the status-quo top three) increases total gifting income by 2.6%. Revenue can be further improved by 6.5% by adjusting the number of rewarded ranks to scale with the number of contributors on the leaderboard. The third counterfactual explores the optimal score rule—how gifting contributions should be aggregated to determine leaderboard rankings. This design responds to our empirical finding that large disparities in scores weaken competitive incentives, thereby reducing gifting behavior. To counter this, we implement a recency-weighted score scheme that gives greater weight to recent gifting activity. This adjustment boosts total gifting income by 45%.

2 Literature Review

Our paper contributes to three strands of literature. The first strand is on contest design in business. The second strand is on the emerging literature on the rapidly growing livestreaming industry. The third strand is on the use of moment-by-moment data.

I. Contest Design in Business Our paper is closely related to the large stream of literature on contest design. Theoretical works on contest theory have long studied how prizes based on rank orders of performance can be effectively used to provide incentives (Lazear and Rosen, 1981; Green and Stokey, 1983; Nalebuff and Stiglitz, 1983). While most of the works assume a tangible reward structure in the competition, e.g., monetary prize or job promotion in the sales context, a few recent papers explore the optimal design of contests when the players in the contests care about intangible rewards, i.e., their social status or psychological utility related to their ranking. Moldovanu, Sela, and Shi (2007), for example, studies optimal partitions in dividing contestants by their performance when they are motivated by the ranking status.

Motivated by theoretical predictions, subsequent works use experimental methods to examine competitive behavior and evaluate different contest designs, with application ranging from workforce management (Lazear, 2000; Lim, Ahearne, and Ham, 2009; Lim, 2010; Hong, Hossain, and List, 2015; Boudreau, Lakhani, and Menietti, 2016; Hossain, Shi, and Waiser, 2019), sports (Ehrenberg and Bognanno, 1990; Abrevaya, 2002; Szymanski, 2003; Sunde, 2009; Genakos and Pagliero, 2012), to school learning (Leuven, Oosterbeek, and Van der Klaauw, 2010; Leuven et al., 2011; Fershtman and Gneezy, 2011). While these studies focus on offline context, there is a small but emerging stream of literature studying the competition on digital platforms, using field data instead of data from controlled experiments. Most of the work focuses on crowdsourcing platforms, where firms publicly post a well-defined task to a community (crowd) to obtain a submitted solution (Liu et al., 2014; Lemus and Marshall, 2021; Chan, Chen, and Wu, 2023; Lemus and Marshall, 2024). Almost all these papers study the competition with monetary reward, except Chan, Chen, and Wu (2023) in which they design the optimal non-monetary reward of platform points, as a reputation signal of users' working ability. Our paper contribute to the understanding of a prevalent yet understudied context, contest with non-monetary reward of social recognition on social media platforms, differentiating from prior studies in three main directions. First, instead of studying contests with a lump-sum reward at the end, our paper features the real-time property of contests, in which leaderboard continuously updates metrics about consumers' activities and accrue rank-based flow utility. Second, instead of studying incentivizing effort on production, we study how social media platforms seek to motivate consumer voluntary spending through competition. Third, we model the social value associated with ranking on the leaderboard, which is an intangible reward prevalently exists on digital platforms.

A few papers directly study the effectiveness of competitive gamification on incentivizing user engagement on digital platforms. Hydari, Adjerid, and Striegel (2023) investigates the effect of health leaderboards on the exercise performance of the users, and finds heterogeneous effect on users with different active level. This papers employs reduced-form method without providing quatifiable policy suggestions about contest design. Several other papers take the structural modeling approach to capture competitive behavior and provide counterfactual analysis about the effectiveness of leaderboard and contest design. Lemus and Marshall (2021) finds that information about contestants' performance on the leaderboard positively improves both the number of submissions and the quality of submission on crowdsourcing platforms. Our study differ from these works by investigating how leaderboard with different reward structure and performance evaluation system affect the voluntary contribution of consumers.

II. The Emerging Livestreaming Industry Our paper contributes to the small but growing literature on the emerging phenomenon of live streaming. Most existing papers study the effectiveness of live-streaming promotion. Huang and Morozov (2025) examine the impact of video game live streaming on the demand for the broadcasted games. Gu, Zhang, and Kannan (2024) study firm's strategy in choosing influencers for its marketing campaign and shows that there is a negative interaction effect between big and small influencers. Liu (2023) uses reinforcement learning method to create dynamic coupon targeting strategies in live stream shopping. Liu et al. (2022) investigate the lead indicators of the success and survival of livestream shopping sellers. There are few papers that study the cause of viewership and viewer engagement in live streams. Lin, Yao, and Chen (2021) examine the role of emotion in live streaming and find that showing positive emotions helps broadcasters increase tips and maximize viewer engagement. Cong, Liu, and Manchanda (2021) show that consumers strongly prefer watching live streams over their recordings because live streams enable them to interact with influencers in real-time. Two closely related papers are Lu et al. (2021), who conduct field experiments to manipulate the live stream audience size by adding synthetic viewers and find a positive relationship between the size of the audience and viewers' willingness to tip, and Yao, Lu, and Chen (2023), who investigate the spillover effect of gifting among the audience and find the crowding-out effect in gifting. Both papers find that social image is the driver of those findings in gifting behavior. By contrast, we analyze consumers' motives to send gift to creator, and study how these motives is impacted by the leaderboard-a central design on livestreaming platforms.

III. Moment-by-moment Data Our paper contributes to the growing literature on the use of moment-by-moment data. Enabled by granular data, high-frequency identification has been widely used in contexts where the study objects are notoriously endogenous, like the effect of TV advertising (Lewis and Reiley, 2013; Liaukonyte, Teixeira, and Wilbur, 2015; Joo, Wilbur, and

Zhu, 2016; Joo et al., 2014; Du, Xu, and Wilbur, 2019; Liu and Hill, 2021; He and Klein, 2023; Fossen and Schweidel, 2017; Tirunillai and Tellis, 2017), and the effect of monetary policy (Bernanke and Kuttner, 2005; Nakamura and Steinsson, 2018).

The use of continuous-time models dates back to the 1970s, with most of the work focusing on the relation between underlying continuous-time data-generating processes and approximations by a discrete-time model(Phillips (1972), Sims (1971)). Heckman and Singer (1986) argue for the use of continuous-time models instead of discrete-time models, motivated by a better match with the fact that the underlying data-generating processes are continuous-time and the frequency of data collection may not match with the frequency of decision making.

Although discrete-time choice models are still the standard in the economic literature in structural work, recent developments in data science and econometric methods provide more opportunities for continuous-time research. With the digitization of data, it is increasingly efficient to collect/store real-time data, which allows us to study the real data-generating process instead of forcing agents' decisions to be simultaneous. Doraszelski and Judd (2012), Arcidiacono et al. (2016), Blevins (2016) recently contributed to estimation methods to accommodate discrete-time data collection into continuous-time modeling. Moreover, they demonstrate that continuous-time modeling can be especially powerful in solving dynamic stochastic games. By accommodating sequential decision making, continuous time avoids the curse of dimensionality in dynamic games and speeds up the computation by orders of magnitude.

In marketing, continuous-time models have been primarily used to study the timing of consumer purchases through hazard models, explaining the timing of the purchase or adoption of products(Naik, Raman, and Winer (2005), Sinha and Chandrashekaran (1992)). The large majority of continuous-time models have been estimated on product adoption or purchase data sets, with the notable exception of Deng and Mela (2018), who modeled the process of TV viewing, and Nevskaya and Albuquerque (2019), who model the process of online gaming usage. We add to this literature by developing a continuous-time stochastic game model to explain the competition among consumers on gifting decisions and conduct counterfactual design on competition mechanics.

3 Institutional Background and Data

This section introduces TikTok Live's institutional background, including platform operation status, gamification design, consumer engagement, and the data sample used for our analysis.

3.1 Institutional Background

TikTok Live is the livestreaming platform within the TikTok app that allows creators to broadcast video in real-time to engage with their consumers more personally and interactively. Consumers can join and leave the session anytime during a live stream, send likes and gifts, and post comments, all in real time. The dominant monetization of TikTok Live is the voluntary gifting system. Consumers can purchase virtual coins through the app to send virtual gifts to creators during a live stream. On average, one TikTok coin costs about 1.4 US cents. The total revenue split is about one-third to each party: the App Store (i.e., Google Play), TikTok, and the creator. Creators can then redeem the gifts they receive for dollars after commissioning the platforms.

The voluntary gifting system on TikTok continues to grow substantially, even as the platform holds the No.1 global ranking for in-app purchase revenue. According to the fourth quarter digital marketing index report by Sensor Tower, consumers spent a staggering $6 billion on in-app purchases in TikTok in 2024, up from $4.4 billion in 2023, with a 36% year-over-year increase (SensorTower, 2024). At this pace, the in-app purchase revenue of TikTok is projected to surpass $11 billion by 2027. While TikTok offers other monetization tools, such as monthly subscriptions to creators, gifting accounts for the vast majority of its in-app purchases, underscoring the central role of user generosity in driving platform revenue.[3] In our data, we find that gifting constitutes of over 99% of all income for the average creator on TikTok Live.

The competitive gamification design on TikTok Live is centered around a leaderboard and corresponding badges for top consumers. The leaderboard ranks consumers by their cumulative gifting amounts. During a session, whenever a consumer sends a gift, the leaderboard automatically refreshes to track that consumer's cumulative gifting amounts up to that moment. At the end of each live stream, the leaderboard automatically resets and does not extend the record

[3]Subscribing to the creator unlocks special features, such as custom emojis and subscriber badges.

to future streams. The leaderboard displays each consumer's identity, ranking, and cumulative gifting amount, with special emphasis on the top three consumers, who are showcased more prominently. These top contributors are pinned at the top of the leaderboard and are awarded ranking badges. These badges are also displayed alongside their usernames in the comment section, enhancing their visibility and status throughout the live session.

Figure 1: An Example of the Consumer Interface of TikTok Live

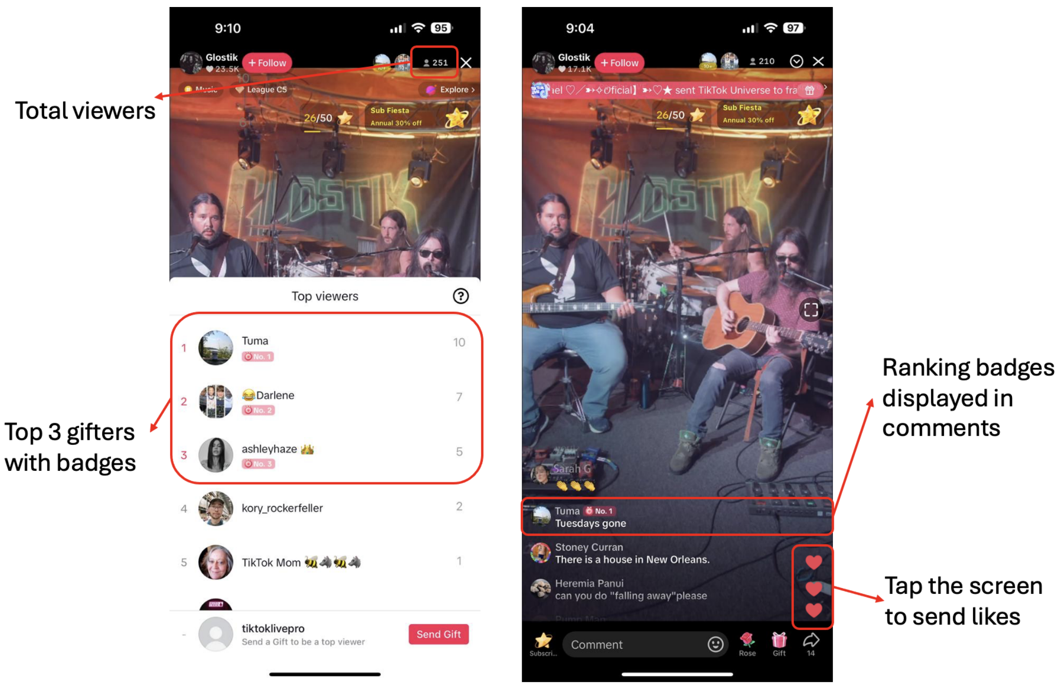


Figure 1 presents an example of the consumer interface on TikTok Live during a live music performance. The left panel displays the total number of viewers (hereafter, ***consumers***) in the top-right corner. Tapping this number opens the detailed leaderboard, listing all consumers who have sent gifts (hereafter, ***gifters***), ranked from 1 to 99 based on their total gifting amounts. The top three gifters receive a visible ranking badge next to their names. For instance, consumer "Tuma" gifted 10 virtual coins and ranks No.1, consumer "Darlene" gifted 7 and ranks No.2, and consumer "Ashleyhaze" gifted 5 and ranks No.3. Gifters ranked fourth and below are listed without badges. The right panel shows the engagement activities of likes and comments. First, consumers can tap the screen at any time to send likes, which appear as floating heart animations. Sending likes is free, anonymous, reflecting how much consumers like the content. Second, consumers can submit text comments via the comment box at the bottom of the screen.

Notably, comments from the top three gifters are accompanied by their ranking badges, further highlighting their status during the session.

3.2 Data Collection and Summary Statistics

It is particularly challenging to identify specific motives of consumers during a live stream due to the rapid changes in the livestreaming content. Therefore, we need to rely on moment-to-moment data and high-frequency identification. Our requirement on the desired data should satisfy the following goals: (1) including continuous real-time activities of all consumers in each live session (non-interrupted period of broadcast), so that we could capture all of their interactions, (2) having long enough period with many sessions of the same creators and consumers attending their sessions, so that we could control for various unobserved heterogeneity with fixed effects.

Data Collection To fulfill the above goals, we developed a live scripting software to collect livestreaming activities across many active creators and consumers. The software has two features: monitoring and recording. It first monitors if pre-selected creators turn on their live stream, then starts recording all the live stream activities in real-time. Due to the immense challenges of monitoring and recording individual-level activities in real-time, we conduct our data collection in two stages. In the first stage, we started data collection by pre-selecting creators as follows. During the first week of May 2023, we scraped all the recommended creators on the front page of TikTok Live. By restricting to creators with at least 5000 followers, our database includes 222 creators. In the second stage, for seven months from June to December 2023, we continuously monitored and recorded the live schedule of pre-selected creators and gathered information about real-time activities of consumers attending their live sessions, resulting in a total of 32468 sessions with an average of 146 sessions per creator.

The collected data includes which creators are live, the topic of each session, the number of concurrent consumers at each moment, and all moment-to-moment consumer activities in the live stream, including gifting, liking, commenting, entry, and exit in real-time. For each activity instance, we record the consumer ID, live stream ID, creator ID, timestamp of activity, and activity information. The gifting activity information records the gifting value measured in the unit of virtual coins.[4] For like activity, a consumer at any point in time can press 'like' to express their appreciation of content at that particular moment in time. The liking activity records the number of likes a consumer sends. The commenting activity information records the message sent by the consumer. Entry and exit activities only include information on the timestamps.

Table 1: Summary Statistics of Major Activities

			Percentile				
Variable	Mean	Std.Dev	Min	25	50	75	Max
Panel A: Session level ($N = 32,468$)							
Session length in minutes	128	178	1	59	96	166	10445
Number of consumers	8600	42100	0	28	364	2726	1784518
Number of gifters	30	56	1	5	13	32	1159
Number of gifts in coins	7279	43940	1	76	767	5268	116538
Number of likes	24265	51763	0	2252	7591	22954	1773973
Panel B: Gifter-session-minute level ($N = 31,705,888$)							
Number of gifts in coins	12.10	402.23	0	0	0	0	419988
Frequency of positive gifts	0.07	0.25	0	0	0	0	1
Number of gifts if positive	154.30	1429.09	1	1	2	14	419988
Number of likes	9.70	37.33	0	0	0	0	1947

Notes: This table provides summary statistics of our data in two panels. Panel A shows session-level sample statistics. It shows that the statistics on sessions are very skewed. Panel B shows the statistics when we restrict the moment-by-moment sample to include only individual-session-minute-level observations of gifters. This dataset in Panel B will be used in the following empirical analysis section. The summary statistics show that gifting behavior is still very sparse, even with this restriction.

Summary Statistics of Major Activities Table 1 provides summary statistics of the major activities in two panels. Panel A shows session-level sample statistics. The statistics on sessions are very skewed. An average session lasts for 128 minutes with a standard deviation of 178 minutes. It has, on average, 8600 consumers attending the session but only 30 consumers sending gifts to the creators. We define these consumers who ever send positive gifts in a live session as gifters in that live session. The total gift revenue of different sessions is very skewed, with the

[4]On TikTok Live, consumers have a balance of virtual coins and can charge the balance anytime at the cost of $0.014 per coin. Each gift's price is listed in the unit of coin. Consumers with a positive balance can purchase the gifts during the live session. For instance, a rose is worth a virtual coin.

mean level at 7179 coins, worth around $100, and a median level at 767 coins, worth only about $11. Finally, the average number of likes is 24265, about three times higher than the median.

Panel B shows the same statistics when we restrict the moment-by-moment sample to include only individual-session-minute-level observations of gifters. This dataset will be used in the empirical analysis section. The summary statistics show that gifting behavior is still very sparse, even with this restriction. First, gifters made a positive gifting contribution in only about 7% of the time. Second, the gifting value is very skewed conditional on positive contribution: with a mean level of 154.30 coins for the conditional number of gifts and a standard deviation of 1429.09, whereas the median of the number of gifts if positive is only 2 coins.

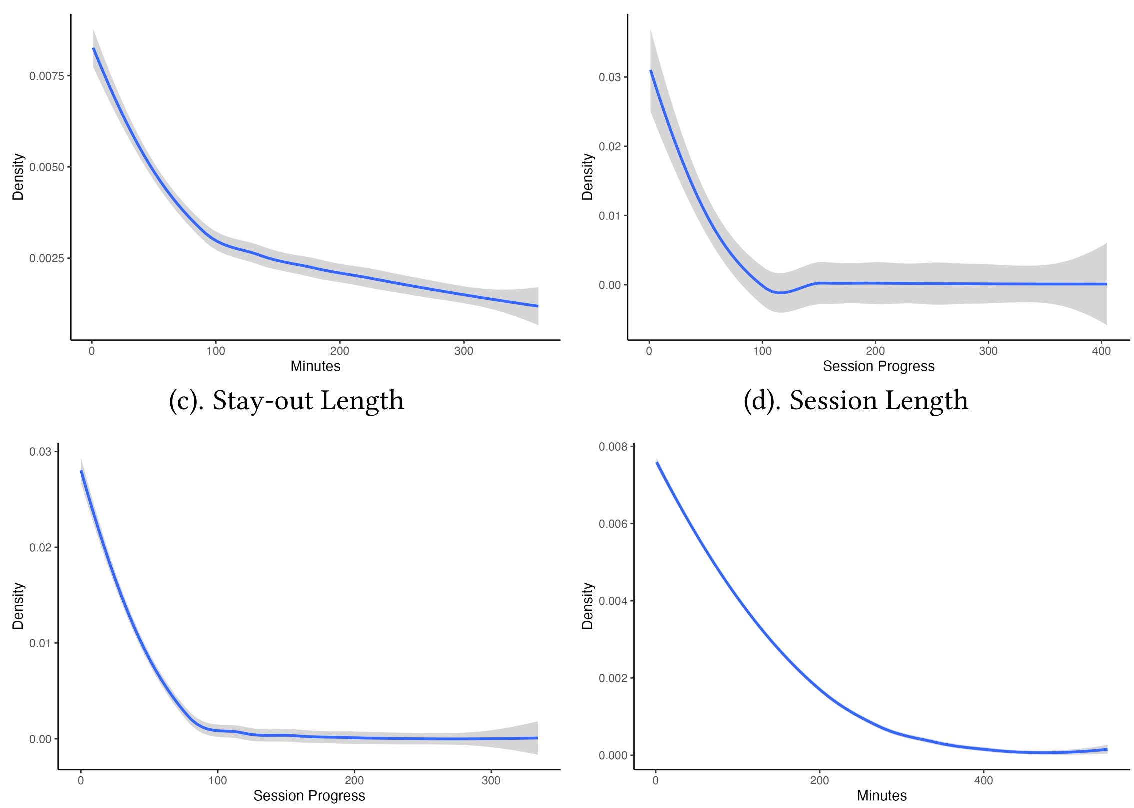
Figure 2: Distribution of Entry and Exit Activities of Gifters

(a). Entry Time

(b). Stay-in Length

(c). Stay-out Length

(d). Session Length



Notes: This figure presents the distributions of entry time, stay-in length, stay-out length, and session duration over minutes, respectively. All four distributions follow an exponential distribution, which we use later in the structural modeling.

Distribution of Gifter Entry/Exit Activities In addition to the major activities, we maintain a complete history of the infrequent activities: the entry and exit timestamps of each gifter. These entry and exit timestamps play an essential role in our empirical analysis, so we jointly show the distributions of entry time, stay-in length, stay-out length, and session length.

Figure 2 presents these distributions over minutes. Panel (a) depicts the distribution of entry times of gifters in the unit of minutes. We find that entry activities are higher at the beginning of the session and gradually become smaller over time. Panel (b) depicts the distribution of stay duration of gifters, i.e., how many minutes gifters stay in the session before exiting. On average, gifters stay in the session for 44 minutes before they exit the session. Since gifters can leave a session and return later, the full participation history allows us to capture their re-entry behavior. About 22% of gifters re-enter the session later after exiting the session. For an average gifter, she stays in the session for 61 minutes. Penal (c) depicts the distribution of gifters' stay-out length, i.e., how many minutes gifters stay outside the session before re-entering the session. For those who re-enter the session, they on average stayed outside for 29 minutes. Finally, Penal (d) shows the distribution of session duration for comparison. All four distributions follow an exponential distribution, which we use later in the structural modeling.

Additional Information of Session Topics Finally, we briefly introduce the session topics of our data to show that our sample spans a wide range of content topics. On TikTok Live, creators have the option to include hashtags in the titles of their live streams. Hashtags—words or phrases preceded by a "#" symbol—serve as searchable keywords that categorize content and enhance its visibility and discoverability. They also assist the recommendation algorithm by TikTok in identifying the nature of the content and matching it to a relevant audience. To identify the topic of each session, we collect the session title and extract any hashtags included. In our sample, approximately half of the sessions include at least one hashtag in the title. Table A1 ranks topic categories by the number of sessions. The five most popular topics, including #Music, #Daily Life, #Chat&Interview, #Art, and #Dance, account for 80% of all sessions.

4 Reduced-form Evidence

This section presents reduced-form evidence that uncovers the underlying gifting motives of consumers on TikTok Live, mainly focusing on the competitive motive. Since the moment-by-moment sample for our regression only includes consumers with positive gifts, we refer to them as ***gifters*** in identification and empirical design for precision, but as ***consumers*** to unify the notation in empirical results. We first present the novel high-frequency identification and empirical specifications to causally identify the competitive motive of gifting. We find that gifters are responsive to variations in leaderboard rankings and are willing to gift to improve their position. Then, through a set of heterogeneous analyses, we also explore how the strength of competitive motive varies across different contexts. Lastly, we show the presence of an appreciation motive by analyzing how gifting behavior responds to content popularity, proxied by the number of likes contemporaneously generated by other viewers in the same session, among the lower-ranked gifters who do not show a competitive motive.

4.1 Identification for Competitive Motive

Identification Challenges To causally test whether gifters value a higher ranking and are willing to gift extra to climb the leaderboard, we need to check whether they will increase their gifting amount if their rankings are exogenously bumped downward. If higher rankings are preferred, after experiencing an exogenous downward shock in their rankings, we expect the gifters bumped downward to increase their gifting, aiming to reclaim their old ranking.

However, conducting such an exercise with observational data presents immense challenges because a clear and sharp exogenous downward shock in ranking is extremely difficult to find. Gifters usually move down the leaderboard only when other gifters out-gift them, which are endogenous actions and could be driven by unobservable contemporary events in the live stream. If a gifter increases her gifting amount after another gifter surpasses her on the leaderboard and moves her ranking downward, it could be either a result of competitive motives to reclaim the old ranking or unobservable events encouraging all viewers to gift simultaneously, i.e, an exciting performance driving a surge of gifts. In extreme cases, even if we could directly collaborate with

TikTok to run AB tests to vary the rankings exogenously, the unnatural changes in the rankings without any gifting activities are likely to raise suspicion among gifters, thus contaminating the measurement for competitive motives and biasing our estimates.

High-frequency Identification Fortunately, the unique platform design of the leaderboard in TikTok Live provides us with a unique identification opportunity in the moment-by-moment data. This unique setup is that the leaderboard only ranks the gifting of those currently present in the live session on TikTok Live, and the leaderboard updates in real-time to reflect the entry and exit of gifters. During a live session, whenever a gifter exits and later re-enters, her previous cumulative gifting amount will be immediately added back to the leaderboard and accounted for in her ranking. Due to this leaderboard feature, a quasi-experiment exists in high-frequencies when a top gifter with a high cumulative gifting amount leaves the session for an extended time, i.e., more than 10 minutes, and later re-enters the session. The re-entering top gifter bumps down the ranking of all gifters with strictly lower cumulative gifting. For re-entry events, we refer to the one who re-enters the session and causes variation of the leaderboard as ***focal gifter***, and the rest of the gifters as ***non-focal gifters***. We could then examine the immediate change in gifting behavior of only the non-focal gifters whose rankings get involuntarily bumped down or up.

High-frequency identification addresses the identification challenges in two ways. First, the scenario of a focal gifter re-entry causes the change in ranking but does not accompany any gifting activities, isolating the effect of the rankings. Bumped-down gifters face a sudden negative shock in their rankings, i.e., they are displayed at less prominent positions on the leaderboard. We could measure the immediate response in gifting behavior towards such adverse shocks to uncover preference for rankings of gifters. Second, the implicit assumption for our identification strategy, such that the timing of re-entry is exogenous, is consistent with TikTok Live's platform setup. According to TikTok, consumers have no information about what is happening inside the session unless they enter. Therefore, it is nearly impossible for focal gifters to coordinate the re-entry time with specific activities in the session.

To further address the concerns on re-entry endogeneity, we restrict further to those focal gifters who left the session for an extended time, i.e., more than 10 minutes, to minimize inference about session popularity from previous consumption experience. For all the reasons above, we are confident that the timing of re-entry will be largely exogenous. We will conduct an event study design for our main analysis to validate this assumption systematically.

4.2 Empirical Design for Competitive Motive

We then follow a quasi-experimental research design as a narrow window event study. Such a design is usually adopted in the financial market analysis (Gürkaynak, Sack, and Swansonc, 2005; Nakamura and Steinsson, 2018), when continuous financial data is observable, and more recently, a paper in marketing (Liaukonyte, Teixeira, and Wilbur, 2015), when television advertising and online shopping activities are jointly observed in real-time. Our design naturally fits into the above category. The significant difference is that our quasi-experimental research design is in conjunction with a narrow window around the event created by a specific consumer, the re-entry time of a top gifter, instead of an event of specific economic or marketing activities. Specifically, we focus on top gifters re-entering instead of exiting for two reasons. First, our data precisely records the timestamps when a focal gifter re-enters the session, which gives us a sharp record of treatment time to identify the discontinuity in gifting behavior. Second, compared with gifters' re-entry decisions, gifters' exit decisions are highly correlated with contemporaneous activities in the live session, which may be confounded with gifters' gifting incentives.[5]

Our quasi-experimental design is as follows. For each re-entry event, gifting behavior variables are measured at the sixth minute pre-window before the re-entry moment. This pre-period serves as a baseline against which the effect of bumped ranking is measured. The same variables are measured again in the sixth minute post-window immediately following the re-entry moment. The systematic difference in non-focal gifters' gifting behavior between the pre- and post-windows is then attributed to the exogenous variation of the rankings. By focusing on the tight time window around re-entry moments, it is almost surely only changes in rankings that happened exogenously due to the re-entry. Therefore, we could confidently attribute the systematic change in gifting behavior to the effect of the rankings.[6]

[5]For instance, the focal gifters are more likely to exit when within-session content is of low quality, which results in declining gifting incentives regardless of whether consumers are more satisfied with improved ranking.

[6]We keep the window relatively short to avoid other potential adjustments. For instance, over 50% of bumped-down gifters reclaimed their old rank after the sixth minute, meaning that a wider time window may introduce gifting dynamics after claiming old rank and contaminate the effect of bumped rank.

We identify all instances in our moment-by-moment data where focal gifters re-entered the session and non-focal gifters who are involuntarily bumped down in their rankings due to those instances. Based on the non-focal gifters' original rankings, we divide non-focal gifters into those who are bumped from top 1 to top 6.[7] We isolate the 12-minute event windows around all the re-entry moments of focal gifters and run the following regression specifications:

$$\begin{aligned} \text{Total gifts}_{ist} = &\sum_{k=1}^{6} I\{\text{Old rank} = k\} \times \text{Post}_{st} + \sum_{k=1}^{6} I\{\text{Old rank} = k\} \\ &+ \text{Total likes by others}_{ist} + \text{Consumer size}_{st} + \text{Since start}_{st} + FE_s + FE_{ic} + \epsilon_{ist} \end{aligned} \tag{1}$$

where i indicates the bumped individual, s indicates the session, and t indicates time in minute. Dependent variable *Total gifts*$_{ist}$ is the total gifts sent by non-focal gifter i in session s at time t. Independent variable *Post*$_{st}$ is a dummy variable equal to one if a focal gifter had entered the session s at time t, and *Total likes by others*$_{ist}$ is the total number of likes sent by viewers other than i in session s at time t to proxy the popularity of the session and control for appreciation motive. We also control the size of consumers of the session *Consumer size*$_{st}$, the number of minutes since the start of the session *Since start*$_{st}$, session fixed effect FE_s, and individual times creator fixed effect FE_{ic}. Specifically, *Consumer size*$_{st}$ controls for the effect of viewer size on gifting motive Lu et al. (2021), and also controls for the fact that viewer size is positively related to a larger number of likes sent, and *Since start*$_{st}$ captures that the sessions often become more or less popular over time due to the natural life progression of sessions. Session fixed effects FE_s capture unobserved characteristics of sessions that affect the viewers' incentive to gift, such as whether a popular creator holds the session or whether the session is during holidays. Finally, the consumer times creator fixed effects FE_{ic} capture unobserved characteristics of individuals that affect their incentive to gift to a specific creator, such as income level or how much they like specific creators. The error terms can be correlated within a session by allowing clustered standard errors at the session level. This is because the re-entry event is at the session level, and

[7] For the clarity of results, we focus on direct bumps when non-focal gifters are directly bumped down by focal gifters who take their position. In other words, we focus on the focal gifter who lands on the k^{th} rank and bumps the k^{th} non-focal gifter from the k^{th} position to $k + 1^{th}$ position. In robustness checks, we also analyze indirect bumps, where a non-focal gifter could be bumped down from k^{th} position to $k + 1^{th}$ position as long as a focal gifter re-enters and claims the rank above the $k + 1^{th}$ position.

the gifting behavior in the same session is likely to be correlated across viewers and time.

4.3 Evidence of the Competitive Motive

This section presents the evidence for the competitive motive estimated from the regression equation (1). We first show that the leaderboard design generates the presence of the competitive motive - a specific preference for ranking by consumers. We then show heterogeneity analysis that the competitive motive is stronger if it is easier to climb up the leaderboard. The accumulated evidence suggests that the leaderboard design of TikTok Live generates significant competition.

Table 2: Change in Gifting Behavior for Bumped-down Consumers

	Total gifts by bumped-down consumers					
	1 to 2	2 to 3	3 to 4	4 to 5	5 to 6	6 to 7
Post	4.5063***	6.0212	2.8618***	4.5876***	0.9069	0.5386
	(1.7227)	(4.4558)	(1.0292)	(1.7038)	(0.6950)	(0.4553)
Total likes by others	0.0085***					
	(0.0018)					
Observations	261,948					
Controls	√					
Session FE	√					
Consumer × Creator FE	√					

Note: This table presents the evidence for the competitive motive estimated from the regression equation (1). Controls and fixed effects include the size of the viewers (consumers) of the session $Viewer\ size_{st}$, the number of minutes since the start of the session $Since\ start_{st}$, session fixed effect FE_s, and individual times creator fixed effect FE_{ic}. Standard errors are in parentheses. Significance: *p<0.1; **p<0.05; ***p<0.01. Standard errors are clustered at the session level.

The Presence of the Competitive Motive We find a specific preference for ranking by consumers, which is closely related to the leaderboard design for displaying the ranking and the badges. More specifically, the particular preference is as follows:

$$\{\text{top } 1\} \succ \{\text{top } 2 \sim \text{top } 3\} \succ \{\text{top } 4\} \succ \{\text{top } 5 \sim \text{top } 6 \sim \text{top } 7\} \tag{2}$$

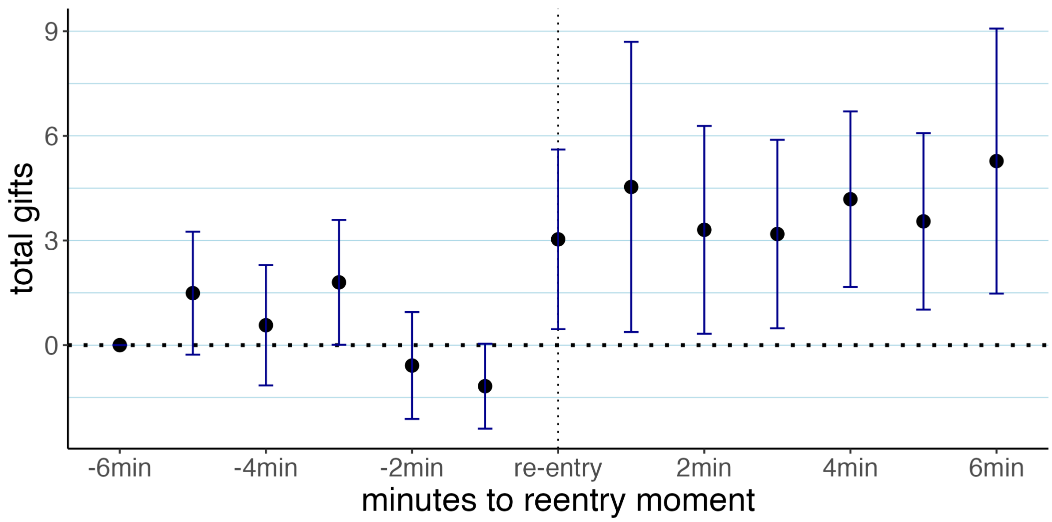
which is shown in the regression results in Table 2. More specifically, the table shows the change in gifting behavior of consumers when their ranking is bumped down by one due to the re-entry of focal gifters above them, i.e., a top 3 gifter is bumped to top 4 due to the re-entry of a focal gifter who claims a new top 3 position. We find significant increases in gifting amount when a gifter gets bumped down from the top 1 to the top 2 (column 1), top 3 to the top 4 (column 3), and top 4 to top 5 (column 3). However, we find a positive but insignificant change in gifting amount when bumped down from other rankings. This indicates a particular ordered preference of gifters towards ranking on the leaderboard: consumers strictly value rank 1 over rank 2, rank 3 over rank 4, and rank 4 over rank 5, but are indifferent between rank 2 and rank 3. When consumers get bumped down from top 5 to top 6, or from top 6 to top 7, the change in gifting amount is insignificant, suggesting consumers are indifferent between those rankings. We do not present any results after the top 6 because those are all insignificant, following the same trend.

The results in Table 2 and Equation (2) exhibit the direct impacts of the specific details of the leaderboard design of TikTok Live on the competitive motives of consumers. The first key cutoff is at the No.1 position, with the highest visual prominence. Consumers place a heavy value on the No.1 position because of their visual presence at the top of the leaderboard and the No.1 badge when they engage in activities. As shown in our institutional background. The second key cutoff is at the No.3 and No.4 positions, where visual prominence can fluctuate, either lost or gained. First, the risk of losing the visual prominence at the No.3 position generates a strong desire to reclaim their original spot and badge. Second, the opportunity to gain visual prominence generates an even stronger desire for consumers at the No.4 position to intensely compete when they see that the chance to join the top 3 diminishes. These competition effects are insignificant for other positions where visual prominence does not fluctuate much.

We further validate the results in Table 2 and Equation (2) with an event study in Figure 3 to address the worry that focal gifters strategically choose their re-entry time to coincide with significant in-live events, such as highlighted performance or thrilling challenges. However, in this case, we expect total gifts by consumers to smoothly increase even before the focal gifter re-enters the live session, reflecting that the session is already trending up before the re-entry moment. Figure 3 shows that the total gifts of bumped consumers remain stable before the stream and increase immediately after the re-entry moment. Therefore, we do not find any indication that endogeneity from re-entry time poses a substantial threat to our empirical strategy.

Moving beyond the average preference for rankings above, we want to understand when con-

Figure 3: Total Gifts of Bumped-down Consumers Around the Re-entry Moments



Note: This figure plots the regression coefficients from a linear model that regress the total gifts of bumped consumers (from rank 1, 3, 4) on a set of dummies to capture one-minute periods for the 6 minutes before and 6 minutes after the re-entry of focal gifters, while setting minus-six minute as the baseline and controlling for number of minutes since the start of session, total likes by others, viewer size, session fixed effect, and individual × creator fixed effects. The error bar is at a 10% confidence interval.

sumers exhibit a more intense competitive motive in gifting, either from more competition from above rankings or below rankings. Answering that question would help us analyze the mechanism design of leaderboards. This motivation leads us to explore heterogeneity in competitive motive against the above and the below competition in evidence 2 and 3, respectively.

Heterogeneous Responses to Competition A core question in many game design contexts is how the relationship between difficulty and reward affects the effectiveness of gamification. In Table 3, we investigate how the heterogeneity in the difficulty of competition moderates the competitive motive of consumers, responding to competition from above. Specifically, we take the cumulative gifting amount (henceforth, ***score***) distance between focal and non-focal gifters before the re-entry event to proxy the competition difficulty, and conduct heterogeneous analysis on competitive motive, following the same non-focal gifters bumped down scenarios. We take the cumulative gifting amount distance between focal and non-focal gifters before the re-entry event to avoid any changes caused by endogenous responses of the non-focal gifters. The idea is that a consumer will find it more difficult to reclaim her original ranking if her gifting amount is far

Table 3: Heterogeneous Effect of Gifting Distance to Climb Up

	Total gifts by bumped-down consumers			
	1 to 2	2 to 3	3 to 4	4 to 5
Post × Low distance	3.1830*	4.5521	4.1195**	1.1501*
	(1.7395)	(3.9104)	(2.0096)	(0.6210)
Post × Median distance	2.9703***	0.4444	2.4118**	9.3613**
	(1.0018)	(0.5400)	(1.0389)	(4.6201)
Post × High distance	7.6755	13.0429	2.2791	3.6932*
	(4.6817)	(12.0901)	(1.9202)	(2.2161)
Total likes by others	0.0094***			
	(0.0026)			
Observations	198,996			
Controls	√			
Session FE	√			
Consumer × Creator FE	√			

Note: This table presents the evidence for the competitive motive estimated from the regression equation (1) by adding additional interaction term $Post_{st} \times I\{Distance\}$ and distance group dummy $I\{Distance\}$ for each rank k into the regression. Other controls and fixed effects include the size of the viewers (consumers) of the session $Viewer\ size_{st}$, the number of minutes since the start of the session $Since\ start_{st}$, session fixed effect FE_s, and individual times creator fixed effect FE_{ic}. Standard errors are in parentheses. Significance: *p<0.1; **p<0.05; ***p<0.01. Standard errors are clustered at the session level.

from that of the focal gifter. For each group of consumers bumped down from ranks $k = \{1, 2, 3, 4\}$, we divide them equally by their total gifting amount distance into low, median, and high.[8] We then add additional interaction term $Post_{st} \times I\{Distance\}$ and also control for the score distance group dummy $I\{Distance\}$ for each rank k in regression (1).

Table 3 shows the results. We find that the incentivized bump-down consumers in our previous analysis (Columns 1, 3, and 4) are more likely to exhibit competitive motives by significantly increasing their gifting amount after re-entry when the score distance is low or median. This effect is generally more substantial when the distance is lower.[9] These results show that consumers are most engaged in competition when their scores are close to each other. In other words, the competitive motive is strongest when the competition intensity is high (head-to-head) and win-

[8]We no longer show consumers with rank $k \geq 5$ because all the results are insignificant.

[9]The effects of those who bumped from rank 4 to rank 5 (the immediate potential candidate to enter the top 3) exhibit more complex and interesting patterns. Their competitive motives are hump-shaped over the distance measure, and they respond even when the distance is high, signaling potentially deeper interesting mechanisms.

ning is neither too difficult nor too easy. In cases where winning is either too difficult (the lagged distance of catching up with other players is too far) or too easy (the leaded distance between their scores and that of others is substantial), consumers have little incentive to competitive gift, given the weak connection between their action and their competition payoff.

We are also interested in top k gifters' gifting behavior around the time of top $k+1$ gifter's re-entry. We want to know whether top k gifters will increase their gifting amount to avoid being caught up, and how their incentive is moderated by the difficulty of being caught up. Similarly, we measure the difficulties of being caught up by the score distance between non-focal gifters(top k) and focal gifters(top $k+1$). In Table 4, we find that non-focal gifters are more likely to increase their gifting amount and avoid being caught up when the distance is low or median. When the distance is high, non-focal gifters did not significantly increase their gifting amount, given that they are almost impossible being catch up on the leaderboard.

Table 4: Heterogeneous Effect of Gifting Distance to be Caught Up

	total gifts by consumers with re-entry from below			
	$k=1$	$k=2$	$k=3$	$k=4$
Post × Low distance	0.2972	1.3202	0.7492**	0.7177*
	(0.9064)	(0.9852)	(0.3242)	(0.3816)
Post × Median distance	4.0559***	2.0625**	0.7806	0.8115**
	(1.5014)	(0.8256)	(0.5247)	(0.4017)
Post × High distance	-6.9807	-2.7299	9.1212	-1.1004
	(6.5837)	(5.8502)	(7.3475)	(3.2178)
Total likes by others		0.0132***		
		(0.0037)		
Observations		278,832		
Controls		√		
Session FE		√		
Consumer × Creator FE		√		

Note: This table presents the evidence for the competitive motive estimated from the regression equation (1) by focusing on gifters at rank k while re-entrant is at rank $k+1$, and adding additional interaction term $Post_{st} \times I\{Distance\}$ and distance group dummy $I\{Distance\}$ for each rank k into the regression. Other controls and fixed effects include the size of the viewers (consumers) of the session $Viewer\ size_{st}$, the number of minutes since the start of the session $Since\ start_{st}$, session fixed effect FE_s, and individual times creator fixed effect FE_{ic}. Standard errors are in parentheses. Significance: *p<0.1; **p<0.05; ***p<0.01. Standard errors are clustered at the session level.

4.4 Evidence of the Appreciation Motive

Finally, we show evidence of the appreciation motive, such as consumers tending to send gifts to show their appreciation for high-quality content. This motive is a spontaneous reaction to content quality, requiring no strategic interaction with other consumers in the sessions. Same as above, for a typical consumer i, we use the total number of likes sent by all other consumers in the same session to proxy the popularity of the content at each minute of the session and investigate how the quality of content affects the gifting motive of consumer i.

Table 5: Appreciation Motive for Gifting

	Total gifts
Total like by others	0.0012***
	(0.0001)
Consumer size	0.0006**
	(0.0002)
Since start	0.00005
	(0.00006)
Observations	1,241,826
Session FE	√
Consumer × Creator FE	√

Note: Standard errors are in parentheses. Significance: *p<0.1; **p<0.05; ***p<0.01. Standard errors are clustered at the session level.

Our evidence comes in two ways. First, in the previous analysis in both Tables 2 and 3, we find that besides the competitive motive, all consumers among the top ranks show positive responses in gifting to the total likes by others. Second, we run a linear regression with the same moment-by-moment sample, but restrict our analysis to those consumers who ranked weakly lower than the top 5 on the leaderboard to rule out the potential influence of competitive motive. Since these consumers are not responding to re-entry events, we discard the re-entry and rank dummy; otherwise, all other controls and fixed effects are the same. Table 5 shows that the popularity of content, proxied by the total likes by others, positively increases the total gifts of these consumers who do not show any competitive motives, also supporting the presence of the appreciation motive. Both results show that the motive for appreciation is universal across all consumers.

4.5 Robustness Checks, Survey Support, and Takeaways

Robustness Checks We conducted the following additional analyses. First, we conducted a placebo test by randomly selecting a time point in each session and designating it as an "artificial" re-entry moment. Our placebo test finds that gifters did not significantly change their gifting behavior around the "artificial" re-entry moments, ruling out the unobservable temporal trend; Second, we replicate the results in Table 2 to running separate regressions for each subgroup of gifters who bumped from different rankings. This flexibily allows the gifters' responses to content quality, i.e., appreciation motive, and other control factors to differ depending on their old rankings; Third, we replicate the results in Table 2 by implementing a zero-inflated model to the re-entry event to categorize players who have no intention to gift and those two have the intention to gift. We find that following re-entry events, the proportion of gifters with no gift intent increased, but they send a greater amount, conditional on having gift intent.

Survey Support We also conducted interviews to better understand the motives for gifting in live streaming and the underlying backgrounds of our empirical analysis. We received answers from 319 participants who had previously watched online live streams. Specifically, we showed interviewees a TikTok Live clip showcasing gifting and the setup of the leaderboard and asked them to speculate why consumers gift in TikTok Live in an open-ended question. Two research assistants, blind to our hypotheses, categorized the written responses unsupervised. Because each response may mention multiple motivations, we allowed for multi-label classification.

Based on the categorized written responses, we again identified the above two primary motivations. First, most interviewees also mentioned "content-supporting", which is the appreciation motive irrelevant to relative standings, aiming to express genuine support, gratitude, encouragement, and enjoyment of the live-stream content. Second, most interviewees also mentioned "attention-seeking", which is the competitive motive that reflects consumer desire for relative attention and recognition. Results showed that the most frequently mentioned motivation was content-supporting (61.3%), then followed by attention-seeking (59.4%). These categorization results are corroborated to be consistent by Chat-GPT 4.0 (Content: 67.2%, Attention: 59.9%).

Takeaways Our empirical analysis shows strong and significant motives for competition among livestreaming consumers under TikTok Live's gamification design, besides the universal appreciation motives. We also show that the leaderboard and the competition intensity among consumers significantly shape the patterns of competitive motive. These empirical findings are interesting standing alone. However, we need to construct a structural model to match these empirical facts further to understand the mechanisms, the importance of each motive, and conduct counterfactual leaderboard designs.

5 Continuous-time Dynamic Game Model

5.1 Overview of the Model

In this section, we develop a structural model of gifting behavior, building on the insights from the reduced-form analysis presented in Section 4. We model the gifting behavior of gifters across sessions as a dynamic game, because consumers compete for a limited number of positions on the leaderboard. Decisions are dynamic in the sense that a gift will impact a consumer's future position—if nobody outbids the consumer in the top position, for example, they will stay there for the duration of the session. We model play using a continuous time, rather than a discrete time game for several reasons. The first is realism: sessions evolve in continuous time, and consumers' decisions can occur at any instant during play. Assuming discrete play would involve arbitrarily breaking the observed sessions into a finite number of discrete intervals (Heckman and Singer, 1986). The second reason is that the formulations of continuous time games used in empirical work, e.g. Arcidiacono et al. (2016), have appealing theoretical and computational properties. A pivotal assumption in many empirical applications of continuous time games, which we employ, is that the timing at which agents make decisions is determined by a continuous process. Importantly, this assumption implies that the probability that two or more agents can make decisions simultaneously is zero. In discrete time games, simultaneous decisions are a source of multiple equilibria. The fact that this source of multiple equilibria is ruled out makes computing counterfactuals much simpler (Blevins and Kim, 2024). An additional computational advantage of continuous-time games is that, since only a single agent can make a decision at any instant, solving for the equilibrium is computationally easier. In a discrete-time game, one must iterate on the best responses of each agent to find an equilibrium, increasing the solution time exponentially as the number of players rises.

Following the literature outlined previously on continuous time models, we impose that the instant at which a player may make a decision, as well as the evolution of state variables, is governed by a continuous process that we estimate. Thus, we model gifters' entry and re-entry with exogenous continuous processes. By exogenous, we mean that the entry and re-entry probabilities are modeled as functions of observable states, and do not depend on variables that are unobserved to the researcher, but observed to gifters. This assumption is informed by the way TikTok Live is set up. Gifters cannot access any information inside a session–such as the content quality, leaderboard rankings, or other gifters' gifting behavior–until they enter or re-enter the session. This lack of outside visibility limits their ability to make informed entry decisions based on the current state of a session. As a result, we model entry and re-entry as being driven by external factors (e.g., the day of the week, or session-level variables that may enter TikTok's matching algorithm), rather than strategic considerations about in-session dynamics. This assumption allows us to treat the entry flow as exogenous to the gifting decision process modeled within the session. We assume that the entry and re-entry times are determined by exponential distributions. This assumption is consistent with the empirical distributions of entry and re-entry timing presented in Figure 2, panels (a) and (b), which can be seen to have a shape similar to an exponential distribution.

Turning to gifter decisions on the amount they spend, we allow them to be driven by two motives, the competition and appreciation motives, as suggested by our reduced-form evidence in Section 4. The competition motive stems from the fact that we observe consumers are willing to gift more to recapture the top spot, or to enter the leaderboard, after they are exogenously moved out of those slots. Additionally, we find that the competition motive is influenced by the gap between a focal gifter and the ones above and below them in the leaderboard. This finding suggests that gifters trade off the cost of making a gift with the benefit–if it would cost too much to claim the top spot on the leaderboard, they do not incur the expense. The appreciation motive stems from the fact that consumers are observed to gift more when the number of audience likes is higher, controlling for the overall size of the audience. In our structural model, we build these motives into the utility function of consumers. The gifters in the game receive higher utility from being on the leaderboard and achieving a higher rank on it (in particular, being in the top spot). Since only one gifter can occupy a given slot, gifters will have an incentive to gift more to be in the more valuable positions. We model the appreciation motive by allowing the marginal utility of giving a gift to be an increasing function of the overall content quality.

In addition to gifting, a gifter may also exit a session. We allow gifters to exit endogenously, meaning they will appropriately trade off the utility of continuing to accrue payoffs from gifting in the session and enjoying its content, or exiting the session with the possibility of re-entering later.

5.2 Entry, Re-entry, and Evolution of Exogenous States

We now present the details on how we specify the evolution of gifter entry and re-entry, along with the exogenous states determining content quality and the end of the session. We denote the maximum number of active gifters in the game as at any given point in time as N. An active gifter is defined as a user who is (i) attending the session in a given instant; and (ii) ever gifts during a particular session. Regarding point (ii), we distinguish between gifters and consumers who never gift, but simply attend sessions to view and like them. We denote these latter consumers as viewers and treat them as passive and non-strategic agents, since they do not engage in gifting behavior. As we will describe below, we view the actions of the viewers as reflecting the content quality: if they enjoy it, some will hit the like button. Since these agents are non-strategic, we model the evolution of likes as an exogenous state variable. In estimation and our counterfactuals, we limit $N = 7$ for computational tractability. This limitation is not likely to be problematic, since in our data the top 7 gifters contribute to 95% of a session's overall gifting amount.

We model the entry time as a random variable, τ_e, drawn from an exponential distribution with parameter $\lambda_e(W_t^e) = (W_t^e)'\boldsymbol{\theta}^e > 0$, where W_t^e is a vector of session-level characteristics and $\boldsymbol{\theta}^e$ is a vector of parameters. Figure 2(a) shows the empirical distribution of entry times, which follows an exponential distribution, consistent with our distributional assumption for the entry time. We include two covariates in W_t: indicators for the day of the week, which may reflect the opportunity cost of time of attending live sessions, and the session's content quality, which we describe in detail below. Our choice of covariates is motivated by the setup of TikTok. Viewers typically enter the session for the first time by receiving a prompt from TikTok's algorithm and swiping into a session. As a result, it is unlikely that first-time entrants can condition on anything happening in a live session. The session content quality is thus included as a covariate to capture the impact of TikTok's recommendation algorithm on the probability that a gifter enters a session.

Conditional on exiting the session, the length of time that a gifter stays out before re-entry, τ_{re}, is also a random variable, drawn from an exponential distribution with parameter $\lambda_{re}(W_t^{re}) = (W_t^{re})'\boldsymbol{\theta}^{re} > 0$.[10] The arrival rate of re-entry λ_{re} is exogenous and depends on a vector of session-level characteristics, W_t^{re}, and a parameter vector $\boldsymbol{\theta}^{re}$. Our regression analysis of gifting, presented in Section 4, suggests that re-entry is not being conditioned on unobserved variables, because we do not see evidence of pre-trends in gifting prior to re-entry. Figure 2(c) presents the empirical distribution of re-entry times, and shows it follows an exponential distribution, consistent with our assumption.

At any moment of the session, we call the gifters who are present in the session *incumbents*, and the gifters who have exited the session *idle gifters*, which we capture with a state variable $g = \{0, 1\}$. At any point in time, a gifter is either in the active state $g = 1$, and present in the session at that moment; in the idle state, $g = 0$, the gifter has exited the session and has not re-entered yet. At any moment of the session t, a gifter's expectation about the future number of incumbents depends on the rate of entry (λ_e), the rate of re-entry (λ_{re}), the number of incumbent gifters, N_t^{inc}, the number of idle gifters, N_t^{idle}, and the policy functions describing an incumbent's exit decision, which we will present in more detail in the next section. Note that entry and re-entry are only possible when the number of active incumbents is smaller than N - $N_t^{inc} < N$. We assume that gifters understand this restriction and internalize it in their expectations.

We assume that in any instant, there is a constant probability that the session ends, q_{live}, implying that the mean duration of a session is $1/q_{live}$. The assumption that a session ends stochastically is motivated by the institutional structure of TikTok: in particular, the platform does not provide any formal tools for a creator to plan a schedule for their sessions. Anecdotally, performances in many livestreaming sessions appear relatively spontaneous, consistent with the idea that they may end at any time. As with entry and re-entry, our specification for session duration

[10]Note that most gifters who exit do not re-enter. The fraction of gifters who re-enter $0, 1, 2$ and 3 times are 76%, 15%, 5%, and 2%, respectively.

implies it follows an exponential distribution. Figure 2(d) supports this assumption, as it suggests the distribution of session length follows an exponential distribution. We note that our stochastic process for the length of a session assumes that it is exogenous to gifter actions such as gifting (in other words, gifters do not influence the length of a session). We present supporting evidence for this assumption in the second column of Table B1, which regresses an indicator for the end of a session on previous gifts. The coefficient on gifts is insignificant, suggesting creators do not end their sessions based on recent gifting behavior.

We capture content quality with the number of viewer (non-gifter) likes in a session at a particular instant. We model this as an exogenous state variable, which we discretize for computational tractability. We divide the content quality into two levels, governed by a stochastic variable $l_t \in \{1, 2\}$, where $1 = low$ and $2 = high$.[11] The transition between the two levels of content quality is governed by a Markov jump process with intensity matrix Q_q, where

$$Q_q = \begin{pmatrix} -q_{12} & q_{12} \\ q_{21} & -q_{21} \end{pmatrix}. \tag{3}$$

Importantly, as with the session length, we assume that the content quality is exogenous to gifter actions such as gifting. In other words, if a gifter makes a gift, that action does not directly influence the content quality at the time of the gift or afterwards. This assumption is also supported by the regression analysis presented in the first column of Table B1. That regression shows that total likes are significantly correlated with the number of likes in the previous minute, supporting the assumption of a Markov transition process, but also shows that gifts in the previous minute do not impact the number of likes in the following minute.

5.3 Gifter Decisions, Utility and Dynamic Problem

In this section, we develop the structure of the gifters' dynamic problem. We model two endogenous decisions that gifters can make: whether and how much to gift, and whether or not to exit. Following the previous literature on empirical continuous time games such as Arcidiacono et al.

[11] To construct values for l_t, we split the number of likes in a given minute of a session by the median. l_1 is the average number of likes for minutes below the median, and l_2 is the average above the median.

(2016), we assume that the time at which a gifter can make a decision arrives stochastically, at a constant rate λ_a. Gifters may only gift or exit when they are given an opportunity to make a decision. This assumption stands in contrast to discrete-time games, where it is usually assumed that all players may make decisions at any discrete time period. As described in Section 5.1, the assumption that decision points arrive stochastically rules out the possibility that agents make simultaneous decisions, simplifying the computation of equilibrium relative to discrete time games.

When a gifter has an opportunity to make a decision, she will condition on the current state of the session, as well as her beliefs about the evolution of the session state variables. We now describe each of the state variables we include in the model.[12] The first two variables capture player scores. In TikTok livestreams, a player's score reflects the amount of money they have gifted. Recall from Section 3.1 that players purchase TikTok coins for a price of about 1.4 cents per coin. The leaderboard continuously updates how many coins has been contributed by each gifters during the live stream. In our structural model, we discretize the possible number of scores into $K + 1$ different levels: $s_{it} \in \mathbb{S} = \{score_0, score_1, \cdots, score_K\}$.[13] A score of $s_{it} = score_0 = 0$ means the gifter has not gifted yet.

We assume that gifters track both their own score, s, as well as the distribution of all incumbents' scores, $D = (d_0, d_1, \cdots, d_K)$, where d_k is the number of gifters whose score is at level $score_k$. We emphasize that we assume gifters only track the distribution of scores among incumbents: the score distribution does not depend on the identity of particular incumbents. Gifters also track their own rank, r. Note that this state is not redundant with the score, because the score is discretized. On TikTok, if two gifters have the same score, then the gifter who arrived first at a given level has a higher rank. Because of the underlying discretizations, the rank must be tracked as a separate state.[14] We assume gifters track whether they are rank 1, 2, 3 or 4. A gifter is rank 4 if

[12] Although the model states are time-varying, for notational simplicity we drop the time subscript on them in this section.

[13] We choose grid points of 0 100, 300, 600, 1000 and 1500.

[14] The fact that we assume that gifters do not track the identities of competitors means we do not need to track the rank of competitors. The number of gifters and the focal gifter's rank are enough to form expectations about future rank if other gifters enter or exit. For example, if there are 3 gifters at the top score level, and the focal gifter is rank 2, they know that one other gifter is rank 1, and the other is rank 3. When forming expectations, they therefore know that if the rank 1 gifter exits, the focal gifter will become rank 1. If the rank 3 gifter exits, the focal gifter's rank will not change.

they are not on the leaderboard, i.e., not one of the top 3 gifters.

Besides the three state variables described in the previous paragraph, gifters also track the following three state variables: First, whether the gifter is idle or not, which is captured by g. Recall that $g = 0$ if a gifter is idle (has exited and not re-entered) and $g = 1$ if they are active in the session. Second, they also track the content quality, l, which follows an exogenous Markov process, as described in the previous section. Third, they track the total number of idle gifters, N^{idle}. For computational tractability, we assume that players do not track the scores of idle gifters. We will describe how we model expectations about the scores of idle gifters who re-enter later in this section.

Next, we describe the structure of gifters' utility functions. A gifter's utility from taking an action (gifting, exiting, or doing nothing) has two components: an instantaneous utility, which is immediately incurred on taking the gifting action, and a flow utility that is received continuously until another gifting action happens. The flow and instantaneous utility a gifter gets from gifting a particular amount and/or staying in the session are functions of three state variables: their own score, s, their rank, r, and the content quality, l. If a gifter decides to make a gift, we denote the score the gifter will have after gifting as s'. Thus, if a gifter gifts, the action will be to increase her score by an amount $s' - s$. Motivated by the fact that scores are discrete, we model the action of gifting as a discrete action: the choice set is the set of possible scores the gifter may achieve, $s' - s \geq 0$. When a gifter has an opportunity to take an action, she receives an instantaneous utility as follows:

$$u_{inst}(s', s, l) = \underbrace{(\gamma_0 + \gamma_1 \cdot l) * \log(1 + 0.01 * (s' - s))}_{\text{appreciation utility}} + \underbrace{\beta_p \times 0.01 * (s' - s)}_{\text{gifting disutility}}, \tag{4}$$

where the first term represents her utility from showing appreciation, and the second term represents her disutility from paying for the gifts, i.e., β_p is the price coefficient. Notice that we normalize the gifting amount to hundreds when it enters the utility. We model the appreciation motive by allowing the marginal utility of giving a gift to be an increasing function of the overall content quality, i.e., $\gamma_1 > 0$. This assumption is motivated by the fact that we find empirically that gifts increase when total likes in the audience are higher (Table 5). It is important to note that the appreciation utility contains two terms: the first term, γ_0, captures the baseline marginal utility from showing appreciation, and γ_1 captures how the marginal utility from showing appreciation varies with content quality. We assume a linear disutility of gifting because scores reflect total amount gifted, and there is a linear exchange rate between money and virtual coins. Thus, following standard practice, we model the disutility of spending money as linear. The concavity of the appreciation utility in the amount gifted helps to guarantee an interior solution for gifting amounts. If the appreciation utility were linear, then individuals would either gift nothing, or as much as they could, which is inconsistent with how gifting occurs in the data (individuals often gift small or intermediate amounts of coins).

We model the flow utility of being in a session to be a function of the gifter's rank, r, and the number of likes, l. The specification we use for the flow utility is as follows:

$$u_{flow}(r, l) = u_r + \gamma_2 + \gamma_3 \cdot l \text{ where } u_1 > u_2 = u_3. \tag{5}$$

The first term reflects the gifters' social value of being on the leaderboard (in one of the top 3 positions). We assume that $u_1 \geq u_2 = u_3 \geq u_4 = 0$. The assumption that $u_4 = 0$ is motivated by the fact that on TikTok LIVE, the leaderboard only displays the identity of the top 3 gifters. Thus, there will be no additional social value from being in rank 4. Additionally, we assume that $u_2 = u_3$, because our reduced form evidence presented in Table 2 suggests that gifters are indifferent between the top 2 and the top 3 positions on the leaderboard. The regression results in the table show that gifters who are bumped from position 2 to 3 do not increase their gifting behavior significantly in order to reclaim the second spot. Finally, it is important to note that the flow utility contains two terms which capture a gifter's value of simply watching and participating in a session: the second term, γ_2, is the flow utility from watching content, and γ_3 captures how the utility from consuming content varies with content quality. If a gifter decides to exit, she receives a flow utility of 0. Whenever an agent makes a choice, her instantaneous utility also receives an additive choice-specific shock, $\varepsilon_{i,s'-s,t}$ for a choice of gift amount, and $\varepsilon_{i,e,t}$ if she exits. We assume that the choice-specific error follows a type-1 extreme value distribution.

The decision of a gifter to give a certain amount, exit, or do nothing are the outcome of a continuous time dynamic game. The state of the dynamic game may change if a gifter has an opportunity to make a decision and gifts or exits, a new gifter enters, an idle gifter re-enters, or an exogenous variable changes. Importantly, we assume that gifters are forward-looking. This means that when a gifter has an opportunity to make a decision, that decision will depend on both the instantaneous utility, as well as the flow utility and how she expects the state of the game to evolve over time. For example, the value of gifting will be determined by both the instantaneous utility from appreciation, as well as the longer-term flow utility the player may achieve if she is able to move to a higher slot on the leaderboard. If the player expects that it is unlikely new players will enter or idle players will re-enter, then she may have a greater incentive to gift since she can stay on the leaderboard for a longer period of time. If, however, the gifter is in a low rank and the session is very competitive, she may have a greater likelihood of exiting, since it is less likely she will be able to get on the leaderboard and accrue the utility benefits of it.

As the examples above illustrate, gifters' expectations will be determined by the model's states and their transition process. We denote the state vector as $k = (g, s, r, D, l, N^{idle})$, where (g, s, r) are the gifter's own states, (D, l, N^{idle}) are public states. g, s, and r are state variables because they directly enter the gifter's flow utility function, and thus inflence their decisions to gift or exit. Similarly, l also directly impacts utility, and thus gifting/exit decisions. D is a state variable because it impacts a gifter's flow utility through its effect on rank. A gifter may be less likely to gift, for example, if the top slot on the leaderboard is occupied by someone who has a much higher score. Finally, N^{idle} is a state because it impacts the likelihood an idle gifter re-enters, and hence the future competitiveness of the game and the value of gifting or exiting. As we will describe in more detail below, we allow the likelihood of re-entry to be increasing in the number of idle gifters.[15]

Notationally, we denote the current value of the state vector using k, and future values using k'. The state transition process determines how the state vector may change from a particular value of k to $k'(k; ev)$, where ev describes an event that happens in the game. The value of ev will determine how k' changes, and how a particular event will impact a gifter's expectations about the future state of the session. The event ev can take on 7 different values, which we list as follows:

[15] This assumption is intuitive, and is also supported by the data.

1. $ev = gift_f(s')$: a focal incumbent increases her score from s to s' by gifting. In this case, $k'(k; gift_f(s')) = (g, s', r', D', l, N^{idle})$. D' will be the new distribution of scores when the gifter has score level s'. In particular, $D' = D - e_s + e_{s'}$, where e_j is a vector with 1 in element j and 0 in all other elements. r' will be the new rank obtained by the gifter. The new rank will be determined as follows according to the gifter's new score slot s' and the number of gifters at or above that slot. Denote the state vector $\tilde{D} = D - e_s$ as describing the states of all incumbents except the focal one, and $\tilde{d}_l$ as the each element of $\tilde{D}$. If the focal gifter spend positive amount, her rank is $r' = \min\{\sum_{s''>s} \tilde{d}_{s''} + 1, 4\}$.

2. $ev = gift_o(s^{m\prime})$: Another incumbent m who has score s^m chooses to increase her score to $s^{m\prime}$. $k'(k; gift_o(s^{m\prime})) = (g, s, r', D', l, N^{idle})$, where r' is the new rank of the focal gifter after incumbent m changes their score, and D' is the corresponding new distribution of scores. Similar to event $gift_f$, $D' = D - e_{s^m} + e_{s^{m\prime}}$. The focal gifter's rank will change as follows: if the non-focal incumbent initially has a lower ranking than the focal gifter ($r^m \geqslant r$), and later surpasses the focal gifter's score ($s^{m\prime} > s$), the focal gifters' rank is bumped down, $r' = min(r + 1, 4)$. Otherwise, its rank does not change, i.e., $r' = r$.

3. $ev = entry$: A new entrant enters the session. $k'(k; entry) = (g, s, r, D', l, N^{idle})$, where D' is the post-entry score distribution. Note that since new entrants come in with a score of 0, $d'_0 = d_0 + 1$. The focal gifter's rank will remain unchanged.

4. $ev = exit_f$: The focal incumbent i chooses to exit the session. $k'(k; exit_f) = (g', s, r', D', l, N^{idle\prime})$. Since the incumbent has exited, $g' = 0$. When the incumbent has exited, their rank becomes irrelevant, so we set $r' = 4$. The distribution of scores will also change, in that the entry for score s will be reduced by 1: $d'_s = d_s - 1$. Finally, since there is now another idle gifter, $N^{idle\prime} = N^{idle} + 1$.

5. $ev = exit_o(m)$: Another incumbent m exits the session. Suppose the incumbent m who exits has score s^m, and rank r^m, the state transition for gifter i is denoted as $k'(k, exit_o(m))$. The exit of incumbent m changes the score distribution, $d'_{s^m} = d_{s^m} - 1$, increases the number of idle gifters by one, $N^{idle\prime} = N^{idle} + 1$, and sometimes focal incumbent i's ranks if the exited incumbent m originally ranked higher than focal incumbent i.

6. $ev = re - entry(s^m)$: An idle gifter, m, re-enters the session. $k'(k; re - entry(s^m)) = (g, s, r', D', l, N^{idle\prime})$. D' is the new score distribution, where $d'_{s^m} = d_{s^m} + 1$ and s^m is the idle gifter's score at the time they exited the session. r' is the focal gifter's new rank. It will evolve in the same way as in item 2, when the event $gift_0(s^{m\prime})$ occurs. The number of idle gifters decreases, $N^{idle\prime} = N^{idle} - 1$.

7. $ev = quality(l')$: An exogenous change in content quality from l to l' occurs. The state transition process for content quality is shown in Equation (3). The state transition for this event will be $k'(k; quality(l')) = (g, s, r, D, l', N^{idle})$

For computational tractability, we simplify the expectation process for the re-entry of idle gifters presented in item 6 above. Note that in item 6, if an idle gifter re-enters, her score is the same as the score was when the gifter exited. A fully rational gifter would have to track the distribution of scores for idle gifters, which could become very high dimensional if the number of gifters who have exited is large. The model would become computationally intractable if we were to track this state; moreover, we also believe it is not behaviorally realistic that gifters will track the entire distribution of idle gifters due to the cognitive complexity of the task. To simplify expectations, we assume that gifters have a non-state dependent expectation of what an idle gifter's score will be if they re-enter, which we denote as $f(\cdot)$. In estimation, we set $f(\cdot)$ to be the empirical distribution of scores that are realized when an idle gifter re-enters, across all sessions in our data.[16] We view this assumption as analogous to the commonly made assumption of oblivious equilibrium (Benkard, Jeziorski, and Weintraub, 2015), where rather than tracking complicated high-dimensional state transitions, agents only track summary statistics of the steady state for an entire market.

Before presenting the Bellman equation, we make one more note on state transitions. Because we impose that the maximum number of gifters is capped at N, when the number of incumbents equals N, no further entry or re-entry can occur. We assume that gifters account for this limit when forming their expectations. We denote the number of incumbents as $N^{incumbent}$, i.e., $N^{incumbent} = \sum_{l \in \mathbb{S}} d_l$. When agents form expectations about entry, they correctly expect that

[16]In our counterfactuals, we will enforce consistency of beliefs by simulating outcomes conditional on an initial guess of beliefs, re-solving for the agent's dynamic programming problem given the distribution in the simulated data, and re-simulating until beliefs converge.

if a new entrant can come in (at rate λ_e), only one potential entrant may enter. However, if the event that an idle incumbent is allowed to re-enter happens, the rate at which entry occurs is $\lambda_{re} \cdot N^{idle}$. In other words, all idle incumbents have a chance to re-enter.

We denote V_k to be the value function of the incumbent that assigns to each state k the discounted value of future utility obtained from starting in that state and behaving optimally from then on. The Bellman Equation 6 is defined as the recursion.[17]

$$
\begin{aligned}
V_k = & \frac{1}{\rho + \lambda_a \cdot N^{incumbent} + (N^{incumbent} < 7) * (\lambda_e + \lambda_{re} \cdot N^{idle}) + \sum_{l' \neq l} q_{ll'} + q_{live}} \times \\
& \Bigg[\underbrace{u_{flow}}_{\text{flow utility}} + \underbrace{\lambda_a \cdot E \max_{s' \geqslant s, exit} \left[u_{inst} + V_{k'(k, gift_f(s'))} + \epsilon_{i,s'-s}, V_{k'(k, exit_f) + \epsilon_{i,e}} \right]}_{\text{focal incumbent } i\text{'s gift \& exit decision}} \\
& + \underbrace{\sum_{m \in \mathcal{N}^{incumbent}/i} \lambda_a \cdot \left(\sum_{s^{m'} \geqslant s^m} \zeta_{m,k,s^{m'}} \cdot V_{k'(k, gift_o(s^{m'}))} \right)}_{\text{other incumbent } m\text{'s gift event}} + \underbrace{\sum_{m \in \mathcal{N}^{incumbent}/i} \lambda_a \cdot \left(1 - \sum_{s^{m'} \geqslant s^m} \zeta_{m,k,s^{m'}} \right) \cdot V_{k'(k, exit_o(m))}}_{\text{other incumbent } m\text{'s exit event}} \\
& + \underbrace{\lambda_e \cdot (N^{incumbent} < 7) \cdot V_{k'(k; entry)}}_{\text{entry event}} + \underbrace{\lambda_{re} \cdot N^{idle} \cdot (N^{incumbent} < 7) \cdot \left(\sum_{s^m} f(s^m) \cdot V_{k'(k; re-entry(s^m))} \right)}_{\text{re-entry event}} \\
& + \underbrace{\sum_{l' \neq l} q_{ll'} V_{k'(k; quality(l'))}}_{\text{Changes in Content Quality}} + \underbrace{q_{live}}_{\text{session end}} \cdot 0 \Bigg]
\end{aligned} \tag{6}
$$

where $\zeta_{m,k,s^{m'}}$ is the focal incumbent i's belief about the other incumbent m's gifting to $s^{m'}$ when the state is k, which is consistent with gifters' policy on equilibrium. Given the assumption of a type-1 extreme value distribution for the choice-specific shocks, we define the conditional choice probability of gifting to be

$$
P(s'|k) = \frac{exp(u_{inst}(s', s, l) + V_{k'(k; gift_f(s'))})}{\left[\sum_{s'' \geqslant s} exp(u_{inst}(s'', s, l) + V_{k'(k; gift_f(s''))})\right] + exp(V_{k'(k; exit_f)})}
$$

[17] In the presentation of the Bellman equation in continuous time, we follow Arcidiacono et al. (2016). For brevity, we refer the reader to Arcidiacono et al. (2016) for details on the derivation.

and the conditional choice probability of exit decisions as

$$P(exit|k) = \frac{exp(V_{k'(k;exit_f)})}{\left[\sum_{s''\geqslant s} exp(u_{inst}(s'', s, l) + V_{k'(k;gift_f(s''))})\right] + exp(V_{k'(k;exit_f)})}$$

6 Estimation and Identification

In this section, we present how we estimate and identify the parameters for our model. We first estimate a set of primitives without using the full structure of the model, including parameters governing entry, reentry, content quality transitions, session termination, and the rate at which consumers receive opportunities to make gifting and exit decisions. We then use these estimates for the estimation of the remaining parameters employing a nested fixed-point (NFXP) algorithm combined with the Simulated Method of Moments (SMM).

6.1 Estimation

The complete set of parameters to estimate includes (1) parameter $\boldsymbol{\theta}^e$, determining the arrival rate of entry event $\lambda_e(W_t^e; \theta^e)$; (2) parameter $\boldsymbol{\theta}^{re}$, determining the arrival rate of re-entry event $\lambda_{re}(W_t^{re}; \theta^{re})$; (3) transition matrix for content quality, Q_q and live end rate q_{live}; (4) the arrival rate of decision opportunity, λ_a; (5) price coefficient, β_p; (6) parameters for appreciation motive γ_0 and γ_1; (7) parameter for rank-based utility, $u_r, r = 1, 3$; (8) flow utility from consuming content γ_2 and γ_3. For the rest of the section, we provide an overview of the estimation procedure used to estimate the model's primitives.

To estimate the model, we employ a nested fixed-point (NFXP) algorithm combined with the Simulated Method of Moments (SMM). The estimation proceeds in two stages. In the first stage, we estimate the structural parameters (1)-(3) outside the full structure of the model, using maximum likelihood. In the second stage, we estimate the structural parameters (4)-(8) by minimizing an SMM objective function that matches simulated moments from the model to their empirical counterparts in the data. The estimation follows the standard NFXP structure. In the inner loop, fix estimated primitives $(\hat{\theta}^e, \hat{\theta}^{re}, \hat{Q}_q, \hat{q}_{live})$ from the first stage, we solve the equilibrium policy for each candidate vector of parameters in (4)-(8), i.e., $\theta = (\lambda_a, \beta_p, \gamma_0, \gamma_1, u_1, u_3, \gamma_2, \gamma_3)$. To solve for equilibrium, we use the Bellman equation 6 to iterate on the value function until convergence (at precision $1e-5$). We recover the gifters' optimal policy (on exit, gift, and doing nothing) using the value function. Then, we forward simulate the entire environment—including the gifters' actions, entry, reentry, content quality evolution, and session termination—for $20,000$ sessions to generate model-implied moments. In the outer loop, we compare the model-implied moments—generated from the equilibrium policy functions—with their empirical counterparts observed in the data. We compute the following SMM objective function:

$$\Pi(\theta) = g(\theta)' W g(\theta) \tag{7}$$

where $g(\theta)$ is the vector of moment conditions (differences between empirical and model-implied moments), and W is the weighting matrix. Table B1 provides a comprehensive list of target moments we match. We search for the optimal parameter vector θ that minimizes SMM objective value:

$$\hat{\theta} = \arg\min_{\theta} \Pi(\theta) \tag{8}$$

This minimization is carried out using NelderMead optimizer built in Julia, where the convergence precision is set to be $1e-5$.

6.2 Identification

Table 6 summarizes the data moments we used for identify our model parameters.

Table 6: Summary of Data Moments Used to Identify Each Parameter.

Concept	Parameter	Data Moments
Rank utility for top 1	u_1	The increment of gifting after top 1 gifters get bumped
Rank utility for top 2, 3	u_3	The increment of gifting after top 3 gifters get bumped
Appreciation motive	$\gamma_0,\ \gamma_1$	Gifting at varying levels of content quality
Flow utility for content consumption	$\gamma_2,\ \gamma_3$	Exit frequency at varying levels of content quality
Price coefficient	β_p	Choice probability conditional on gifting
Arrival rate of decision making	λ_a	Exclusion restriction of rank on utility
Arrival rate of entry	λ_e	Length of time before entry
Arrival rate of re-entry	λ_{re}	Length of time before re-entry
Content quality transition rate	$q_{l,l'}$	Length of time between different content quality levels
Arrival rate of session ending	q_{live}	Length of session duration

Competitive Motive Based on our empirical findings in Table 2, gifters increase their spending after being bumped from the top 1 and top 3, indicating their competitive motive. Based on this observation, we isolate the 6-minute time interval around re-entry moments and calculate the average gifting difference between the post-period and the pre-period. We separately calculate the differences for gifters bumped from the top 1 and gifter bumped from the top 3. These differences are the targeted moments to identify rank-based utilities.

Appreciation Motive and Price Coefficient For consumers who already ranked at the top 5 or lower, their gifting behavior is primarily driven by the appreciation motive. Their tendency to gift towards different levels at varying levels of content quality identifies the appreciation motive and price coefficient. Conditional on gifting a positive amount, we calculate the conditional choice probability of gifting to different levels. A higher gifting level from gifters indicates a higher baseline appreciation level and lower price sensitivity. Given that the baseline appreciation is concave in gifting amount, while the disutility from spending is linear in gifting amount, we could separately identify (γ_0, β_p) by targeting choice probability. Moreover, how their gifting willingness changes across varying levels of content quality identifies their appreciation motive γ_1, i.e., in which we use the percentage of gifting contributed at high-quality content as the targeting moment.

Flow Utility from Content Consumption Utility from consuming content changes gifters' consumption value from staying in the session. Therefore, a higher content consumption value reduces the gifters' exit probability. Moreover, the different levels of exit frequency at varying levels of content quality identify gifters' baseline utility and marginal utility from content consumption.

Gifting Arrival Rate Unlike the discrete-time model, consumers make decisions every single period; consumers in the continuous-time model have decision chances arriving randomly. No observation of actions could be a result of either no decision chance or a high preference to stay inaction. To disentangle those two possibilities and identify the gifting arrival rate, we leverage an exclusion restriction where exogenous re-entry events affect bumped gifters' tendency to give gifts but have no impact on their decision arrival rate.

6.3 Estimation Results

Table 7 presents the model estimates for all parameters. The cost coefficient of gifting is significant at 1.857, which provides an interpretation about the monetary worth of utilities. Because gifters generate 1.857 units of disutility whenever they spend one hundred TikTok coins on gifts, and each 100 coin is worth \$1.4. Therefore, one unit of utility is worth $(1/1.857) * 1.4 = 0.753$ dollar.

With the above conversion rule between utility and monetary value, we could directly interpret gifters' willingness to gift. Competitive motive stems from the flow utility of ranking the top positions. According to the estimates, utility for top 1 position is positive and significant at 0.737 and the utility for top 3 position is positive and significant at 0.227. Our estimates also validate that gifters value higher positions to lower positions, i.e., $u_1 > u_2 = u_3$. We further interpret the rank-based utility by its monetary value. Gifters value each minute of staying in the top 1 positions at $0.737 * 0.753 = 0.554$\$. Similarly, each minute of staying in the top 2 or 3 positions is worth $0.227 * 0.753 = 0.170$\$.

For the appreciation motive, gifters' baseline appreciation factor and marginal appreciation factor are both positively significant at 1.374 and 0.689. Since the utility from showing appreciation is concave in the gifting amount, we interpret the appreciation motives through considering how much is the utility of showing appreciation when a gifter contributed one-hundred TikTok coins (worth \$1.4). Firstly, baseline appreciation factor is positive significant at 1.374, indicating how much gifters value showing appreciation when the content quality is of median level. We find that gifters generate 0.717 dollar worth of utility from showing appreciation at a median-quality content.[18] Second, appreciation factor is positive and significant, indicating utility from showing appreciation is greater with higher content quality. For the same one-hundred coins spend, if the content quality is improved by one standard-deviation, the value of showing appreciation will increase by 0.359 dollar.[19]

[18] The interpretation of appreciation motive is slightly difficult given the utility from showing appreciation is concave in gifting amount. One-hundred coins generates $1.374 * \ln(2) = 0.952$ unit utility, which is worth $0.952 * 0.753 = 0.717$\$.

[19] Note our content quality are discretized number of likes and normalized by its standard deviation. Given one-hundred coins spent, one-standard deviation of content quality improvement further improves the utility from showing appreciation by $0.689 * \ln(2) = 0.477$, which is worth $0.477 * 0.753 = 0.359$.

Table 7: Model Estimates

Concept	Parameter	Data Moments
Competition motive		
Rank utility for top 1 gifter	u_1	0.737
Rank utility for top 2/3 gifter	u_3	0.227
Appreciation motive		
Baseline appreciation factor	γ_0	1.374
Marginal appreciation factor	γ_1	0.689
Content consumption value		
Baseline value	γ_2	0.130
Return of quality	γ_3	0.100
Cost function		
cost coefficient	β_p	1.857

Lastly, we find that consumers derive substantial consumption value simply from watching the livestream itself. The baseline consumption value is significant at 0.13, indicating consumers value watching at $0.130 * 0.753 = 0.097$ dollar per minute at median content quality. Moreover, the return of quality from watching content is 0.1, meaning that a one-standard-deviation increase in content quality further enhancing this content consumption value by $0.01 * 0.753 = 0.007$ dollar per minute.

Our model estimates validate and improve our understanding of consumers' gifting motive. We find gifters' competitive motive is not only significant, but also substantial in its monetary value. They place a greater value on higher rankings, i.e., $u_1 > u_2 = u_3$. Moreover, we also find substantial size of appreciation motive for gifting and consumption value for watching and participating in the session.

7 Counterfactuals

In this section, we conduct three counterfactual analyses. The first is an income decomposition that analyzes how the two gifting motives separately contribute to the creators' income (Section 7.1). In the second and third counterfactuals, we analyze the incentive design of the leaderboard. In the second counterfactual (Section 7.2), we provide an optimal design for the reward rule of the leaderboard: how many rewards should be provided on the leaderboard? In the third counterfactual (Section 7.3), we provide an optimal design for the score rule of the leaderboard: how gifting contributions should be aggregated to determine leaderboard rankings.

In all counterfactuals, we assume that creators' content production remains unaffected by changes in the leaderboard's reward or score structure. The reward rule affects the prominence of rankings—for example, reducing the number of rewards from three to two causes the third-ranked gifter to lose the badge next to their comment, thus reducing the total number of comments with a badge. This could potentially influence creators' content production process, given their content production might be influenced by those prominent comments with badges. Table (TBA) shows that the number of prominent comments does not influence content production (i.e., content quality and session-ending probability).

In contrast, the score rule shuffles the ranking of gifters on the leaderboard without changing the number of rewards. Table B1 indicates that content production is unrelated to gifting behavior, but is responsive to commenting behavior. Furthermore, Table B2 shows that changes in leaderboard ranking do not significantly impact bumped gifters' subsequent commenting behavior. Together, these findings justify treating content production as exogenous to leaderboard design.

7.1 Income Decomposition

In the first counterfactual, we want to separate the effects of competitive and appreciation motives on total gifting. We sequentially remove the rank-based utility and the utility of showing appreciation to study how much income is from the two gifting motives. From Table 8, we find that the competitive motive and the appreciation motive separately contribute to 45% and 37% of the total income.

Table 8: Income Decomposition

	All	Competitive motive	Appreciation motive	Other
Total gifts	2797	1257	1025	515
		(45%)	(37%)	(18%)

7.2 Reward Design

In the second counterfactual, we want to design the optimal number of rewards on the leaderboard. Platforms can manipulate the rewards by changing the leaderboard display or the number of badges. On TikTok Live, two kinds of rewards are tied to gifters' ranking. First, top gifters are prominently displayed on the leaderboard, where they are acknowledged for their generosity and earn social respect. Second, top gifters receive top-gifter badges, which are displayed along with their names in the comment section to draw creators' attention. The platform can design the number of rewards by altering how many gifters are highlighted on the leaderboard or how many badges are given out to top gifters.

A challenge of this counterfactual is that changing the number of rewards could have a redistribution effect. For example, removing the top 3 positions could potentially improve the value of the top 1 and 2, because the same prominent space on the leaderboard is allocated to fewer people, and gifters' badges are more effective in drawing creators' attention because of improved scarcity. However, we do not know the conversion rate between these top positions since TikTok always rewards top 3 gifters. Despite this challenge, we take a conservative approach to study three cases in Table 9. The benchmark is the status quo of TikTok Live with rewards to top 1/2/3 gifters, estimated from our model. Compared to the benchmark, we consider two other cases where the rewards are removed to varying degrees. In case 1, we remove the rank utility of the top 3 positions while retaining the rank utility for the top 1 and 2 unchanged. In case 2, we further remove the rank utility for the top 2 positions. Although removing the number of rewards might positively affect the utility of the remaining reward, we take a conservative approach to evaluate the effect of reward removal by ignoring the positive redistribution effect.

Intuitively, reducing the number of rewards has an ambiguous effect on total gifting. First, it

Table 9: Demonstration of Reward Design

	rank utility		
	top 1	top 2	top 3
benchmark	0.737	0.227	0.227
case 1	0.737	0.227	0
case 2	0.737	0	0

may negatively impact participation by reducing the number of gifters-*participation effect.* Fewer rewards reduce the expected benefit of gifting, deterring the participation of gifters; Second, conditional on participating, it shrinks the proportion of gifters are with competitive motive-*motive-shifting effect.* Fewer rewards may discourage gifters from competing for top positions. This shifts their motivation from both competitive and appreciation motives to primarily appreciation. This shift can reduce the gifting per gifter; Third, fewer rewards raise the bar for winning, which can intensify competition among those who do compete for top positions-*competition-intensity effect.* For example, reducing rewards from three to two raises the bar of obtaining rewards from being top 3 to being top 2, potentially increasing the gifting per gifter. Note the effect of reducing rewards on gifting per gifter is ambiguously determined by the relative strength of the last two effects.

Table 10 shows that the number of rewards has a non-trivial impact on total gifting. First, the participation effect consistently reduces the number of gifters as rewards become more limited. Second, the motive-shifting effect and competition-intensity effects jointly produce a non-monotonic pattern in gifting per gifter. When rewards decrease from three to two, few gifters shift to pure appreciation motives, allowing the competition-intensity effect to dominate, resulting in greater gifting per gifter. However, when rewards drop to just one, many gifters shift away from competition, and the motive-shifting effect dominates, leading to lower gifting per gifter. Taken together, these effects suggest that rewarding the top 1 or top 2 gifters is optimal, increasing total gifting by 2.8%.

We also investigate dynamic reward design by allowing the number of rewards to be conditional on the number of gifters on the leaderboard in real-time. Assuming such a policy is well understood by the consumers, we find that an optimal dynamic policy could improve the total gifting by 6.5%, which can be translated to 143 million increment in revenue.[20] More specifically, the optimal policy suggests a positive relationship between the number of rewards and the number of gifters on the leaderboard: when the number of gifters is 0, 1, or 2, only a Top 1 reward is offered. When there are 3 gifters, both Top 1 and Top 2 rewards are offered. When the number of gifters is 4 or above, Top 1, Top 2, and Top 3 rewards are provided.

Table 10: Optimal Number of Reward

	total gifting	% change in gifting	# gifters	gifting per gifter
benchmark	2797	0%	7.09	388.87
top1/top 2	2879	+2.9%	6.90	414.51
top 1	2733	-2.2%	6.69	408.74
dynamic # rewards	2979	+6.5%	7.05	420.68

Note: The optimal dynamic number of rewards is conditional on the number of gifters. When the number of gifters is 0, 1, or 2, only a Top 1 reward is offered. When there are 3 gifters, both Top 1 and Top 2 rewards are offered. When the number of gifters is 4 or above, Top 1, Top 2, and Top 3 rewards are provided.

7.3 Score Design

In the third counterfactual, we want to design a score policy accounting for gifters' contributions to maximize their total gifting amount. Our empirical study reveals a negative relationship between score disparity and players' willingness to gift. When the score gap widens, gifters with a high rank often cease contributing, knowing their position is secure and unlikely to be challenged (Table 4). Similarly, lower-ranked gifters are discouraged from competing, as the cost to climb the leaderboard becomes prohibitively high and unlikely to be rewarded (Table 3).

To address this rigidity in rank-based competition, we propose a recency-weighted score design. Specifically, we introduce random score discounting over time, which gives more weight to recent gifting. Under this mechanism, each player's score is subject to downward adjustments over time through stochastic "discount shocks". We modeled discount shocks to arrive randomly,

[20] According to statistics by Business of Apps, TikTok generates over 2.2 billion in-app purchase in year 2024, which mostly comes from gifting to creators in the LIVE section. https://www.businessofapps.com/data/tik-tok-statistics/

and the time between discount shocks followed an exponential distribution at rate λ. Upon arrival, each player's score is demoted to the next lower level on a fixed grid (e.g., from 600 to 300 on the grid $[0, 100, 300, 600, 1000, 1500]$). As a result, more distant contributions are more likely to be discounted, while recent contributions have a larger influence on current rankings.

The discounting intensity, governed by the arrival rate λ, controls the weight placed on recency. For example, at $\lambda = 0.1$, scores are discounted once every 10 minutes on average; at $\lambda = 1$, discounting occurs every minute. In the extreme case where $\lambda \to \infty$, gifts are immediately depreciated and never affect the leaderboard.

The effect of this recency-based scoring is ambiguous in theory: On the one hand, discounting past contributions reduces score disparity over time. This dynamic benefits lower-ranked gifters—who might otherwise avoid competition and give purely out of appreciation. This can increase both participation and average gifting amounts of lower-ranked gifters. At the same time, high-ranked gifters are also motivated to gift more due to intensified competition. On the other hand, agents at the early stage of the session may anticipate future discounting and withhold effort, knowing their early contributions will decay. This could reduce both their participation and average gifting amount. The overall effect thus depends on the balance between these opposing forces. Our counterfactual simulations evaluate this trade-off by varying the discounting rate and solving for the new equilibrium under each setting.

Table 11 shows that the discounting rate has a non-trivial impact on total gifting. We show the gifting behavior under three levels of discount arrival rate, 0.05, 0.09, and 0.15, which translate to a discount once in 20, 11.1, and 6.7 minutes. First, we find that score discounting unambiguously increases the number of gifters in the session due to a positive effect on the participation of later entrants, who originally suffer from competitive disadvantage due to entering the session at a later stage of the session. Second, the gifting per gifter increases when the discount rate rises from 0.05 to 0.09, given that the reduced disparity between scores substantially encourages the gifting behavior of later entrants. As the discounting rate further increases to 0.15, the gifting per gifters takes a turn, given that the forward-looking behavior of gifters substantially decreases their contribution in their gifting amount at the early stage of the session. Taken together, these effects suggest an optimal discounting rate at 0.09, increasing total gifting by 29%, which trans-

Table 11: Optimal Score Discounting

	total gifting	% change in gifting	# gifters	gifting per gifter
benchmark	2797	0%	7.09	388.87
	policy 1: uniform discounting on all score levels			
0.05	3442	23%	7.41	452.72
0.09	3623	29%	7.55	466.17
0.15	3615	29%	7.63	458.81
	policy 2: non-uniform discounting on score levels			
NA	4045	45%	7.45	525.37

Note: We allow the policy to choose among discount arrival rates $\{0.0, 0.1, 0.2, 0.5, 1.0\}$ for each score level (which maps to discount once in $(\text{inf}, 10, 5, 2, 1)$ minutes in expectation). The optimal non-uniform discounting policy discounts the scores $(100, 300, 600, 1000, 1500)$ in rate $(0.0, 1.0, 0.2, 0.2, 0.5)$.

lates into a 638$ million increment in yearly revenue. We also evaluate a second non-uniform discounting policy allowing the discount rate to vary across different score levels for the top-one gifter. By assuming players understand this policy and make the optimal responses in the dynamic games, it improves the revenue by 45%, which translates into nearly 1 billion increment in yearly revenue.

8 Conclusion

This paper provides empirical evidence on how gamification elements shape consumer behavior and platform revenue in digital consumption. Using data from TikTok Live, we document that consumer gifting behavior is driven not only by appreciation for content but also by a distinct competitive motive to climb real-time leaderboards. Importantly, the strength of this motive varies with the intensity of competition, declining when individuals perceive little opportunity to change their relative standing.

Our structural model quantifies the economic significance of these motives, revealing that competitive incentives contribute nearly half of total platform revenue. Through counterfactual analysis, we demonstrate that leaderboard incentive design can meaningfully influence competitive behavior and revenue outcomes. Specifically, offering rewards to fewer top positions and emphasizing recent gifting activity both serve to intensify competition, substantially increasing revenue.

These findings contribute to the broader literature on contest design, livestreaming, and digital platform monetization. More broadly, they highlight the intricate relationship between platform design choices and consumer behavior, underscoring that well-designed gamification mechanisms can transform competitive dynamics into meaningful economic value. Future research could extend this analysis by exploring heterogeneity across different types of consumers or platform contexts and by investigating potential long-term effects of competitive gamification on consumer retention and platform health.

References

Abrevaya, Jason. 2002. "Ladder tournaments and underdogs: lessons from professional bowling." *Journal of Economic Behavior & Organization* 47 (1):87–101.

Arcidiacono, Peter, Patrick Bayer, Jason R Blevins, and Paul B Ellickson. 2016. "Estimation of dynamic discrete choice models in continuous time with an application to retail competition." *The Review of Economic Studies* 83 (3):889–931.

Benkard, C Lanier, Przemyslaw Jeziorski, and Gabriel Y Weintraub. 2015. "Oblivious equilibrium for concentrated industries." *The RAND Journal of Economics* 46 (4):671–708.

Bernanke, Ben S and Kenneth N Kuttner. 2005. "What explains the stock market's reaction to Federal Reserve policy?" *The Journal of finance* 60 (3):1221–1257.

Blevins, Jason R. 2016. "Identification and estimation of continuous time dynamic discrete choice games." *Ohio State University Working Paper* .

Blevins, Jason R. and Minhae Kim. 2024. "Nested Pseudo likelihood estimation of continuous-time dynamic discrete games." *Journal of Econometrics* 238 (2):105576.

Boudreau, Kevin J, Karim R Lakhani, and Michael Menietti. 2016. "Performance responses to competition across skill levels in rank-order tournaments: field evidence and implications for tournament design." *The RAND Journal of Economics* 47 (1):140–165.

Chan, Tat, Yijun Chen, and Chunhua Wu. 2023. "Collaborate to compete: An empirical matching game under incomplete information in rank-order tournaments." *Marketing Science* 42 (5):1004–1026.

Cong, Ziwei, Jia Liu, and Puneet Manchanda. 2021. "The Role of" Live" in Livestreaming Markets: Evidence Using Orthogonal Random Forest." *Working Paper* .

Dechenaux, Emmanuel, Dan Kovenock, and Roman M Sheremeta. 2015. "A survey of experimental research on contests, all-pay auctions and tournaments." *Experimental Economics* 18:609–669.

Deng, Yiting and Carl F Mela. 2018. "TV viewing and advertising targeting." *Journal of Marketing Research* 55 (1):99–118.

Deterding, Sebastian, Dan Dixon, Rilla Khaled, and Lennart Nacke. 2011. "From game design elements to gamefulness: defining" gamification"." In *Proceedings of the 15th international academic MindTrek conference: Envisioning future media environments*. 9–15.

Doraszelski, Ulrich and Kenneth L Judd. 2012. "Avoiding the curse of dimensionality in dynamic stochastic games." *Quantitative Economics* 3 (1):53–93.

Du, Rex Yuxing, Linli Xu, and Kenneth C Wilbur. 2019. "Immediate responses of online brand search and price search to TV ads." *Journal of Marketing* 83 (4):81–100.

Ehrenberg, Ronald G and Michael L Bognanno. 1990. "Do tournaments have incentive effects?" *Journal of political Economy* 98 (6):1307–1324.

Fershtman, Chaim and Uri Gneezy. 2011. "The tradeoff between performance and quitting in high power tournaments." *Journal of the European Economic Association* 9 (2):318–336.

Forbes. 2025. "TikTok Has The Highest In-App Earnings In The World (Again), Beating YouTube, Disney, Tinder." Https://www.forbes.com/sites/johnkoetsier/2024/03/30/tiktok-is-the-highest-earning-app-in-the-world-again-beating-youtube-disney-tinder/.

Fossen, Beth L and David A Schweidel. 2017. "Television advertising and online word-of-mouth: An empirical investigation of social TV activity." *Marketing Science* 36 (1):105–123.

Genakos, Christos and Mario Pagliero. 2012. "Interim rank, risk taking, and performance in dynamic tournaments." *Journal of Political Economy* 120 (4):782–813.

Green, Jerry R and Nancy L Stokey. 1983. "A comparison of tournaments and contracts." *Journal of Political Economy* 91 (3):349–364.

Gu, Xian, Xiaoxi Zhang, and PK Kannan. 2024. "Influencer mix strategies in livestream commerce: impact on product sales." *Journal of Marketing* 88 (4):64–83.

Gürkaynak, Refet S, Brian Sack, and Eric T Swansonc. 2005. "Do Actions Speak Louder Than Words? The Response of Asset Prices to Monetary Policy Actions and Statements." *International Journal of Central Banking* .

He, Chen and Tobias J Klein. 2023. "Advertising as a reminder: Evidence from the Dutch State Lottery." *Marketing Science* 42 (5):892–909.

Heckman, James J and Burton Singer. 1986. "Econometric analysis of longitudinal data." *Handbook of Econometrics* 3:1689–1763.

Hong, Fuhai, Tanjim Hossain, and John A List. 2015. "Framing manipulations in contests: a natural field experiment." *Journal of Economic Behavior & Organization* 118:372–382.

Hossain, Tanjim, Mengze Shi, and Robert Waiser. 2019. "Measuring rank-based utility in contests: The effect of disclosure schemes." *Journal of Marketing Research* 56 (6):981–994.

Huang, Yufeng and Ilya Morozov. 2025. "The promotional effects of live streams by Twitch influencers." *Marketing Science* .

Hydari, Muhammad Zia, Idris Adjerid, and Aaron D Striegel. 2023. "Health wearables, gamification, and healthful activity." *Management science* 69 (7):3920–3938.

Imarc. 2025. "Live streaming market report by component (platforms, services), end user (media and entertainment, education, events, retail, government, and others), and region 2025-2033." Https://www.imarcgroup.com/live-streaming-market.

Joo, Mingyu, Kenneth C Wilbur, Bo Cowgill, and Yi Zhu. 2014. "Television advertising and online search." *Management Science* 60 (1):56–73.

Joo, Mingyu, Kenneth C Wilbur, and Yi Zhu. 2016. "Effects of TV advertising on keyword search." *International Journal of Research in Marketing* 33 (3):508–523.

Lazear, Edward P. 2000. "Performance pay and productivity." *American Economic Review* 90 (5):1346–1361.

Lazear, Edward P and Sherwin Rosen. 1981. "Rank-order tournaments as optimum labor contracts." *Journal of Political Economy* 89 (5):841–864.

Lemus, Jorge and Guillermo Marshall. 2021. "Dynamic tournament design: Evidence from prediction contests." *Journal of Political Economy* 129 (2):383–420.

———. 2024. "Teamwork in Contests." *Review of Economics and Statistics* :1–45.

Leuven, Edwin, Hessel Oosterbeek, Joep Sonnemans, and Bas Van Der Klaauw. 2011. "Incentives versus sorting in tournaments: Evidence from a field experiment." *Journal of Labor Economics* 29 (3):637–658.

Leuven, Edwin, Hessel Oosterbeek, and Bas Van der Klaauw. 2010. "The effect of financial rewards on students' achievement: Evidence from a randomized experiment." *Journal of the European Economic Association* 8 (6):1243–1265.

Lewis, Randall A and David H Reiley. 2013. "Down-to-the-minute effects of super bowl advertising on online search behavior." In *Proceedings of the fourteenth ACM conference on Electronic commerce*. 639–656.

Liaukonyte, Jura, Thales Teixeira, and Kenneth C Wilbur. 2015. "Television advertising and online shopping." *Marketing Science* 34 (3):311–330.

Lim, Noah. 2010. "Social loss aversion and optimal contest design." *Journal of Marketing Research* 47 (4):777–787.

Lim, Noah, Michael J Ahearne, and Sung H Ham. 2009. "Designing sales contests: Does the prize structure matter?" *Journal of Marketing Research* 46 (3):356–371.

Lin, Yan, Dai Yao, and Xingyu Chen. 2021. "Happiness begets money: Emotion and engagement in live streaming." *Journal of Marketing Research* 58 (3):417–438.

Liu, Jia and Shawndra Hill. 2021. "Frontiers: Moment marketing: Measuring dynamics in cross-channel ad effectiveness." *Marketing Science* 40 (1):13–22.

Liu, Tracy Xiao, Jiang Yang, Lada A Adamic, and Yan Chen. 2014. "Crowdsourcing with all-pay auctions: A field experiment on taskcn." *Management Science* 60 (8):2020–2037.

Liu, Xiao. 2023. "Dynamic coupon targeting using batch deep reinforcement learning: An application to livestream shopping." *Marketing Science* 42 (4):637–658.

Liu, Zekun, Weiqing Zhang, Xiao Liu, Eitan Muller, and Feiyu Xiong. 2022. "Success and survival in livestream shopping." *Available at SSRN 4028092* .

Lu, Shijie, Dai Yao, Xingyu Chen, and Rajdeep Grewal. 2021. "Do larger audiences generate greater revenues under pay what you want? Evidence from a live streaming platform." *Marketing Science* 40 (5):964–984.

Meltwater. 2025. "Digital 2025: global overview report." Https://indd.adobe.com/view/9d9a68f6-38a9-4278-b61c-4506b24240b0.

Moldovanu, Benny, Aner Sela, and Xianwen Shi. 2007. "Contests for status." *Journal of Political Economy* 115 (2):338–363.

Naik, Prasad A, Kalyan Raman, and Russell S Winer. 2005. "Planning marketing-mix strategies in the presence of interaction effects." *Marketing Science* 24 (1):25–34.

Nakamura, Emi and Jón Steinsson. 2018. "High-frequency identification of monetary non-neutrality: the information effect." *The Quarterly Journal of Economics* 133 (3):1283–1330.

Nalebuff, Barry J and Joseph E Stiglitz. 1983. "Prizes and incentives: towards a general theory of compensation and competition." *The Bell Journal of Economics* :21–43.

Nevskaya, Yulia and Paulo Albuquerque. 2019. "How should firms manage excessive product use? A continuous-time demand model to test reward schedules, notifications, and time limits." *Journal of Marketing Research* 56 (3):379–400.

Phillips, PCB. 1972. "The structural estimation of a stochastic differential equation system." *Econometrica: Journal of the Econometric Society* :1021–1041.

SensorTower. 2024. "Digital Advertising Insights Q4 2024 Market Index." *https://dataai.infogram.com/1p06653n19r6lgie60rny3vkv5bnmlxw291* .

Sims, Christopher A. 1971. "Discrete approximations to continuous time distributed lags in econometrics." *Econometrica: Journal of the Econometric Society* :545–563.

Sinha, Rajiv K and Murali Chandrashekaran. 1992. "A split hazard model for analyzing the diffusion of innovations." *Journal of Marketing Research* 29 (1):116–127.

Sunde, Uwe. 2009. "Heterogeneity and performance in tournaments: a test for incentive effects using professional tennis data." *Applied Economics* 41 (25):3199–3208.

Szymanski, Stefan. 2003. "The economic design of sporting contests." *Journal of Economic Literature* 41 (4):1137–1187.

Tirunillai, Seshadri and Gerard J Tellis. 2017. "Does offline TV advertising affect online chatter? Quasi-experimental analysis using synthetic control." *Marketing Science* 36 (6):862–878.

Yao, Dai, Shijie Lu, and Xingyu Chen. 2023. "Crowding-Out in Content Monetization Under Pay What You Want: Evidence From Live Streaming." *Production and Operations Management* :10591478231224948.

Online Appendix to "Competitive Gamification in Digital Consumption: Evidence from TikTok" by Zirou Chen, Matthew Osborne, and Nitin Mehta

Contents

**Detailed appendix is under construction and will be updated soon with the new version.*