Competitive Gamification in Digital Consumption: Evidence from TikTok

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August 28, 2025

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Abstract

We study the gifting behavior of consumers and leaderboard design in the context of livestreaming. Using real-time data from TikTok, we provide causal evidence for two distinct gifting motives: the competitive motive and the appreciation motive. The appreciation motive reflects the tendency to gift in response to popular content. The competitive motive arises from TikTok's gifting leaderboard, which prominently displays the ranks and cumulative gifting amounts of the top three contributors. This public visibility creates incentives to compete for recognition and social utility. We find that the strength of the competitive motive depends on the consumer's relative position: when a consumer's cumulative gifting amount is far from that of immediate competitors, the return from competing diminishes, reducing the competitive motive. To evaluate the economic value of the leaderboard and guide the design of the leaderboard, we build and estimate a continuous-time dynamic game model of consumers' gifting behavior. Our results show that, for an average session, the leaderboard-induced competitive motive accounts for 43% of the total revenue. We also conduct leaderboard design to manage the competitive intensity and optimize the platform revenue. We find that (1) reducing the number of rewarded top ranks from three to two intensifies the competition among top-ranked consumers, increasing total revenue by 2.9%; and (2) revising the performance metrics to weigh recent gifting activity more heavily increases revenue by 19.7%. Our findings underscore the critical role of leaderboards in driving engagement on digital platforms and the importance of leaderboard 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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*Job Market Paper. Email: zirou.chen@rotman.utoronto.ca. Address: Rotman School of Management, University of Toronto, 105 St George St, Toronto, ON, Canada, M5S 3E6. I am incredibly grateful to my advisor, Nitin Mehta, and the committee members, Matthew Osborne, Mengze Shi, and Zachary Zhong, for their continuous guidance and support. I am also very fortunate to have both Matthew and Nitin coauthoring the paper, and their emails are matthew.osborne@rotman.utoronto.ca and nmehta@rotman.utoronto.ca, respectively. We are grateful for the helpful comments from Dinara Akchurina, Rhia Catapano, Lorenzo Cecutti, Cindy Chen, Yijiun Chen, Hana Choi, Kristen Duke, Min Fang, Limin Fang, Xuhang Fan, Hortense Fong, Mohsen Foroughifar, Runshan Fu, Daniel Goetz, Avi Goldfarb, Brett Hollenbeck, Tanjim Hossain, Jordan Hutchings, Zibin Huang, Raghuram Iyengar, Samsun Knight, Malika Korganbekova, Vineet Kumar, Peter Landry, Chang-Yuan Lee, Sijie Lin, Siyuan Liu, Kanishka Misra, Sridhar Moorthy, Liying Qiu, Venky Shankar, David Soberman, Dilip Soman, Avni Shah, Avner Strulov Shlain, Yuanchen Su, Claire Tsai, Daniella Turetski, Miguel Villas-Boas, Qiaochu Wang, Ryan Webb, Chunhua Wu, Hyesung Yoo, Minwen Yang, Ying Zeng, Juanjuan Zhang, Shunyuan Zhang, Xu Zhang, Clarice Zhao, Han Zhong, and other audiences at seminar and brownbag at the University of Toronto. All names are listed in alphabetical order. All remaining errors are ours.

1 Introduction

Livestreaming of events—such as live performances, interactive chats, gaming, and beauty tutorials—has become an increasingly popular form of digital content. Roughly one-third of internet users worldwide now watch livestreams each week (Meltwater, 2025). In response to this growing demand, major technology companies have expanded their presence in livestreaming: the market has witnessed the launch of Facebook Live and YouTube Live Streaming Channels, the acquisition of Twitch by Amazon.com, and the explosive growth of TikTok Live. The global livestreaming market was valued at $88 billion in 2024 and is projected to grow at 24% annually, reaching $600 billion by 2033 (Imarc, 2025). A key driver of this growth is a distinctive monetization model adopted by most platforms: viewers are granted free access to livestreams but are encouraged to support broadcasters through voluntary payments in the form of virtual gifts.[1] These payments are later split between the platform and broadcasters.

To incentivize gifting, many livestreaming platforms implement leaderboards that publicly display viewers' monetary contributions. However, the effectiveness of the leaderboard in motivating users to increase their gifting remains unclear. While prior research shows that viewers are motivated to gift due to the social recognition from public acts of generosity (Lu et al., 2021), it remains unclear whether leaderboard rankings themselves confer similar social value. Moreover, competition on the leaderboard may inadvertently dampen gifting incentives. Users often report feeling demotivated when a top-ranked participant pulls far ahead, making further competition seem futile. In line with this feedback, product managers frequently caution that leaderboards must be carefully tailored to the player pool and competitive environment; if poorly designed, they risk undermining engagement and revenue (Arbiter, Heather, 2024). Motivated by this tension, we aim to unpack the motives behind consumers' gifting behavior on livestreaming platforms and propose leaderboard design strategies to enhance monetization.

We investigate the effectiveness of the leaderboard in motivating gift giving by focusing on three key research questions. First, how important is a consumer's motive to gift in response to

[1]Voluntary payments constitute the primary revenue source for leading livestreaming platforms such as Twitch (70%), TikTok Live (>99%), Bigo Live (>80%), and Kuaishou (90%). By contrast, platforms such as YouTube, Instagram, and Facebook monetize their livestreaming channels primarily through advertising and brand sponsorship, reflecting their broader business models.

competition, relative to the motivation to gift simply as a result of appreciation for the streamer? Second, what is the economic value of the leaderboard in contributing to total revenue, and how does that value vary across different types of sessions? Third, how should the platform design leaderboards, such as the reward structure and scoring system, to incentivize more gift giving?

Leveraging real-time data from TikTok Live, we provide causal evidence that both the competition and appreciation motives are at play in gifting decisions. The appreciation motive captures consumers' intrinsic gifting tendency on popular content (Wohn, Freeman, and McLaughlin, 2018). To encourage gift giving as a result of the competitive motive, TikTok Live implements a gifting leaderboard that continuously tracks and display consumers' cumulative gifting amounts, hereafter referred to as "score", within the session in real time. The leaderboard resets after each session. Moreover, the leaderboard highlights the top three gifters' usernames, gifting amounts, ranks, and badges, which are dynamically updated throughout the livestream. Users who are recognized on the leaderboard may receive utility from the social status it brings: this social status may be a result of the individual's prestige or generosity as perceived by others (Yao, Lu, and Chen, 2024).

Despite the challenges of studying competitive behavior using observational data, we employ a high-frequency empirical strategy to identify consumer preferences for the top leaderboard positions.[2] Specifically, we exploit a unique setup of the leaderboard-it only ranks the score of consumers who are currently present in a live session, updating in real time to reflect the entry and exit of gifters. Whenever a consumer exits the session, her score is immediately removed from the leaderboard. If she later re-enters the session, her previous score will be immediately added back to the leaderboard, resulting in an update to the leaderboard ranking. Based on this feature, we study the effect of re-entry events, which cause plausibly exogenous variation in the rankings of other consumers who are originally in the session. When a consumer with a high score leaves the session and later re-enters (hereafter, we refer to such a consumer as a re-entrant), her return bumps down the rankings of all consumers who were originally in the session but with strictly lower scores. For example, when a re-entrant remains the biggest contributor up to that point, all other consumers are bumped down by one rank on the leaderboard. We focus on consumers

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

whose rank is involuntarily bumped down due to someone else's re-entry and examine how they adjust their gifting amount within a short window around the re-entry moment.

Based on these re-entry events, we conduct a regression discontinuity analysis and provide evidence of leaderboards inducing competitive motives. We find that immediately after re-entry moments, consumers who are bumped down by one position from the rank one (to rank two) or rank three (to rank four) significantly increase their contributions in an attempt to regain their prior ranks. This behavior suggests a strict preference for their old rankings over the rankings they bumped into, i.e., rank 1 $\succ$ rank 2 and rank 3 $\succ$ rank 4, which highlights the role of the leaderboard in driving competitive motives.[3] In contrast, consumers who were bumped from rank four or lower exhibited no significant change in gifting amount, indicating negligible utility from occupying low-rank leaderboard positions. Furthermore, analysis of treatment effect heterogeneity reveals a key moderating factor of the competitive motive: when a bumped consumer's score substantially exceeds or lags behind that of adjacent competitors on the leaderboard, she has little incentive to compete.

Given that our running variable is time, the key identification assumption is that re-entry timing is plausibly exogenous. A potential concern is that re-entrants might strategically time their return to coincide with session improvements, which could also generate higher gifting. However, this is unlikely for two reasons. First, TikTok provides no information about ongoing session events outside the stream—there are no preview clips or real-time popularity indicators (e.g., likes or audience size) that would allow viewers to optimize re-entry. Second, we restrict our analysis to re-entrants who had been absent for more than ten minutes, making it implausible that expectations based on prior experience could precisely coordinate re-entry with improvements in the session. Our event study finds no pre-trend in the gifting behavior of bumped consumers, and the sharp increase in gifting within one minute after re-entry can only be explained by the change in rankings resulting from re-entry.

We also provide reduced-form evidence supporting the appreciation motive. Specifically, we find that consumers who rank fifth or lower continue to gift, despite having little motive to com-

[3]Consumers bumped from rank two did not significantly increase their gifting, suggesting indifference between the second and third positions.

pete for leaderboard positions. Moreover, they tend to gift more when content quality is higher.[4] This pattern suggests that consumers derive utility from gifting as an expression of appreciation for the high-quality content.

To quantify the economic value of the leaderboard and design leaderboards through counterfactual analysis, we build a continuous-time dynamic game model to capture consumers' gifting behavior on TikTok Live. In our model, each consumer can endogenously decide whether they want to exit at any moment during the session. If they chose to stay in the session, they can decide how much to gift. They have the option to stay in the session without gifting anything. The leaderboard updates immediately following each action, removing the score if the consumer exits, refreshing with an increased score if she gifts, or remaining unchanged if she does nothing. We model play using continuous time rather than a discrete time game for two main reasons. First, the continuous-time model can better capture consumers' decision processes: the session evolves continuously, and consumers can make exit and gifting decisions at any time during the livestreams. Second, the continuous-time model can drastically reduce the computation burden for dynamic game problems, as players move sequentially in the continuous-time model rather than simultaneously in the traditional discrete-time model.[5]

Consumers' decisions are modeled as the outcome of a dynamic optimization problem, in which they compete with each other over time in each session. Consumers are forward-looking because gifting out of competitive motive requires them to weigh not only the immediate disutility of spending, but also the effect of their score on subsequent competition. For example, gifting a lot may help a viewer obtain the top-three positions on the leaderboard, increasing her subsequent utility from holding the top positions on the leaderboard[6]. In contrast, gifting out of appreciation only induces myopic utility maximization: consumers trade off the immediate disutility of spending against the instantaneous utility of expressing appreciation for contemporaneously popular content, with no continuation value beyond the moment of action. Consumers' gifting

[4]We focus on consumers ranked below five who have litte competitive motives to provide clean identification of the appreciation motive.

[5]In continuous-time models, the probability that multiple agents make decisions at exactly the same moment is zero.

[6]In our model, the competition is driven by the utility of badges on the leaderboard, which are backed by the institutional fact that only top-three contributors are awarded with badges, and our reduced-form results also indicate consumers care about getting into top-three positions, i.e., rank 1 $\succ$ rank 2$\sim$ rank 3 $\succ$ rank 4 $\sim$ rank 5 and beyond.

is a joint outcome of these two motives. 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. 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.

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. 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 second-stage estimation follows the standard NFXP structure. In the inner loop, for each candidate set of structural parameters, we solve consumers' dynamic decision problems through iteration, and simulate the model-implied moments. In the outer loop, we search for the parameter vector that minimizes the distance between these simulated moments and the observed data moments.

Our model estimation reveals substantial roles for both competitive and appreciation motives in driving consumers' gifting. First, we find that consumers place significant value on achieving top leaderboard positions. The estimated utility of holding the first position is worth $0.66 per minute, while the second and third positions are each valued at $0.20 per minute. These rewards create a strong incentive for top gifters to climb the leaderboard by outgifting others. Second, we find strong evidence for the appreciation motive. At the median level of content quality, consumers derive 0.85 dollar of utility for 100 coins gifted (worth approximately 1.4 dollars). Moreover, higher-quality content improves the utility from appreciation: a one-standard-deviation increase in content quality raises the appreciation utility by an additional $0.43 for 100 coins sent. The utility from showing appreciation equals the monetary cost when content quality is approximately 1.2 standard deviations above the baseline.

We conduct a series of counterfactual analyses to unpack the economic value of the leaderboard and examine its optimal design. Our first counterfactual is to examine the economic value of the leaderboard. Specifically, we remove the competitive motive induced by the leaderboard by setting the rank-based utility to zero and examining how much revenue drops. We find that the average total revenue for an average session is $40, and the competitive motive accounts for 43% of total revenue. This finding highlights the central role of leaderboards in generating revenue on TikTok Live. We further conduct heterogeneous analysis by dividing the sessions into long sessions and short sessions, and find that leaderboards play a less important role in generating revenue for long sessions than short sessions, i.e., the percentage of revenue from the leaderboard and the revenue per minute generated by the leaderboard are both smaller in long sessions. The reason is that long sessions suffer from a stagnation problem more severely; i.e., leaderboards become stagnant when top contributors are far ahead on the leaderboard, making it seem futile to exert additional effort in gifting.

The second counterfactual examines the optimal reward rule-how many top-ranked consumers should be highlighted on the leaderboard. To understand the impact of changing the number of rewards on revenue, we identify three competing effects that emerge when the number of rewarded ranks is reduced. First, reducing the number of rewards negatively affects consumers' participation in the gifting activity(the "participation effect"). Fewer rewards lower the expected benefits of gifting, discouraging consumers from participating at the extensive margin. Second, reducing the number of rewards makes each reward harder to reach, thereby some consumers switch from having both competitive and appreciation motives to gifting primarily out of appreciation(the "motive-shifting effect"). For instance, if rewards are reduced from three to two, a rank-four gifter may quit competing entirely, perceiving the top-two threshold as unattainable and gifting only for appreciation. Fewer rewards lower their gifting per gifter(gifting effort?) at the intensive margin. Third, reducing the number of rewards makes each reward harder to reach, thereby consumers who remain in the contests have to spend more to secure one of the limited top positions(the "competition-intensity effect"). Fewer rewards raise gifting per gifter at the intensive margin.

Our estimation reveals that rewarding only the top two gifters (instead of the status quo of top three) increases total gifting income by 2.9%. This gain reflects a tradeoff between opposing forces: while the participation effect reduces the number of gifters, the competition-intensity effect dominates the relatively weak motive-shifting effect, leading to higher gifting per gifter that outweighs the loss in participation. However, further reducing the number of rewards to just one reverses this gain. In that case, the motive-shifting effect becomes stronger—many gifters disengage from competition—undermining the competition-intensity effect at the intensive margin. Meanwhile, participation continues to decline at the extensive margin. Together, these effects reduce both the number of gifters and the average gifting per gifter, lowering total gifting revenue. To manage this tradeoff dynamically, we design an adaptive reward rule that ties the number of rewarded leaderboard ranks to the real-time number of active gifters on the leaderboard. This flexible design balances effects on both margins and further increases total revenue by 6.5% relative to the baseline.

The third counterfactual investigates the optimal score rule—how gifting contributions should be aggregated to a single score to determine leaderboard rankings. This design is motivated by our empirical finding that gifters are less likely to gift competitively when top players gradually build up their scores over time and become far ahead on the leaderboard. Players feel demotivated to contribute, as they either perceive little threat to their rank or low chances of catching up. To address this, we propose a discounted score scheme that discounts individuals' gifting scores over time, effectively placing greater weight on recent gifting contributions and less weight on more distant ones in ranking players. In terms of operation, we allow the platform to discount each individual's scores after each 30 minutes by multiplying a discount factor β.

On the one hand, if the discount factor β is too large, the leaderboard still suffers from the problem of stagnation: the top players' scores can still build up again and be far ahead on the leaderboard, leading to players feeling demotivated to contribute over time. On the other hand, if the discount factor β is too small, the consumers may not contribute in the first place as they are forward-looking agents. They rationally expect that their contribution will be discounted heavily and gifts lose value quickly in determining leaderboard ranking. Based on these two opposing forces, we derive a unique optimal discount factor 0.55, which boosts the platform revenue by 19.7%. Heterogeneous analysis further shows that long sessions benefit more from discounting than short sessions, as they require smaller β to mitigate more severe stagnation.

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 (2024), 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.

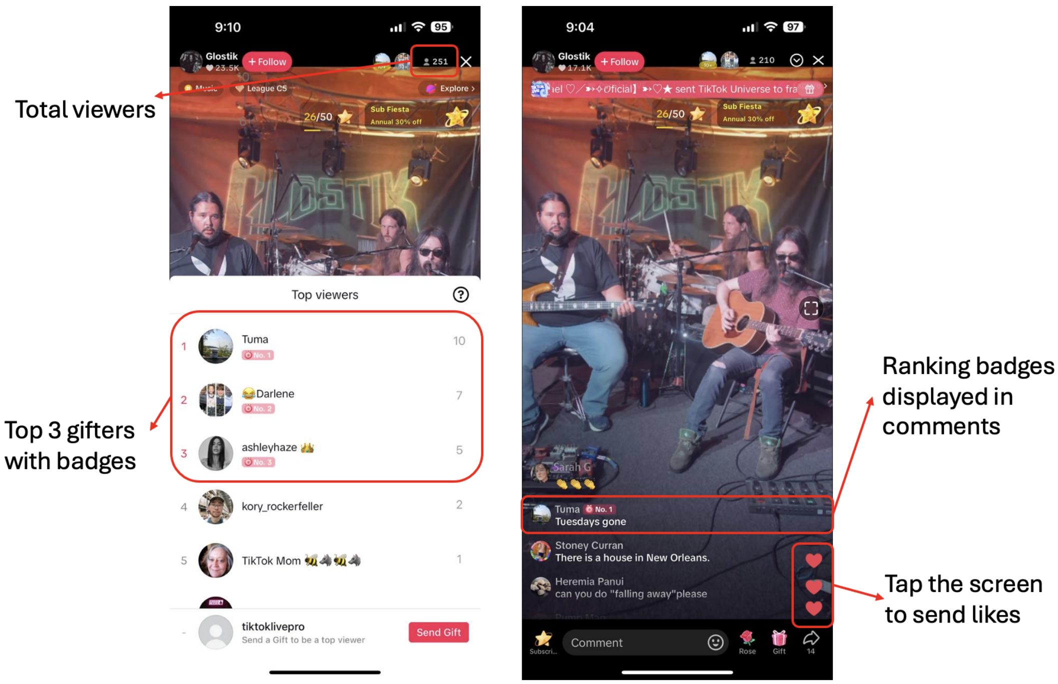
The voluntary gifting system on TikTok continues to grow substantially, even as the platform holds the No.1 global ranking for in-app purchase revenue. According to the fourth quarter digital marketing index report by Sensor Tower, consumers spent a staggering $6 billion on in-app purchases in TikTok 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 $15 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.[7] 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 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 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.

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

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



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.[8] 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.

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 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 em-

[8] 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.

Table 1: Summary Statistics of Major Activities

Variable	Mean	Std.Dev	Percentile 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

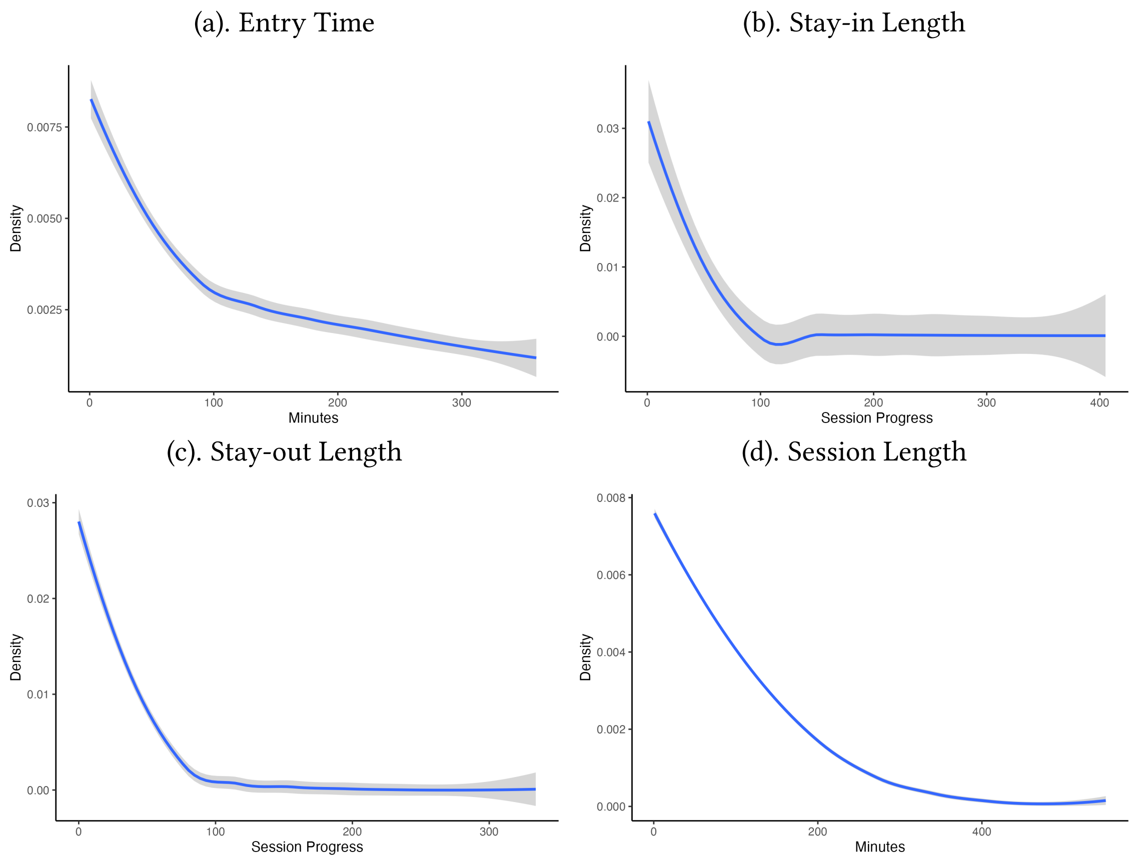
Notes: This table provides summary statistics of our data in two panels. Panel A shows session-level sample statistics. It shows that the statistics on sessions are very skewed. Panel B shows the statistics when we restrict the moment-by-moment sample to include only individual-session-minute-level observations 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.

pirical 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.

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

Figure 2: Distribution of Entry and Exit Activities of Gifters



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.

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 on the underlying motives behind consumer gifting on TikTok Live, with a primary focus on the competitive motive. As our regression sample includes only consumers who have given gifts, we refer to them as ***gifters*** for clarity when discussing identification and empirical design. For consistency, we use ***consumers*** throughout the presentation of results.

We begin by introducing a novel high-frequency identification strategy and empirical specifications to identify the competitive motive in gifting causally. We find that gifters respond to variations in leaderboard rankings and are willing to increase their contributions to improve their standing. We then conduct heterogeneous analyses to examine how the strength of this competitive motive varies across different contexts. Finally, we provide evidence of an appreciation motive by analyzing how gifting behavior among lower-ranked gifters—who do not exhibit competitive motives—responds to content popularity, which is proxied by the number of likes pressed by other viewers in real-time during the same session.

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 design of the leaderboard on TikTok Live provides a distinctive identification opportunity using moment-by-moment data. The leaderboard only ranks the contribution of gifters who are currently present in a live session, updating in real time to reflect the entry and exit of gifters. Whenever a gifter exits and later re-enters the session, their previous cumulative gifting amount is immediately accounted for and reflected on the leaderboard.

This feature creates a quasi-experimental setting at high frequency. When a top gifter with a large cumulative gifting amount leaves the session for an extended period (more than 10 minutes) and later re-enters, their return bumps down the rankings of all gifters with strictly lower cumulative gifting. For these re-entry events, we refer to the individual re-entering as the ***focal gifter*** and to the remaining gifters as ***non-focal gifters***. We then examine the immediate change in gifting behavior among the non-focal gifters whose rankings are involuntarily reduced by the focal gifter's return.

High-frequency identification addresses the identification challenges in two ways. First, the re-entry of a focal gifter changes the ranking without involving any new gifting activity, isolating the effect of leaderboard position. Bumped-down gifters face a sudden negative shock to their ranking, i.e., they are displayed at less prominent positions on the leaderboard and may have their rank-associated badges downgraded or removed. We could measure the immediate response in gifting behavior towards such adverse shocks to uncover gifters' preference for maintaining higher leaderboard positions. Second, the key assumption for our identification strategy, that the timing of re-entry is exogenous, is supported by TikTok Live's platform setup. According to TikTok, consumers have no information about the ongoing activities in a live session unless they join it. As such, it is nearly impossible for focal gifters to coordinate their re-entry time with specific activities in the session.

To further address the concerns about re-entry endogeneity, we restrict further to focal gifters who left the session for an extended time, i.e., more than 10 minutes, to minimize their inference about session progression from previous consumption experience. Taken together, these considerations give us confidence that the timing of re-entry is plausibly exogenous. We will systematically validate this assumption in the main analysis using an event study design.

4.2 Empirical Design for Competitive Motive

We then follow a quasi-experimental research design with 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. Moreover, 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.[9]

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.[10]

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.[11] We isolate the 12-minute event windows around the re-entry moment t_0 and run the following regression specifications:

$$
\begin{aligned}
\text{gift}_{ist} = & \sum_{k=1}^{6} \alpha_{k,k+1} * I\{\text{rank}_{is,t_0-1} = k, t \geqslant t_0\} + \sum_{k=1}^{5} \beta_{k,k+1} * I\{\text{rank}_{is,t_0-1} = k\} \\
& + \lambda * \text{others' like}_{ist} + \psi * \text{number of viewers}_{st} + \phi * t + \theta_s + \delta_{ic(s)} + \epsilon_{ist}
\end{aligned} \tag{1}
$$

where i indicates the bumped individual, s indicates the session, and t indicates time in minute. Dependent variable gift_{ist} is the total gifts sent by non-focal gifter i in session s at time t. rank_{is,t_0-1}

[9]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 due to exit of competitors.

[10]We keep the window relatively short to avoid other potential adjustments. For instance, over 50% of non-focal 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.

[11]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.

indicates the non-focal gifters' original rank from which they get bumped down. Independent variable $I\{\text{rank}_{is,t_0-1} = k, t \geqslant t_0\}$ is a dummy variable equal to one if the non-focal gifter i was bumped from rank k and the focal gifter had entered the session s at time t, and others' like_{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 viewers who are watching the content of in session s at time t, through number of viewers_{st}, the number of minutes since the start of the session t, session fixed effect θ_s, and individual-creator fixed effect $\delta_{ic(s)}$, where $c(s)$ is the creator for session s. Specifically, number of viewers_{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 t captures that the sessions often become more or less popular over time due to the natural life progression of sessions. Session fixed effects θ_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-creator fixed effects $\delta_{ic(s)}$ 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 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 generates a competitive motive in gifting activities - a preference for ranking by consumers. We then show that the competitive motive is stronger when leaderboard positions can be easily altered by gifting, either by surpassing a competitor above or being caught up by a competitor below. Taken together, our findings suggest that the leaderboard on TikTok Live induces significant competition among consumers.

The Presence of the Competitive Motive We find a rank-ordered preference by consumers, which is closely related to the leaderboard design to highlight the rankings, the identities, the

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

	Gift by bumped-down gifters					
	1 to 2	2 to 3	3 to 4	4 to 5	5 to 6	6 to 7
$\alpha_{k,k+1}$	3.4688**	1.4125	3.0476**	1.5827	1.4376	0.3505
	(1.4157)	(2.0483)	(1.3012)	(1.0224)	(1.7741)	(0.5943)
λ	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 consumers of the session number of viewers$_{st}$, the number of minutes since the start of the session t, session fixed effect θ_s, and individual times creator fixed effect $\delta_{ic(s)}$. Standard errors are in parentheses. Significance: *p<0.1; **p<0.05; ***p<0.01. Standard errors are clustered at the session level.

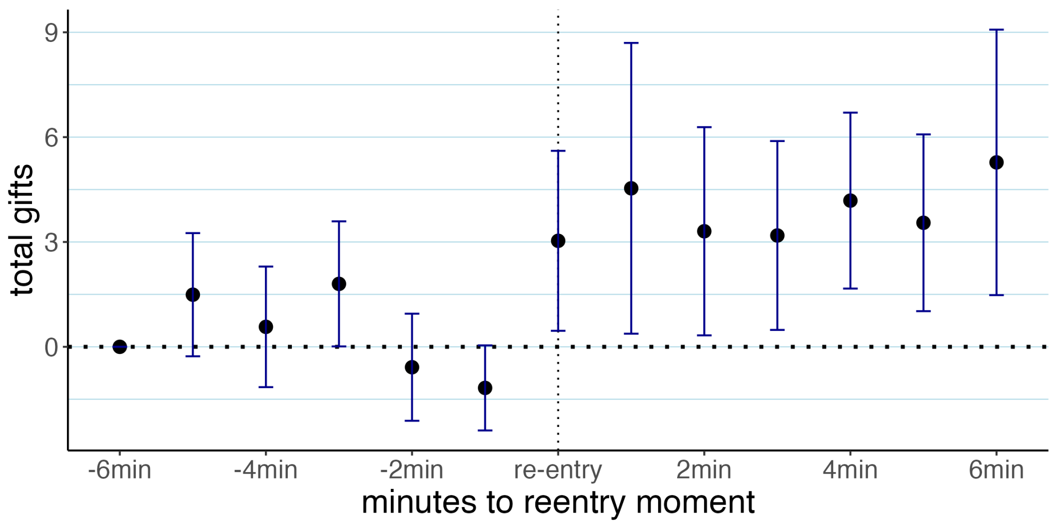
scores, and the badges of the top-three gifters. More specifically, the particular preference is as follows:

$$\text{rank } 1 \succ \text{rank } 2 \sim \text{rank } 3 \succ \text{rank } 4 \sim \text{rank } 5 \text{ and beyond} \tag{2}$$

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 directly 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), and top 3 to the top 4 (column 3). However, we find a positive but insignificant change in gifting amount when bumped down from other rankings. This indicates an ordered preference among gifters for ranking on the leaderboard: consumers strictly value rank 1 over rank 2 and rank 3 over rank 4, but are indifferent between rank 2 and rank 3. When consumers get bumped down from top 4 to top 5, or from any ranking beyond rank 5, 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 logic.

The results in Table 2 and Equation (2) exhibit the direct impacts 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 high value on the No. 1 position due to its visual prominence at the top of the leaderboard and the "No.1" badge when commenting. As shown in our institutional background. The second key cutoff is at the No. 3 and No. 4 positions, where the badge is on the margin of being lost or gained. Losing the badge at the No. 3 position generates a strong desire among consumers bumped from the third position to reclaim their original spot and badge.

Figure 3: Gift 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) on a set of dummies to capture one-minute intervals within 12-minutes time span around the re-entry moment of focal gifters, while setting minus-six minute as the baseline and controlling for number of minutes since the start of session, others' likes, number of viewers, session fixed effect, and consumer × creator fixed effects. The error bar is at a 10% confidence interval.

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 unchanged 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 how consumers' competitive motives vary across different live-stream conditions. This leads us to explore heterogeneity in competitive motives at varying levels of competition difficulties faced by non-focal gifters in the next section.

Table 3: Heterogeneous Effect of Gifting Distance to Climb Up

	Gift by bumped-down consumers		
	1 to 2	2 to 3	3 to 4
$\alpha_{k,k+1,\text{low}}$	3.1830*	4.5521	4.1195**
	(1.7395)	(3.9104)	(2.0096)
$\alpha_{k,k+1,\text{median}}$	2.9703***	0.4444	2.4118**
	(1.0018)	(0.5400)	(1.0389)
$\alpha_{k,k+1,\text{high}}$	7.6755	13.0429	2.2791
	(4.6817)	(12.0901)	(1.9202)
λ		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 interacting $I\{\text{rank}_{is,t_0-1} = k, t \geqslant t_0\}$ with $I\{\text{Distance}\}$ and controlling for distance group dummy $I\{\text{Distance}\}$ for Distance $\in \{\text{low}, \text{median}\}$ the regression. Controls and fixed effects include the size of the consumers of the session number of viewers$_{st}$, the number of minutes since the start of the session t, session fixed effect θ_s, and individual times creator fixed effect $\delta_{ic(s)}$. Standard errors are in parentheses. Significance: *p<0.1; **p<0.05; ***p<0.01. Standard errors are clustered at the session level.

Heterogeneous Responses to Competition A core question in many game design contexts is how the relationship between game difficulty and reward affects the effectiveness of gamification. In Table 3, we investigate how the difficulty of catching up with the competitors from above moderates the competitive motive of consumers. Specifically, we take the cumulative gifting amount (henceforth, ***score***) distance between focal and non-focal gifters right 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 score distance between focal and non-focal gifters right 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 score is far from that of the focal gifter. Conditional on non-focal gifters' prior ranks, we divide them into different groups, i.e., $k \in \{1, 2, 3\}$. Within each group $k \in \{1, 2, 3\}$, we further categorize consumers by their score distance into low, median, and high groups, where the score thresholds are 33 and 66 percentiles. We then iteract $I\{\text{rank}_{is,t_0-1} = k, t \geqslant t_0\}$ in regression (1) with $I\{\text{Distance}\}$ and examine how consumers' response to the re-entry event depends on their distance to their competitors.[12]

Table 3 shows the results. We find that the consumers bumped from rank one and three 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.

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. 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.

Our evidence comes in two ways. First, in the previous analysis in both Tables 2 and 3, we find that besides the competitive motive top-ranked gifters also gift out of appreciation. They show positive responses in gifting to the total likes by others. Second, we further investigate the appreciation motive by restricting our sample to lower-ranked gifters (who never ranked top 4 or above throughout the session they attend) 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 in equation (1), while keep all other controls and fixed effects are the same. Table 4 shows that the popularity of content, proxied by the total likes by others, positively increases the

[12] In the full regression, we also add control for distance group dummy $I\{\text{Distance}\}$ for Distance $\in \{\text{low, median}\}$ in additional on all other controls in regression (1). We no longer show consumers with rank $k \geq 4$ because all the results are insignificant.

Table 4: Appreciation Motive for Gifting

	gift
others' like	0.0012***
	(0.0001)
number of viewers	0.0006**
	(0.0002)
t	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.

total gifts of these consumers who do not show any competitive motives, 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 replicate the results in Table 2 by dividing non-focal gifters into groups based on their old rankings and running separate regressions for each subgroup of gifters. This flexibility allows the gifters' appreciation motive and other control factors to differ depending on their old rankings. Table A2 persistently find consumers' preference over rankings on the leaderboard; Second, we replicate the high-frequency analysis in Table 2 by varying the time span around the re-entry events. We find our results are robust to 4-min, 5-min, 6-min, and 7-min time window in Table A3. Third, we replicate the results in Table 2 to include all gifters who are directly or indirectly bumped down in ranking due to the re-entry of focal gifters whose accumulative gifts are above them. We persistently find that consumers have a preference for higher positions on the leaderboard (Table A4).

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 supporting: 67.2%, attention seeking: 59.9%).

Takeaways Our empirical analysis shows strong and significant motives for competition among 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 $\lambda_{re}(W_t^{re}) = (W_t^{re})'\boldsymbol{\theta}^{re} > 0$.[13] 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.

[13] 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.

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 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 B2, 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 $2 = high$.[14] The transition between the two levels of

[14] 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.

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 B2. 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. (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.[15] The first two variables capture player scores. In TikTok livestreams, a player's score reflects the amount of money they have

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

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: $s_{it} \in \mathbb{S} = \{score_0, score_1, \cdots, score_K\}$.[16] 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.[17] We assume gifters track whether they are rank 1, 2, 3 or 4. A gifter is rank 4 if 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

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

[17] 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.

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 4). 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.[18]

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:

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

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

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.[19] 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 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.[20]

[19] 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.

[20] 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.

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

where $\zeta_{m,k,s^{m\prime}}$ is the focal incumbent i's belief about the other incumbent m's gifting to $s^{m\prime}$ 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

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

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. The second column of Table 5 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 $1e - 5$. The third column of Table 5 provides the model-implied moments after optimization.

6.2 Identification

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

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

Table 5: Targeted Moments for GMM Estimation

Targeted moment	Empirical moment	Model-implied moment
Session-level Moments		
total gifts	2692	2797
total gifts% at high-quality content	0.800	0.76
exit probability at high-quality content	0.112	0.1376
exit probability at low-quality content	0.127	0.1621
Re-entry Event Moments (6-min post v.s. 6-min pre)		
change in gifts for bumped top 1	25.2	22.22
change in gifts for bumped top 3	15.5	17.3
Conditional Choice Probability		
p_{12}	0.719	0.792
p_{13}	0.186	0.185
p_{14}	0.053	0.021
p_{15}	0.037	0.000
p_{16}	0.002	0.000
p_{23}	0.804	0.877
p_{24}	0.155	0.120
p_{25}	0.040	0.002
p_{26}	0.000	0.000
p_{34}	0.855	0.924
p_{35}	0.121	0.075
p_{36}	0.022	0.000

Note: This table provide a complete list of moments used for SMM estimation. The first column is the name for the target moments. The second column is the empirical moments calculated from the observational data. The third column is the model-implied moments, generated from the data simulation. At the session level, we calculate the total gifts contributed by the gifters, percentage of total gifts contributed at the high-quality content, the exit probability when the cotent quality is high, and the exit probability when the content quality is low. Leveraging re-entry events, we separately calculated bumped gifters' total gifts within 6-min timespan post and pre the re-entry moments. Then we construct the changed in total gifts by taking the differences, i.e., post minus pre. We separately calculate the average level of change in total gifts for gifters who get bumped from rank 1 and who get bumped from rank 3. Conditional choice probability $p_{s,s'}$ is the probability of consumers gift to s' conditional on they are originally at s and send positive amount of gifts.

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

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 1.561, which provides an interpretation about the monetary worth of utilities. Because gifters generate 1.561 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 $(1/1.561) * 1.4 = 0.896$

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 $0.737 * 0.896 = 0.660$ dollar. Similarly, each minute of staying in the top 2 or 3 positions is worth $0.227 * 0.896 = 0.203$ dollar.

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 0.853 dollar worth of utility from showing appreciation at a median-quality content.[21] 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 0.428 dollar.[22]

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 $0.130 * 0.896 = 0.116$ 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 $0.1 * 0.896 = 0.089$ dollar per minute.

[21]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 $0.952 * 0.896 = 0.853$ dollar.

[22]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 $0.477 * 0.896 = 0.428$ dollar.

Table 7: Model Estimates

Concept	Parameter	Estimates
Competition motive		
Rank utility for top 1	u_1	0.737
		(0.012)
Rank utility for top 2/3	u_3	0.227
		(0.001)
Appreciation motive		
Baseline appreciation	γ_0	1.374
		(0.0004)
Quality multiplier	γ_1	0.689
		(0.001)
Content consumption value		
Baseline value	γ_2	0.130
		(0.026)
Quality multiplier	γ_3	0.100
		(0.012)
Cost function		
cost coefficient	β_p	1.561
		(0.016)

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 a study of the economic value of the leaderboard (Section 7.1). In the second and third counterfactuals, we analyze the 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 B2 indicates that content production is unrelated to gifting behavior, but is responsive to commenting behavior. Furthermore, Table B3 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 Economic Value of the Leaderboard

In our first counterfactual, we evaluate the economic value of the leaderboard by setting the rank-based utility to zero and measuring the resulting revenue loss. As shown in Table 8, the average total revenue per session is $40, with leaderboards contributing 43% of this amount and generating $0.154 per minute. This highlights the substantial role leaderboards play in driving revenue on TikTok Live.

To explore heterogeneity, we divide sessions into long and short ones and find that leaderboards are relatively less important in long sessions: both the share of leaderboard-driven revenue and the revenue per minute attributable to the leaderboard are smaller. The leaderboard contributes to 40% of total revenue and generates $0.150 per minute in long sessions, whereas the leaderboard contributes to 46% of total revenue and generates $0.162 per minute in long sessions.

The reason is that long sessions are more prone to stagnation. Early in a session, gifting dynamics look similar across both types, but as the session progresses, top contributors accumulate a large competitive advantage. Once this happens, other viewers perceive little chance of improving their rank, causing the leaderboard to "freeze up." Because long sessions extend further into this stagnation phase, they experience a larger proportion of time in which leaderboard competition no longer generates incremental revenue. We provide supporting evidence for this intuition using a proxy for stagnation: the inverse of the turnover rate in each session. Specifically, we define the turnover rate as the number of times the top three gifters are displaced on the leaderboard due to others surpassing them through gifting, normalized by session duration (minutes). We find that turnover rates are lower in long sessions (4.1) than in short ones (4.6), confirming that long sessions suffer more severely from stagnation.

Table 8: How Much Revenue is Contributed by the Leaderboard

	average total revenue per session: \$40		
	revenue from leaderboard%	revenue per minute from leaderboards	turnover rate (×100)
average session (110 min)	43%	\$0.154	
long session (140 min)	40%	\$0.150	4.1
short session (80 min)	46%	\$0.162	4.6

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 3rd position could potentially improve the value of the 1st and 2nd positions, as the same prominent space on the leaderboard is allocated to fewer people. Additionally, gifters' badges are more effective in drawing creators' attention due to 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 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 3rd positions while retaining the rank utility for the 1st and 2nd unchanged. In case 2, we further remove the rank utility for the 2nd 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.

Table 9: Demonstration of Reward Design

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

Intuitively, reducing the number of rewards has an ambiguous effect on total gifting. First, it 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 2 gifters is optimal, increasing total gifting by 2.8%.

Table 10: Optimal Number of Reward

	total gifting	% change in gifting	# gifters	gifting per gifter
benchmark	2797	0%	7.09	388.87
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.

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 390 million dollars increment in revenue.[23] 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 three gifters, both top 3 rewards are offered. When the

[23] According to the fourth quarter digital marketing index report by Sensor Tower, consumers spent a staggering $6.6 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).

number of gifters is four or above, the top 3 rewards are provided.

7.3 Score Design

In the third counterfactual, we investigate the optimal score rule—how gifting contributions should be aggregated to a single score to determine leaderboard rankings. Our empirical study reveals a negative relationship between score disparity and players' willingness to gift. When the score gap widens, 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 the rigidity of rank-based competition, we propose a discounted score design in which gifters' scores are discounted over time. This design places greater weight on recent contributions and reduces the influence of earlier ones. Operationally, we model discounting such that each gifter's score is reduced when a discount event arrives, with the time between discount events following an exponential distribution with rate $\lambda = 1/30$. On average, therefore, scores are discounted once every 30 minutes. When a discount event occurs, the gifter's score is multiplied by a discount factor β and rounded to the nearest point on the grid $[0, 100, 300, 600, 1000, 1500]$. The intensity of discounting depends inversely on β. When $\beta = 1$, scores are never reduced, and rankings reflect cumulative contributions—the status quo on TikTok Live. At the other extreme, $\beta = 0$ implies a full reset every 30 minutes.

Discounting has two opposing effects on revenue. If β is too large (weak discounting), scores still accumulate and eventually stagnate, with top contributors pulling far ahead and discouraging further competition. If β is too small (strong discounting), forward-looking gifters anticipate that their contributions will lose value too quickly and may withhold gifts altogether.

Balancing these forces, we vary β in increments of 0.05 and identify an optimal discount factor of 0.55 (Table 11), which maximizes platform revenue—an increase of 19.7%. Consistent with the mechanism, stronger discounting (smaller β) prevents top players from accumulating large advantages, thereby reducing stagnation. This effect is reflected in the turnover rate of the leaderboard: as β decreases, turnover in the top three positions increases, indicating reduced stagnation.

Table 11: Optimal Score Discounting after Every 30 Minutes

discount factor	total gifting	% change in revenue	turnover rate (× 100)
1.0	2797	0%	4.4
0.70	3117	+11.4%	5.8
0.60	3342	+19.5%	7.3
0.55	3347	+19.7%	7.3
0.40	3304	+18.1%	8.1
0.30	3292	+17.7%	8.8

Table 12: Heterogeneous Discounting Policy

	discount factor β	% change in revenue	session duration (min)	session popularity	turnover rate (×100)
average session	0.55	+19.7%	110	0.65	4.4
heterogeneity 1: session duration					
long session	0.55	+23.5%	140	0.65	4.1
short session	0.60	+13.3%	80	0.65	4.6
heterogeneity 2: session popularity					
more popular session	0.55	+19.5%	110	0.77	4.4
less popular session	0.55	+20.2%	110	0.54	4.3

Table 12 further explores heterogeneity by session duration and popularity, examining how the optimal discount factor varies with these characteristics. We first explore the heterogeneity in session duration while holding popularity constant. We find that the optimal discount factor is lower in long sessions ($\beta = 0.55$) than in short sessions ($\beta = 0.6$). The intuition is that in longer sessions, top players have more time to accumulate large score advantages, which exacerbates stagnation. To counteract this, more aggressive discounting (a smaller β) is needed to prevent the top players from pulling far ahead. Moreover, because stagnation is more severe in long sessions, these sessions benefit more from discounting, as reflected in the larger percentage improvement in total revenue in long sessions (+23.5%) than in short sessions (13.3%). Consistent with this, we find that the turnover rates are smaller in long sessions (4.1) than in short sessions (4.6). For the second heterogeneity analysis, we then compare more popular and less popular sessions while holding the average duration fixed at 110 minutes. In this case, we do not find significant differences either in the optimal discount factor or in the revenue gains from discounting. This suggests that session popularity does not meaningfully moderate the severity of stagnation. Consistent with this, we find that the turnover rates are similar between more and less popular sessions.

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, we document a common challenge faced by many leaderboards when cumulative performance metrics are used to rank players: when top players cumulate their competitive advantage and are far ahead on the leaderboard, it induces a motivating effect on players' effort to compete, because they perceive little opportunity to change their relative standings.

Our structural model quantifies the economic significance of competitive motive in inducing the platform revenue, revealing that competitive incentives contribute nearly half of the 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.

The learnings presented in this paper have general implications for many digital platforms that utilize real-time leaderboards and cumulative performance metrics, which can induce severe stagnation problems. In our study context, we empirically validate that leaderboards, combined with social status rewards, are effective in driving consumer engagement on digital platforms. Similar marketing combinations have also been implemented by platforms such as Peloton and Kahoot!, in which we should also expect to take effect in encouraging consumer engagement. Secondly, in our study context, leaderboards directly incentivize monetary engagement and play an essential role in driving TikTok Live's revenue. Although many digital platforms use leaderboards to encourage non-monetary engagement, we expect increased consumer engagement to positively contribute to platform revenue, in the sense that it boosts subscription renewal or encourages more ad revenue through increased consumer visits. Lastly, stagnation is a common problem faced by many leaderboards when the cumulative performance metrics are implemented. This paper suggests that we could alleviate the stagnation problem can be alleviated through discounting players' effort over time.

These findings contribute to the broader literature on contest design, livestreaming, and digital platform monetization. More broadly, they highlight the intricate relationship between leaderboard design 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.

Arbiter, Heather. 2024. "Your Leaderboards Probably Won't Work: Get it Right or Skip Them." Https://www.linkedin.com/pulse/your-leaderboard-probably-wont-work-get-right-skip-them-arbiter-1cxje/.

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.

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.

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. "Q4 2024 Digital Market Index."

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.

Wohn, Donghee Yvette, Guo Freeman, and Caitlin McLaughlin. 2018. "Explaining viewers' emotional, instrumental, and financial support provision for live streamers." In *Proceedings of the 2018 CHI conference on human factors in computing systems*. 1–13.

Yao, Dai, Shijie Lu, and Xingyu Chen. 2024. "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.*