Pick the Right Tactics When Online Sales Go Live: An Empirical Analysis of Livestreaming for Amazon Sellers

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Abstract

Using livestreaming to boost sales has become an essential strategy to achieve deeper interactions with customers for many large e-commerce platforms worldwide. Existing livestreaming literature has looked at multiple Chinese e-commerce platforms but not enough attention has been paid to the U.S. market. This study investigates consumer behaviors and the promotion efficacy in the Livestream setting on Amazon Live. We analyze the time patterns of customer engagement and explain why sellers should use different promotion strategies for weekdays and for weekend streamers. Besides, we present evidence that the average video display time per product is crucial for the livestream promotion efficacy and suggest optimal time-exposure intervals as a benchmark for sellers to align with.

Keywords: Livestreaming, E-commerce, Amazon, Network Effect, Customer Engagement

1. Introduction

Livestreaming is a type of audiovisual live broadcasting over the Internet. Through livestreaming, vendors can vividly demonstrate intricate products to attract and retain viewers' interest. Alibaba Group's Taobao marketplace first started combining online shopping and livestreaming in 2016, achieving gross merchandise volume of over 500 billion yuan (about US$ 76 billion) in 2021 (Alibaba Group, 2022). Using livestreaming to boost sales has become an essential strategy for e-commerce platforms worldwide. Many U.S. companies, including big names such as Walmart, Facebook, and Amazon, as well as startups have been competing to attract more consumers through live channels and reshape shopping habits. Surveys show that 20% of U.S. adults have participated in live shopping events (Klarna, 2022), and 11% of people aged 18-34 are regular participants (Insider Intelligence, 2022). In 2021, the live e-commerce market generated 11 billion nationwide sales, and it is expected to achieve 17 billion sales in 2022 and 35 billion in 2024 (Statista, 2022).

Customer engagement is crucial to interactive product sales. 78% of marketers claim that the top reason for using livestream marketing is to achieve a deeper interaction with the audience (Statista, 2020). Therefore, improving the understanding of customer behaviors becomes one of the top priorities for brands and retailers, and it is important for sellers to identify more-effective promotion strategies. In this study, we uncover some valuable patterns that can benefit streamers both before and during the livestream.

2. Research context

Amazon, with the largest e-commerce market cap in the U.S., seems to be an obvious choice for studying livestreaming phenomenon as it has the potential to bring large-scale disruptions to this domain. Existing studies have explored a wide range of topics in the livestreaming setting for Chinese livestreaming platforms, such as online communications (Taylor, 2018), education (Chen et al., 2019), and skill improvement (Lu et al., 2018). Among those few studies focusing on U.S. companies, most consider TikTok and YouTube. To the best of our knowledge, no scientific study has addressed the Amazon livestreaming ecosystem.

Amazon's official livestreaming platform, *Amazon Live*, was launched in 2019 and has developed in various ways, including offering different streaming techniques and seller analytical services over the past three years. With more than 2.45 billion worldwide visits every month (Statista, 2021), *Amazon Live* has the potential to make a real difference in the U.S. e-commerce livestreaming market.

2.1. Comparative advantages of livestream shopping

Streaming techniques enable audiovisual demonstration of product details and real-time streamer-viewer and viewer-viewer interactions. Previous studies have carefully examined the efficacy of different presentation modes (e.g. Shiv and Fedorikhin, 1999, on real vs. symbolic; Roggeveen et

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al., 2015, on static vs. dynamic; Gu et al., 2018, on video vs. graph). We consider livestreaming as an interactive, dynamic, audio plus visual format that with advantages of multiple presentation modes. Besides, real-time interactions supported by live conversations further reduce customer uncertainty and promote purchase intentions (Stoyanova et al., 2015; Ma et al., 2022). Like traditional promotions, coupons and discounts are widely used in livestream sales, acting as a reward that helps to monetize the streamer-viewer relationship (Chen et al., 2017).

2.2. Research questions

We are interested in consumer behaviors and the promotion efficacy of livestream sales. We investigate and provide insights into the following two questions.

Q1: Does consumer engagement contribute equally to the impact of promotion on different days of the week?

Q2: Do the session duration and the number of products per session impact promotion effects?

Question 1 addresses timing. Specifically, we aim to uncover which days of the week are best for livestreaming. Question 2 investigates the impact of session length and the number of promoted products scheduled for a single livestreaming session.

3. Empirical setting

3.1. Livestreaming promotion and product purchase process on Amazon

Amazon Live offers free streaming 24/7 to all Amazon brands and influencers. Each brand or influencer involved in live sales is assigned a unique live channel identified by a permanent URL. Upon streaming, a live video appears on the channel with a "LIVE" tag and an eye-shaped badge showing the number of viewers in a real-time manner, which is visible to all people (see Figure 1). A chat box on the right keeps track of messages sent by viewers (or by the streamer), allowing any viewer, whether or not following the channel, to participate in chat conversations.

Prior to going live, the streamer determines and sets the list of products to be promoted in the session. These products are displayed in a carousel below the video that prompts product windows when clicked. Time-limited coupons, if any, will display on the prompt page, and the live-only promo codes are applicable on the checkout page. All the other steps in placing an order are the same as a normal Amazon order.

Any eligible livestreaming videos may be picked by Amazon's internal algorithm and displayed on the main page of *Amazon Live*. This way, Amazon creates massive exposure for its customers through a diverse set of channels. Our data is collected on the observable results of Amazon's selection mechanism.

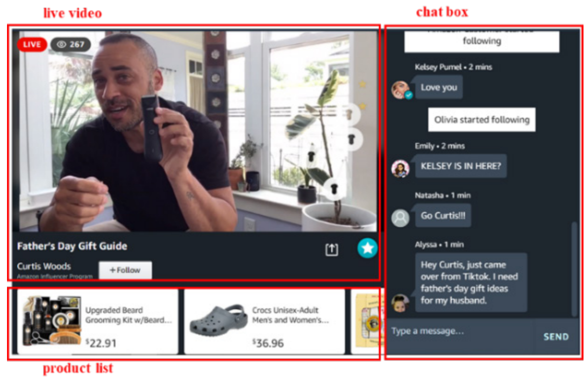


Figure 1. The layout of an Amazon livestreaming video.

3.2. Dataset description

We construct our data collection pipeline using a computerized scraping algorithm. Data is collected at four distinct levels: channel, video, chat, and product. Table 1 summarizes data types.

We gather data on 11,542 livestreaming sessions by 1,296 channels from November 2021 to February 2022. The dataset contains all of the recommended sessions appearing on the home page for our data-crawling algorithm by Amazon, but not all of the video sessions in that period. Descriptive statistics are reported in Table 2. Initial data analysis offers model-free evidence pertaining to time patterns of customer behaviors. Figure 2 illustrates the daily patterns of the number of videos, viewers, chat participants, and chat messages on weekdays and weekends (time in ET). In general, there are more videos (Figure 2(a)) but fewer viewers (Figure 2(b)) on weekdays than on weekends, and the number of both videos and viewers are low from midnight to dawn and high around 1 pm (around lunchtime) and 8 pm (around dinner time). The number of chat participants (Figure 2(c)) and the number of chat messages (Figure 2(d)) follow a similar dynamic. It is worth noting that chat participants in general talk more on weekends than on weekdays.

4. Empirical framework

We propose a general econometrics model to

Table 1. Data summary.

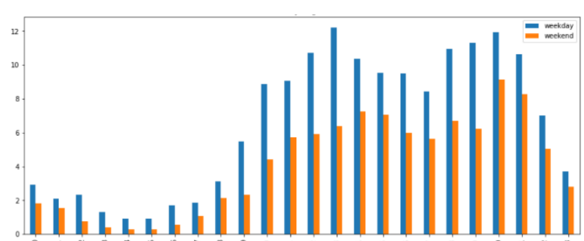
Data Type	Name
Channel Data	Channel ID
Video Data	Video ID
	Date & time
	Duration
	Promotion list
	Number of viewers*
Chat Data*	User ID
	Timestamp
	Message text
Product Data	Product ID (ASIN)
	Price history
	Ranking history

*Real-time data collected on a rolling basis.

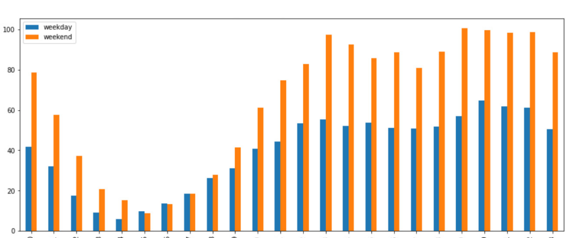
Table 2. Descriptive statistics.

Name	*N*	Mean (SD)
Channel	1,296	-
Frequency (per week)	-	2.6 (1.2)
Video	11,542	-
Duration (min)	-	64.8 (34.2)
Product number	-	28.8 (7.4)
Chat	11,542	-
User	34,479	16.7 (7.3)*
Message	436,758	37.8 (10.2)*
Product	366,868	-

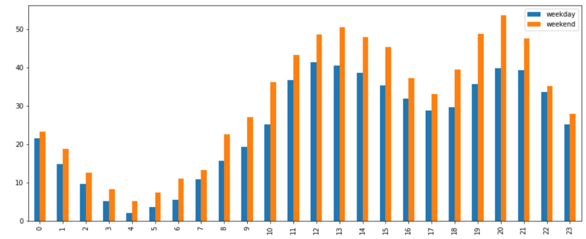
*Per chat.



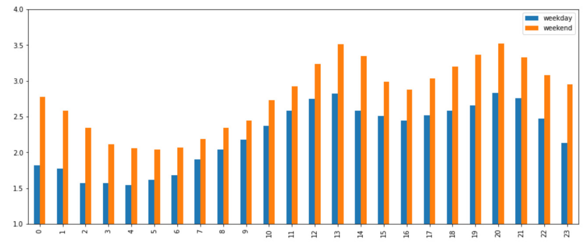
(a) Average number of videos.



(b) Average number of viewers per video.



(c) Average number of chat participants.



(d) Average number of chat messages per user.

Figure 2. Video, viewer, chat participant, and chat message dynamics on a day.

address the two questions listed in Section 2.2. For product i promoted in video j from channel c, we measure the impact of an array of covariates X_{ij} on the percentage change of product sales ranking, r_{ijc}. The product ranking is publicly accessible on the Amazon product page. The covariates include the (average) number of viewers, the (average) percentage price discount, the (average) number of chat participants, and the (average) chat sentiments throughout a livestreaming session. The number of chat participants is scaled to the same unit time (i.e., one hour) to make videos of different durations comparable. Sentiments are measured by VADER (Hutto and Gilbert, 2014), a valence- and intensity-aware NLP algorithm widely used for processing user-generated content in social media. VADER computes a sentiment score between -1 (extremely negative) and 1 (extremely positive) for every message in the chat, and the average score of all messages serves as the average chat sentiment for a session. We control for product-, video-, and channel-specific covariates such as streaming timing and frequency, denoted by Z_{ijc}. This control function method is a standard way to handle endogeneity. All covariates are standardized before being fed into the model. We also control for the channel fixed effect μ_c to account for unobserved channel heterogeneity induced by customer-base differentiation, which is invisible to the public. Lastly, ε_{ijc} is the error term.

$$\%\Delta r_{ijc} = X_{ij}\beta^X + Z_{ijc}\beta^Z + \mu_c + \varepsilon_{ijc} \qquad (1)$$

Table 3. Customer behavior differentiation on weekdays and weekends.

Variable	Weekday Model	Weekend Model
Average number of viewers	-1.3880*** (0.0798)	-2.0550*** (0.1182)
Percentage price discount	-0.2132** (0.0651)	-0.1841** (0.0562)
Average number of chat participants	-0.1286** (0.0440)	-0.1555** (0.0532)
Average chat sentiment	-0.1142*** (0.0247)	-0.0973*** (0.0211)
Constant	1.0332** (0.0346)	1.1281** (0.0317)
Channel fixed effects	Yes	Yes
Additional controls	Yes	Yes
R^2	0.1523	0.1574
Number of observations	264,531	102,337

Notes. Negative coefficients correspond to increase in sales (i.e., lower sales ranking). Robust standard errors are reported.
***p<0.05; ***p<0.001*

Table 4. Indicator model with average product display time.

Variable	Indicator Model
Average number of viewers	-1.4788*** (0.0851)
Percentage price discount	-0.2251** (0.0687)
Average number of chat participants	-0.1311** (0.0449)
Average chat sentiment	-0.1110*** (0.0241)
Average display time (=1 when >= 4 mins, else 0)	-1.2025*** (0.0632)
Constant	1.1654** (0.0487)
Channel fixed effects	Yes
Additional controls	Yes
R^2	0.2467
Number of observations	366,868

Notes. Negative coefficients correspond to increase in sales (i.e., lower sales ranking). Robust standard errors are reported.
***p<0.05; ***p<0.001*

5. Results

5.1. Weekday vs. weekend viewers: evidence of systematic differences in customer engagement

Noticing model-free evidence of customer behavior differentiation in Figures 2(b), (c), and (d), we split the data into weekday and weekend segments. Estimates of the coefficients of interest, β^X , are reported in Table 3. We see that the effects of our main covariates X_{ij} vary. While viewers, chat participants, and chat sentiments are positively correlated indicators of customer engagement, the numbers of viewers and chat participants have greater impacts on product rankings on weekends. In contrast, chat sentiments have a more significant impact on weekdays. Our findings are consistent with Freiermuth and Jarrell's study (2006) of online chat participation, Lee and Busch's finding (2005) on tele-education engagement, and the STPC-PGM model's prediction on mobile payments (Wen et al., 2018).

We summarize that weekend viewers are in general less time-sensitive and, therefore, more willing to stay longer and participate in chat conversations (see Figure 2(d)). As a result, encouraging video sharing and chat participation could bring superlinear benefits for weekend streamers to improve sales. A unit increment in the number of viewers results in a 1.58% product-ranking improvement when the average number of viewers is at the median level (82.3), and this improvement increases to 2.03% when the number is in the 1st quartile (95.6). Similarly, a unit increment in chat participation could bring a 1.67% ranking improvement at the median level, and a 1.77% improvement in the 1st quartile.

In contrast, weekday viewers are generally more time-sensitive and spend less time watching and chatting, and pay more attention to comments and reviews from other customers and are more easily influenced by chat sentiments. Therefore, enhancing the chat environment can be a more effective approach for weekday streamers to increase sales. Numerical evidence shows that a unit increase in a median-level chat sentiment results in a ranking improvement of 1.32%, and a unit increase for a 1st-quartile sentiment can improve the ranking by 1.84%.

5.2. Total vs. average display time: more is not always better than less

Table 2 shows that streamers are heterogeneous in determining the length of their session and the number of products for promotion in the session. However, we find no evidence that better sales are simply from longer sessions or from promoting more products. To disentangle the intertwined effects of duration and the number of products, we calculate the average display time (in minutes) for all products in the same livestreaming session. An initial round of regression implies no significant correlation between this average display time and product rankings. Therefore, we further convert it to a binary indicator by applying a time threshold. We try multiple values between the 1st and 3rd quartiles of average product display time and find four minutes to be an informative threshold based on statistical significance. We take this binary indicator as a new variable Y_j and add it to the baseline model. Table 4 reports the coefficients of interest.

The extended model tells that going through many products in one session is not necessarily appealing to customers. In fact, allocating enough time to each product is beneficial to triggering customer awareness and consideration through Q&A and idea exchanging, which is considered one of the unique advantages of livestreaming. Unfortunately, the average display time across the dataset's livestreams is only 2.45 minutes, and only 22.6% of those videos meet the suggested threshold of four minutes per product. A number of studies draw similar conclusions about product display time (see Brown et al., 2012; Li et al., 2015; and Liu et al., 2016). We strongly encourage streamers to restrict the number of products to enhance the efficacy of their livestream promotions.

6. Conclusion

In this study, we analyze the impact of timing, duration, and the number of products per session on the effectiveness of livestreaming promotion. We find that the number of livestreaming viewers and the number of live chat participants are more influential on weekends, while chat sentiments have greater impacts on weekdays. We also examine the impact of session length and the number of products promoted. Results show that insufficient display time may lead to ineffective promotion. In general, four minutes is a reasonable benchmark, and a longer product display time tends to indicate more-effective promotion.

Our study has managerial implications for both brands and e-commerce platforms. Brands can use our analysis of time patterns to improve sales on different days of the week. A brand streaming on weekdays can enhance its promotions by encouraging video sharing and chat participation, while on weekends brands can achieve better results by paying more attention to chat dynamics. Our analysis also sets a baseline with which brands can better plan their video content and pacing. We strongly suggest brands strike a good balance between the number of products and the quality of the livestream.

Our findings also suggest that e-commerce platforms that offer livestreaming services should adjust their internal video-selection algorithm based on time as well as channel-specific properties to help brands gain more exposure from a larger customer base. In general, platforms can enhance the overall effectiveness of livestreaming by encouraging longer viewing time and chat participation, perhaps through reward mechanisms.

Several avenues for future research exist. First, it would be interesting to look at timing on more finely grained levels, for example, the best hour to stream on a particular day of the week. Second, it would be valuable for brands to understand the impact of offering discounts during livestreams. Third, categorized analysis could offer greater insight into specific sorts of offerings. Fourth, future studies may look at the interactions between live promotions and covariates such as product category and price. Lastly, we believe this study can be extended and applied to different platforms, such as Walmart, Facebook, and Whatnot, or even to other contexts.

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