Success and Survival in Livestream Shopping

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Abstract

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Keywords: livestream shopping, survival, e-commerce, entertainment, social network

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The livestream shopping industry, in which consumers can purchase products directly from live video sessions, is expected to exceed $60 billion in China in 2021 and $25 billion in the US in 2023. Despite the popularity of livestream shopping, many sellers fail within just a few weeks. We investigate the lead indicators of the success and survival of livestream shopping sellers. We ask three questions: 1. Livestream viewers can make purchases directly within the session (the "within-channel direct selling effect") or can use the session to gain information that may inform purchases later on (the "cross-channel spillover effect"). Which of the two effects is more important for seller success? 2. Livestream shopping encompasses three industries: e-commerce, social networks, and entertainment. Which industry-specific key performance indicators (KPIs) predict success? 3. Some sellers use livestream shopping for new product introduction while others use it for mature product inventory liquidation. Which type of seller is more likely to survive? We use a unique dataset from Taobao Live to show that: 1. Sellers who rely more heavily on the within-channel direct selling effect (vs. the cross-channel spillover effect) are less likely to succeed. 2. The e-commerce KPI positively predicts success, while the entertainment KPI negatively predicts success. For the social network KPIs, reach positively predicts success, but engagement rate negatively predicts success, reinforcing the cross-channel spillover effect of livestream shopping. 3. Mature product sellers are more likely to succeed than new product sellers.

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1 Introduction

Livestream shopping, a new format of e-commerce, uses video streaming to demonstrate products in real-time as a strategy for engaging audiences and generating sales. The new format now exists alongside the longstanding options of brick-and-mortar stores and traditional internet shopping. The industry has grown rapidly. In its largest market, China, livestream shopping is expected to reach 560 million people and create $60 billion of revenue in 2021.[1] In the US, online platform giants such as Amazon and Facebook have incorporated livestream shopping into major sales events such as Black Friday, and the value of the livestream shopping industry is expected to exceed $25 billion in 2023.[2]

However, the increased popularity of livestream shopping does not guarantee the success of all sellers—contrarily, many sellers phase out within a year.[3] Identifying key predictors of success and survival of businesses (e.g., Dekimpe and Morrison, 1991; Audretsch et al., 2000; Zhang and Luo, 2022) is of great importance to investors and companies. The predictors often vary across different industries. Given the growing popularity and substantial economic impact of the livestream shopping industry, it is crucial for investors, sellers and retail platforms to understand the predictors of success and failure. In this paper, we address three issues that are critical to the success of sellers who join the new fast-growing industry:

First, livestream shopping can benefit sellers via two effects. In the "within-channel direct selling effect," viewers make purchases directly within the livestreaming session, which functions as a real-time shopping channel. In the "cross-channel spillover effect," viewers use the livestream to collect information about the seller or product (i.e., the session functions as an ad), and they use this information to make purchases from the seller's online store later on. It is not clear *a priori* which of the two effects, within-channel direct selling or cross-channel spillover effect, is more predictive of seller success.

Second, livestream shopping is a combination of three industries: e-commerce, social networks, and entertainment. The most important key performance indicators (KPIs) vary by industry: transaction volume for e-commerce, reach and engagement rate for social networks, and watch time for entertainment. It is not clear which industry-specific KPIs are most predictive of seller success.

Third, because livestream shopping attracts many consumers to make purchases within a short

[1] Source: https://tinyurl.com/4r8tk5ct
[2] Source: https://tinyurl.com/35cyv299
[3] Source: https://tinyurl.com/2mj6a9pu

period of time, it is often used to either introduce new products into the market or liquidate inventory for mature products.[4] It is unclear that selling which type of product, new or mature, is more predictive of seller success.

We address these research questions by collaborating with Taobao Live, the largest livestream shopping platform in the world with a 55% share of China's livestream e-commerce market in 2020.[5] We select a representative sample of 3,568 sellers that newly opened livestreaming channels. Among them, about 27% went out of business within our 20-week observation period. We conduct a clustering analysis based on the transaction volume, and show the clusters in Figure 1. While two clusters (cluster 3 and 4) maintained steadily or thrived, the other 40% of sellers struggled to survive.[6] The struggle faced by many sellers in our sample indicates the importance of understanding the predictors of success in the livestream shopping industry.

We operationalize "success" with three variables: survival (a binary variable), the seller's last-4-weeks transaction volume (an absolute measure of success based on the end of the sample period), and the volume growth rate (a relative measure based on the full sample period).[7] We use both the Cox proportional hazards model and linear regression models to investigate the relationship between the three success measures and various factors. We also create a unified prediction framework using a machine learning model (XGBoost, Chen and Guestrin 2016) and interpret the results using SHapley Additive exPlanations (SHAP, Lundberg and Lee, 2017) to explore the relative importance of different factors.

We obtain the following results. First,we find that sellers that rely more heavily on the within-channel direct selling effect (instead of on the cross-channel spillover effect) of livestream shopping are less likely to succeed or survive. Second, the e-commerce KPI is positively correlated with seller success, while the entertainment KPI is negatively correlated. For the social network KPIs, reach is positively correlated with seller success, but engagement rate is negatively correlated. Because reach concerns the cross-channel spillover effect and engagement rate concerns the within-channel direct selling effect, the diverging effects of reach and engagement rate reinforce the previous finding that the cross-channel spillover effect, instead of the within-channel direct selling effect, indicates livestream shopping success. Third, sellers that use livestream shopping primarily for mature product inventory liquidation are more likely to succeed than those who use it for new product

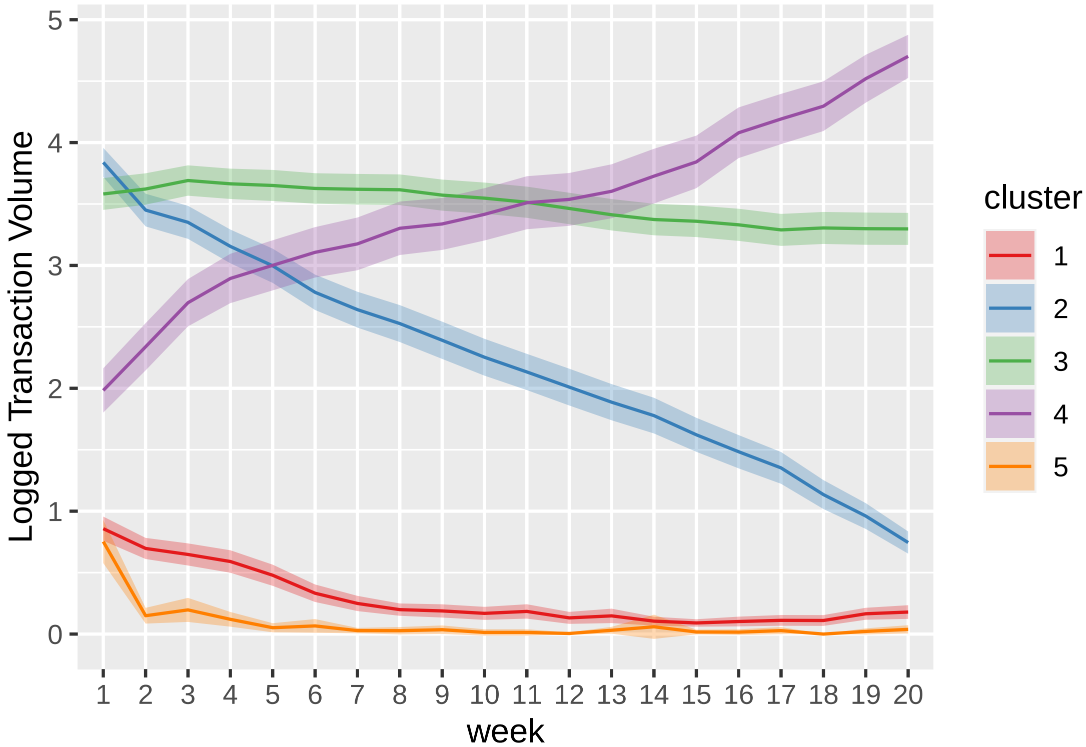
[4] Source: https://tinyurl.com/bdz2brj2

[5] Source: https://www.huxiu. com/article/396903.html

[6] We include the technical details of the clustering analysis in the appendix.

[7] As a robustness check, we use sales and the sales growth rate instead of the transaction volume and volume growth rate. The results remain qualitatively unchanged. We refer readers to the appendix for details.

Figure 1: Cluster average based on logged weekly transaction volume



Cluster size (number of sellers): cluster 1: 422; cluster 2: 909; cluster 3: 1630; cluster 4: 459; cluster 5: 148

introduction. Lastly, we find that seller size, the direct selling share,[8] and product tenure are the strongest predictors of seller success.

The main contributions of our paper are twofold. First, our paper is the first to study and provide descriptive insights into livestream shopping as a new, rapidly expanding retail format. Second, we contribute to the literature on firm survival predictions by introducing three novel factors: the channel strategy (within-channel direct selling effect vs. cross-channel spillover effect), industry-specific KPIs, and product selection (new vs. mature products).

Various stakeholders may apply our findings to their decision-making processes. First, the growing popularity of livestream shopping has rendered the industry a battlefield for *investors*. We are the first to provide a quantitative guide with which investors can better understand the marketplace and screen sellers before committing to expensive investments. Second, *platforms and service providers* that offer analytics for sellers can prioritize the lead indicators we identify and perhaps incorporate the indicators into a dashboard or tracking tools for sellers. Moreover, platforms can provide more early support to firms that are more likely to fail, in order to boost

[8] The direct selling share contributes negatively to seller survival.

the overall platform economy. Third, our findings may inform strategies with which livestream *sellers* can enhance their channel, positioning, and product selection strategies. Additionally, if sellers would like to take actions to improve their chance of long term success, the lead indicators identified in our study can serve as surrogates (Athey et al., 2019; Yang et al., 2020), or short-term proxies variables.

The rest of the paper is organized as follows: In the next section, we describe the livestream shopping industry. In Section 3, we review the relevant literature. In Section 4, we introduce our data and key variables. In Section 5, we describe the methods and report the results. We conclude the paper in Section 6.

2 Background on Livestream Shopping

Livestream shopping lies at the intersection of three industries: e-commerce, social networks, and entertainment. Livestream shopping fundamentally depends on e-commerce platforms for integration with online retail, and revenue is driven by the interactions among networks of consumers, influencers, and business owners. The modest cost of opening a livestreaming channel has tempted many small business owners and influencers to become livestreamers. The streaming format is more interactive than traditional pre-recorded video clips and enables sellers to build real-time social connections with consumers and explain products in details. Moreover, livestreaming content has both informational and entertainment value for consumers. According to McKinsey,[9] livestream shopping offers two main advantages over traditional shopping channels: "accelerating conversion" and "improving brand appeal and differentiation." See Table 1 for an overview of livestream shopping platforms.

At its embryonic stage, livestream shopping was dominated by influencers and celebrity livestreamers, also called "third-party livestreamers." Although livestream shopping incorporates rich features that allow viewers to participate and obtain real-time feedback, livestreaming sessions are essentially commercials. Brands offer compensation to third-party livestreamers in exchange for product promotions. Compensation plan can vary widely; during the Singles' day promotion in 2019, a fashion brand issued a lump sum payment of ¥150,000 (about $22,000) with a 20% profit commission to a top influencer who then promoted the brand's specialized slippers in a livestreaming session (Jiang, 2020).

Third-party livestreamers have ignited consumers' passion for this new type of shopping, but

[9]Source: https://tinyurl.com/4ze2527m

Table 1: Livestream shopping platforms

	Taobao	Kuaishou	TikTok	Amazon	Wayfair	Facebook	Google
Start	2016	2018	2018	2019	2019	2018	2020
Source	Taobao	Taobao	Taobao	Amazon	Wayfair	Multiple	Multiple
DAU	30 m	100 m	100 m	˜	˜	˜	˜
Product	Apparel Cosmetics Jewelry	Deals	Cosmetics	Deals Fashion Beauty	Furniture	Used goods	Cosmetics

Note: DAU is daily active user.

the business model is not without fault. For example, only a few third-party livestreamers are attracting enough consumers to their sessions to clinch deals with brands. According to a recent report, just 2.2% of third-party livestreamers generate nearly 80% of the sales through livestreaming sessions on Taobao Live.[10] The heavy market concentration hinders the growth and sustainability of the industry. Top third-party livestreamers have used the strength of their negotiation power to create stringent requirements for brands (e.g., exclusive clauses, lowest-price guarantees), thereby diminishing the affordability of livestream shopping. In addition, brands that hire third-party livestreamers sacrifice the opportunity to provide the same degree of accurate information and pragmatic feedback, potentially eliminating the advantage of livestreaming over pre-recorded videos and risking damage to brand image. For example, Austin Li, a top influencer in the Chinese livestream shopping industry, once incorrectly used a non-stick wok while promoting it in a livestream, creating the brand a PR nightmare.[11]

To alleviate these concerns, the evolving livestream shopping industry now encourages small business owners to open their own livestreaming channels and promote their brands directly to consumers. Livestreaming sessions operated by store owners now account for 70% of all sessions on Taobao Live.[12] Most owners already operate online stores, so they are compatible with the vision of an e-commerce ecosystem in which consumers can easily move between browsing online stores, watching livestreams, and interacting with others. Figure 2 shows the user interface (UI) of a typical livestreaming session operated by a store owner on Taobao Live. The main difference from

[10]Source: https://pdf.dfcfw.com/pdf/H3_AP202012041436556022_1.pdf?1607092275000.pdf
[11]Source: https://www.sohu.com/a/351015522_120046696
[12]Source: http://www.nbd.com.cn/articles/2021-04-29/1727040.html

a third-party livestreamer is that the store's name and page link are displayed in the left corner of the screen, and viewers can easily subscribe or get access to the online store. This UI design benefits business owners by highlighting the connection between the livestream and the store.

Figure 2: An example of a livestreaming session on Taobao Live

Unfortunately, the increasing popularity of this upgraded business model does not guarantee the success of every seller. In our dataset (introduced in details shortly), 27% of the sellers that launched a livestream shopping channel failed within 20 weeks (i.e., the transaction volume fell to 0 for the last 4 weeks of the sample period), and 50.8% of sellers failed to maintain at least 30% of their initial transaction volume. Researchers, the livestream shopping platform, investors, and sellers all would benefit from a better understanding of the predictors of survival and success in the livestream shopping industry.

3 Literature Review

Our paper contributes to multiple streams of literature on the effects of the digital transformation on business Verhoef and Bijmolt (2019), namely firm's survival; direct and cross selling spillover; KPIs of e-commerce, social networks, and entertainment industries; channel selection for new vs mature products; and lastly the emerging literature on livestream shopping.

3.1 Firm Survival and Success

First and foremost, our paper is concerned with the predictors of firm survival and success. Previous literature has shown that firm survival and success can be predicted by geographic and industry characteristics (Audretsch et al., 2000; Fritsch et al., 2006; Fontana and Nesta, 2009; Agarwal and Gort, 2002), user-generated content and consumer ratings (Zhang and Luo, 2022; Naumzik et al., 2021), public policy changes (Moorman et al., 2005), R&D investment intensity (Parsa et al., 2011), international comparison in retailing (Dekimpe and Morrison, 1991), and abnormal returns (Markovitch and Golder, 2008). However, to the best of our knowledge, no prior research has investigated the roles of the channel strategy (within-channel direct selling vs. cross-channel spillover), industry-specific KPIs, or product selections (new vs. mature products).

3.2 Within-channel Direct Selling and Cross-channel Spillover Effects

Livestream shopping has both a within-channel direct selling and a cross-channel spillover effect. In the within-channel direct selling effect, viewers make purchases while watching the livestreaming session that functions as a real-time shopping channel. In the cross-channel spillover effect, viewers merely collect information about the seller/products when watching but make purchases from the seller later. The livestreaming session functions as an advertisement that may prompt viewers to include the seller/products in their consideration sets for future purchases. The direct selling effect is thought to be effective because livestream content instills a fear of missing out, which shrinks the sales funnel and accelerates the customer journey. Cross-channel spillover, that is generally categorized under cross-selling (Dekimpe, 2020), is related to the complementary effects between the original channel and the newly introduced livestream channel. Previous literature has documented the synergies between the existing channel and the newly introduced channel, including online versus offline (Avery et al., 2012; Wang and Goldfarb, 2017), mobile versus online (Narang and Shankar, 2019), and digital versus telephone (Ravula et al., 2020). Our work focuses on the emerging livestream shopping channel and the traditional online shop channel. Although prior literature has studied the impact of livestreaming on seller sales (Yang et al., 2021; Cheng et al., 2020), no research has investigated whether and which of the two effects can predict seller success. This work fills this gap.

3.3 KPIs of the E-Commerce, Social Network, and Entertainment Industries

As mentioned before, livestream shopping is a combination of the e-commerce, social network, and entertainment industries. Each industry uses unique key performance indicators (KPIs), and it is not clear in the extant literature which industry-specific KPIs are predictive of long-term success in livestream shopping. The most important KPIs are the transaction volume in e-commerce,[13] reach and engagement rate (e.g., likes, comments, and shares) in social networks, and watch time in entertainment. KPIs have been studied to some extent in the literature on livestreaming and e-commerce, e.g., Zerbini et al. (2022) and Stephen and Toubia (2010). Reach and engagement activities have been treated as important metrics for evaluating mobile apps and livestream videos (Van Heerde et al., 2019; Wymer, 2019; Wongkitrungrueng and Assarut, 2020; Hilvert-Bruce et al., 2018), and they are linked with purchase intent and conversion at the session and campaign level (Tucker, 2015; John et al., 2017; Voorveld et al., 2018; Yang et al., 2021). Teixeira et al. (2014) show that entertainment value has an inverted U-shape relationship with purchase intent, and Chen and Lin (2018) conclude that a video's entertainment value is positively related to its perceived value. We integrate these disparate findings by comprehensively comparing the three industry's KPIs in terms of their ability to predict a seller's success in livestream shopping. We find that the e-commerce and social network KPIs are positively correlated with seller success, while the entertainment KPI is negatively correlated. The results suggest that sellers focusing on creating opportunities to communicate with viewers and encourage engagement, not on generating enjoyable content that keeps viewers hooked for as long as possible, are more likely to succeed.

3.4 Channel Selection for New vs. Mature Products

Prior literature suggests that consumers' channel choice is influenced by channel attributes and experience (Reinartz et al., 2019; Gensler et al., 2012). Building on this literature, we hypothesize that sellers can use the newly launched livestream shopping channel to either introduce new products into the market, or liquidate the inventory of existing, mature products. On the one hand, livestream shopping could be an ideal channel for new product introduction because it can reduce consumer's uncertainty associated with new products given the rich information presented by the video format and the frequent interactions between consumers and hosts. On the other hand, livestream shopping might be suitable for mature products because consumers may perceive

[13] We test sales for robustness; see appendix.

the new livestream channel that they have never experienced before as highly risky, especially when sellers have poor communication or interpersonal skills, so they prefer buying mature products to hedge the risk. Our paper provides empirical evidence for these competing hypotheses and shed new light on sellers' product assortment decisions in new channels.

3.5 Livestreaming

Livestreaming has received increasing attention in the marketing literature. Lu et al. (2021) studies the scalability of pay-what-you-want livestreaming events. Jain and Qian (2021) study the revenue sharing strategies of digital content platforms, including livestreaming platforms. Cong et al. (2021) study the value of the "live" component of livestreaming by studying a knowledge-sharing platform. Cheng et al. (2020) measure the impact of livestream shopping on sales. Wongkitrungrueng et al. (2020) identify sales approaches for customer acquisition and retention. However, no prior research has examined seller survival in livestream shopping.

4 Data

Our data are collected by collaborating with Taobao Live, the largest livestream shopping platform in the world, launched by the Alibaba Group in 2016. Nearly 68% of Chinese consumers used the platform's services in 2020 (Ouyang, 2021). The e-commerce ecosystem within Alibaba makes it convenient for sellers to operate online stores and livestreaming channels together. We use three rules to select eligible sellers for our study, including (1) the seller opened a livestreaming channel in Taobao Live's top three product categories: fashion, food, or jewelry, (2) the seller held the first livestreaming session between August 1, 2019, and February 10, 2020, and (3) the seller completed at least one transaction in the first 4 weeks of operation. Among all eligible sellers, we randomly sampled 3,568 ones. We observe each seller's transaction volume and sales that are generated through livestreams and through the seller's traditional online store. Moreover, for each livestream session, we collect engagement metrics (likes, shares, comments, and new subscribers), the average watch time, the product assortment, and pricing information. The dataset contains 20 weeks of observations from each seller.

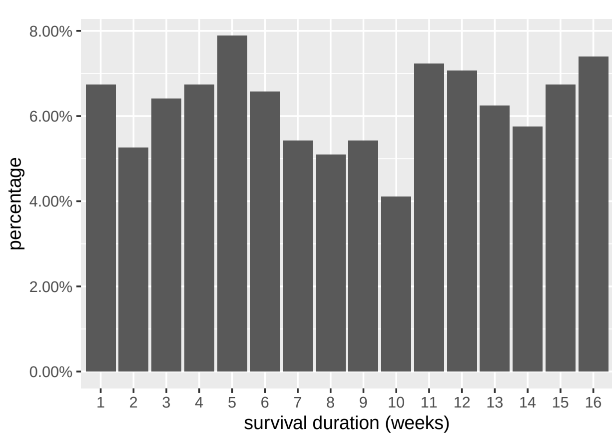
4.1 Measures of Seller Success

We define three measures of seller success: the last-4-weeks transaction volume, volume growth rate, and survival. The *last-4-weeks transaction volume* is the number of transactions obtained in the last 4 weeks of the 20-week observation period. As a measure of the seller's absolute size, the transaction volume is a strong indicator of whether the seller is capable of staying in business. The *volume growth rate* is the ratio of the seller's last-4-weeks transaction volume to the first-4-weeks transaction volume. As a relative measure, the growth rate is helpful for discovering successful sellers that start with a small transaction volume. Lastly, *survival* is an indicator variable, and we test several definitions of survival using thresholds of the volume growth rate, from 0% to 30% in 5% increments. We include a range of non-zero thresholds because a drastic decline in a seller's transaction volume is a sign of probable failure. Using the threshold of a 0% volume growth rate, 2,608 sellers (73.1%) survived; using a threshold of 30%, only 49.2% of sellers survived. Table 2 summarizes the survival rate under each threshold. For sellers who didn't survive, using the 0% volume growth rate as a threshold, we use the last time that they made a sale to define survival duration. Figure 3 displays the distribution of survival duration for failed sellers. As can be seen, survival duration is relatively evenly distributed across the 20 weeks.

Table 2: Survival rate defined by different volume growth rate thresholds

Volume growth rate threshold	0	5%	10%	15%	20%	25%	30%
Survival rate	73.1%	65.4%	61.0%	57.3%	53.9%	51.7%	49.2%

Figure 3: Survival duration for failed sellers



5 Methodology and Results

In this section, we describe the models and estimation results for the three research questions.

5.1 Main Model and Results

Our three research questions are (1) whether the within-channel direct selling or the cross-channel spillover effect is more important to seller success, (2) which industry-specific KPIs predict seller success, and (3) whether selling new versus mature products predicts seller success.

To test the association of survival with these factors, we use the Cox proportional hazard model. Since the survival information is right truncated, we observe not only if a seller survived, but also the survival duration if the seller failed. The Cox proportional hazard model can accommodate the survival information with survival duration (Cox, 1972). We estimate the following specification:

$$h_i(t) = h_0(t) \exp\left(\alpha_{c(i)} + X_i\boldsymbol{\beta}\right), \tag{1}$$

where $h_i(t)$ is the hazard function, $h_0(t)$ is the baseline hazard, the exponential term specifies the possible influence of the covariates on the hazard rate, $\alpha_{c(i)}$ is the category fixed effect, and

$$\begin{aligned} X_i\boldsymbol{\beta} = {} & \beta_1 DirectSellingShare_i \\ & + \beta_2 Volume_i + \beta_3 WatchTime_i + \beta_4 Reach_i + \beta_5 EngagementRate_i \\ & + \beta_6 ProdTenure_i + \beta_7 Price_i + \beta_8 ProdCnt_i + \beta_9 CateCnt_i \\ & + \beta_{10} SellerTenure_i. \end{aligned} \tag{2}$$

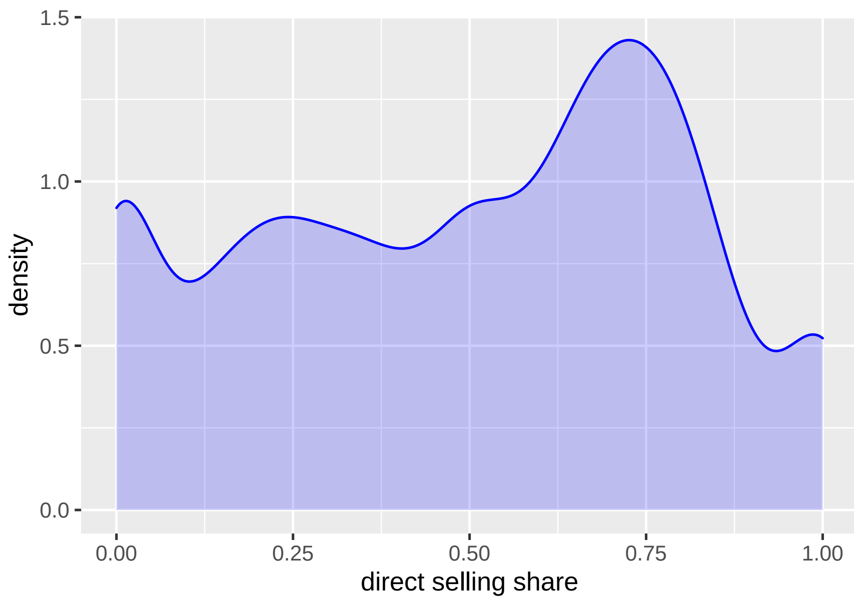
In equation (2), $DirectSellingShare_i$ is the key variable for our first research question. After a consumer watches a seller's livestream for the first time, we divide her subsequent orders (if any) into two groups based on the purchase channel: links in the seller's livestream ("direct selling orders") versus the seller's regular webpage ("indirect selling orders," which reflect the cross-channel spillover effect).[14] Then, we define $DirectSellingShare_i$ as the ratio of the volume of direct selling orders to the total volume of direct and indirect selling orders of seller i.[15] A larger direct selling share indicates that the seller is more reliant on the within-channel direct selling effect, while a

[14]Note that indirect selling orders do not include orders from customers who make purchases from a seller's online store without ever watching the seller's livestreams.

[15]In the appendix, as a robustness check, we calculate the direct selling share using sales instead of the transaction volume.

smaller share indicates more reliance on the cross-channel spillover effect. Although popular press boasts about the direct selling effect of livestream shopping, about half of the sellers in our dataset (48.6%) have more transactions generated by the cross-channel spillover effect than by the within-channel direct selling effect. Figure 4 shows a density plot of the direct selling shares in our sample. The average direct selling share is 49%.

Figure 4: Direct selling share density



To answer the second research question, we define all KPIs based on the first 4 weeks of observations from each seller. For the e-commerce aspect, we use the seller's first-4-weeks transaction volume ($Volume$) as the KPI. For the social network aspect, we include two KPIs. $Reach$ is defined as the average number of unique viewers per hour and $EngagementRate$ is defined as the number of engagements, which include likes, shares, comments and new subscribers, divided by reach and normalized by session length (in hours). Both KPIs are widely used in the industry as signals of quality and popularity, with the former emphasizing the size of the crowd that receives the information, and the latter focusing on the performance of real-time interactions.[16] For the entertainment aspect, we define $WatchTime_i$ as the average watch time (in minutes) among all viewers of seller i's livestreams. The watch time has been used to rate the attractiveness of content on entertainment platforms such as Netflix (Guadiana, 2020). For all KPIs for the social network and entertainment aspect, we first calculate the hourly average within each livestream, and then average it across livestreams within each seller.

[16]Source: https://influencermarketinghub.com/social-media-metrics/

$ProdTenure_i$, the average amount of time for which the featured products of seller i has been listed, is the key variable to answer the third question. This variable captures the seller's choices about promoting new arrivals versus classical products via livestream shopping. To control for a seller's other assortment decisions in livestreams, we also define $Price_i$ as the average product price in seller i's channel; $ProdCnt_i$ as the average number of products introduced per hour. Lastly, we measure product category variety. Sellers in our sample belong to three categories (fashion, food, and jewelry), but all sellers have the flexibility to select a range of products from subcategories. For instance, a seller in the fashion category might choose to introduce shoes, clothes, and accessories all in one livestream. We define $CateCnt_i$ as the average number of subcategories included in one session of seller i. All variables are based on the first 4 weeks of observations from each seller. We also include $SellerTenure_i$, which measures how long seller i has been active on the platform, as a control. Table 3 provides summary statistics for all variables.[17]

Table 3: Descriptive statistics

Variable	N	Mean	St. Dev.	Min	Max
Panel A: Dependent Variables					
survival (threshold: 0% volume growth rate)	3,568	0.73	0.44	0.00	1
last-4-weeks volume	3,568	3,711.82	43,095.90	0.00	1,572,219
volume growth rate	3,568	12.69	327.99	0.00	19,144.00
Panel B: Store Tenure, Direct Selling Share, and Industry-Specific KPIs					
store tenure (weeks)	3,568	177.08	182.50	0.00	771.68
direct selling share	3,568	0.49	0.30	0.00	1.00
e-commerce: first-4-weeks volume	3,568	3,966.73	41,352.72	1	1,236,904
entertainment: watch time (minutes)	3,568	2.63	4.35	0.01	59.16
social networks: reach	3,568	97.18	527.91	0.05	19,139.57
social networks: engagement rate	3,568	91.83	397.03	0.00	15,799.49
Panel C: Marketing Mix					
product tenure (days)	3,568	66.52	101.51	0.00	1,344.67
product count per hour	3,568	8.08	24.57	0.01	613.48
price	3,568	308.57	430.46	1.00	3,378
subcategory count per session	3,568	1.64	2.20	0.05	64.67

For the other two success measures, the last-4-weeks transaction volume and the volume growth rate, we perform the following linear regression,

$$y_i = \alpha_{c(i)} + X_i\boldsymbol{\beta} + \epsilon_i, \tag{3}$$

[17] Figure 6 shows the correlation plot for the independent variables.

where y_i is the success measures of seller i, $X_i\boldsymbol{\beta}$ is the same as in equation (2), and ϵ_i is the normally distributed idiosyncratic error term.

We report the results in Table 4.

5.1.1 Within-Channel Direct Selling versus Cross-Channel Spillover Effect

The dependent variable is survival in columns (1), the last-4-weeks transaction volume in columns (2), and the volume growth rate in columns (3). We find that the direct selling share is negatively correlated with all three measures of seller success, suggesting that sellers are more likely to succeed by leveraging the cross-channel spillover effect. Specifically, column (1) reports that the likelihood of failure increases by 1.007 times ($=e^{0.650\%}$) when the direct selling share increases by 1%.[18] In column (2), the last-4-weeks transaction volume decreases by 0.720% with a 1% increase in the direct selling share. In column (3), the volume growth rate decreases by 0.148% when the direct selling share increases by 1%.

In summary, sellers that rely more on the cross-channel spillover effect of livestream shopping (and, thus, rely less on the within-channel direct selling effect) are more likely to succeed. This result contradicts the conventional wisdom and industry anecdotes that the comparative advantage of livestream shopping over traditional e-commerce comes from the power to accelerate consumers through the purchase funnel by leveraging a fear of missing out.[19]

5.1.2 Industry-Specific KPIs

Column (1) of Table 4 shows that the transaction volume is positively associated with survival, while the watch time is negatively associated with survival. Specifically, the seller's risk of not surviving decreases by 25.7% ($= 1 - e^{-0.296}$) when the transaction volume increases by 1%, and increases by 18.2%($= e^{0.167} - 1$) when the watch time increases by 1%. For the social network KPIs, the seller's risk of not surviving decreases by 9.06% ($= 1 - e^{-0.095}$) when the reach increases by 1%, but the engagement rate shows an insignificant result.

The results in column (2), with the last-4-weeks transaction volume as the success measure, are consistent with the survival analysis. 1% increases in the transaction volume and in the reach are associated with 0.731% and 0.138% increases in the last-4-weeks transaction volume, respectively; a 1% increase in the watch time and in the engagement rate is associated with a 0.169% and 0.037%

[18]We use the interpretation, percentage change, because all variables except direct selling share are log-transformed.
[19]Source: https://streams.live/ shorter-shopping-journeys-with-live-video-commerce/

decrease in the transaction volume, respectively. Finally, in column (3), reach has a directionally positive association (0.030) with the volume growth rate, while watch time and engagement rate have a significant negative association with the volume growth rate ($-0..077$ and -0.020). Unlike in the first two columns, the transaction volume has a negative association with the volume growth rate. This happens because the volume growth rate depends on the initial seller size. Intuitively, it is more difficult for a large seller to grow as fast as a small seller because each percentage increase represents an absolutely larger number.

This negative association with watch time may seem surprising because it suggests that sellers with more entertaining content are more likely to fail. One possible explanation is that the viewer's enjoyment of watching the content may not align with their purchase intentions. A seller may be extremely talented at creating content and attracting viewers to stay for a long time, but if the content is not closely linked with products, then the seller may make few sales. This phenomenon is supported by some anecdotal evidence. In a recent livestream shopping campaign held by Walmart, viewers criticized a famous livestreamer for spending too much time on a dance performance and too little time building connections with the products.[20] For the social network KPIs, the positive association with reach suggests sellers who attract more viewers to livestreams are more likely to survive and succeed. Surprisingly, engagement rate is never positively associated with seller survival nor success. A possible explanation is that consumers view livestream shopping as a channel to collect information rather than to commit real-time interactions and purchases. Thus, reach is positively correlated with a seller's success because more people have acquired information from the seller's livestreams. On the other hand, since viewers may not purchase during livestreams, high engagement rate may not be positively associated with seller success. This explanation is also supported by our findings in the first research question, which show that sellers that heavily rely on the cross-channel spillover effect, as opposed to the within-channel direct selling effect, are more likely to survive.

5.1.3 Channel Selection for New vs. Mature Products

For new versus mature product selection, we find consistent results for all three success measures; here, we interpret only the results in column (2) for parsimony. A 1% increase in the average product tenure (i.e., classical and mature products) is associated with a 0.268% increase in transaction volume. The result supports the hypothesis that consumers may perceive the new livestream

[20] Source: https://www.cbndata.com/information/125467

shopping channel as risky and therefore prefer mature products to hedge the risk in this channel.

For other assortment decisions, a more concentrated selection of subcategories is positively associated with a higher transaction volume and volume growth rate.

Table 4: Association of seller success with direct selling share, industry-specific KPIs and product tenure

	Dependent variable:		
	hazard rate	last-4-weeks volume	volume growth rate
	Cox Prop. Hazards	*OLS*	*OLS*
	(1)	(2)	(3)
direct selling share	0.650^{***}	-0.720^{***}	-0.148^{**}
	(0.142)	(0.130)	(0.060)
first-4-weeks volume	-0.296^{***}	0.731^{***}	-0.070^{***}
	(0.024)	(0.018)	(0.008)
watch time	0.167^{***}	-0.169^{***}	-0.077^{***}
	(0.058)	(0.057)	(0.026)
reach	-0.095^{**}	0.138^{***}	0.030^{**}
	(0.041)	(0.032)	(0.015)
engagement rate	0.026	-0.037^{**}	-0.020^{**}
	(0.019)	(0.018)	(0.008)
product tenure	-0.303^{***}	0.268^{***}	0.069^{***}
	(0.040)	(0.033)	(0.015)
product count per hour	−0.088	0.051	0.018
	(0.057)	(0.046)	(0.021)
price	0.015	-0.069^{**}	−0.017
	(0.031)	(0.030)	(0.014)
subcategory count per session	−0.027	-0.337^{***}	-0.121^{**}
	(0.153)	(0.112)	(0.052)
seller tenure	-0.034^{*}	0.025	−0.008
	(0.019)	(0.019)	(0.009)
Category FE	Yes	Yes	Yes
Observations	3,568	3,568	3,568
R^2	0.145	0.524	0.034
Adjusted R^2		0.522	0.030
Log Likelihood	−4,647.245		

Notes: The table reports the correlations between seller success and factors including direct selling share, industry-specific KPIs and product tenure. Note that the interpretation of the Cox proportional hazards model is different from that of the other two regressions: a positive coefficient indicates a higher hazard (and lower chance of survival). All variables except direct selling share are log-transformed.

*p<0.1; **p<0.05; ***p<0.01

5.2 Unified Prediction Framework

To investigate the relative importance of the features for forecasting seller survival, we propose a unified prediction framework. We include (1) the direct selling share, (2) transaction volume, reach, engagement, and watch time, (3) product tenure and other marketing mix variables, and (4) seller category and seller tenure. We leverage an interpretable machine learning algorithm to estimate feature importance for both individual sellers and the global sample.

5.2.1 Training a Model to Predict Seller Survival

We consider survival based on a 0% volume growth rate as the outcome variable.[21] We use a machine learning classifier, XGBoost (Chen and Guestrin, 2016), which takes the aforementioned factors as inputs and predicts seller survival as the output.We choose XGBoost over other machine learning models (e.g., regression, random forest, artificial neural networks, and other decision trees) because it achieves state-of-the-art accuracy in a wide range of practical applications (Lundberg et al., 2018; Chatzis et al., 2018) as well as various machine-learning challenges held by Kaggle (Chen and Guestrin, 2016; Bissacco et al., 2007; Hutchinson et al., 2011; Johnson and Zhang, 2013). It is known for its efficiency and accuracy.

We randomly split sellers into ten even groups for a 10-fold cross-validation. We use nine groups of sellers as the training set to calibrate the model, and the remaining group of sellers as the test set to assess the model's predictive performance. The training dataset is $\{(x_i, y_i), i = 1, \ldots, N_{train}\}$, where $x_i \in R^D$ is a D-dimensional feature vector including the aforementioned factors, and $y_i \in \{0, 1\}$ is the outcome variable (survival, using thresholds of 0%). As we conduct a 10-fold cross-validation, we perform the predictive task ten times.

Table 5 reports the model performance on the test set averaged over the 10-fold cross-validation using multiple performance measures including accuracy, precision, recall, F1, and area under the ROC curve (AUC). Our model has an out-of-sample accuracy of 77.9% for predicting whether a seller's volume growth rate is higher than 0%. The prediction results suggest that our four categories of factors contain valid information about the seller's likelihood of survival.

[21] As a robustness check, we present the results with survival outcome using 20% volume growth rate in the appendix.

Table 5: Evaluation of the trained model on test data

Survival threshold	Accuracy	Precision	Recall	F1	AUC
0%	0.779 (0.009)	0.811 (0.006)	0.910 (0.006)	0.858 (0.006)	0.805 (0.009)

Note: Results are averaged over 10-fold cross-validation iterations. Standard errors are provided in parentheses.

5.2.2 Ranking and Interpreting Feature Importance

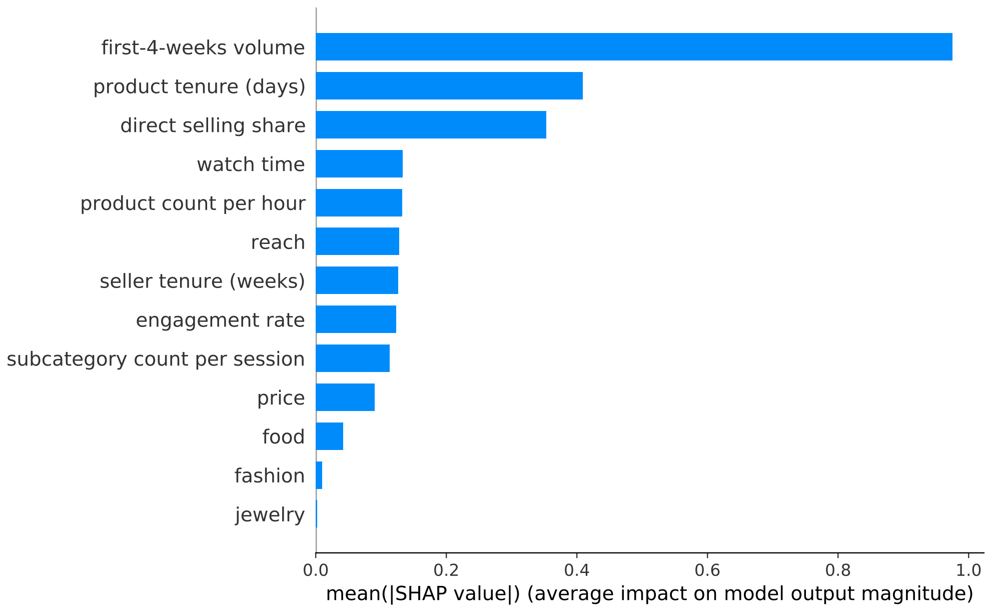
Next, we open the "black box" of the XGBoost algorithm to rank the relative importance of each factor and to offer interpretations of the results. We use SHAP (SHapley Additive exPlanations), proposed by Lundberg and Lee (2017), to interpret feature importance at the seller level. The SHAP method computes Shapley values from coalitional game theory: the feature values of a data instance act as a player in a coalition, and Shapley values tell us how to fairly distribute the payout/prediction among the features. Hence, SHAP explains the prediction of an instance by computing the contribution of each feature to the prediction; features with larger absolute Shapley values are more important. To rank the global importance of the features, we calculate each feature's mean absolute Shapley value across sellers. Figure 5a plots the features in the descending order of the mean absolute Shapley value. Among the top three most important attributes are the first-4-weeks volume, direct selling share, and product tenure.

Figure 5b combines feature importance with feature effects to provide insights into the relationship between the value of the feature and its impact on the prediction. Each point on the plot is the feature's Shapley value for one seller. The position of the point is determined by feature importance on the vertical axis and by the Shapley value on the horizontal axis. The color strip represents the value of the feature, from low (red) to high (green). Overlapping points are jittered vertically to provide information about the distribution of the Shapley values for each feature. The direction of the association between each feature and survival are consistent with our findings in Table 4. For example, high values (green) of the direct selling share are negatively associated with the probability of survival.

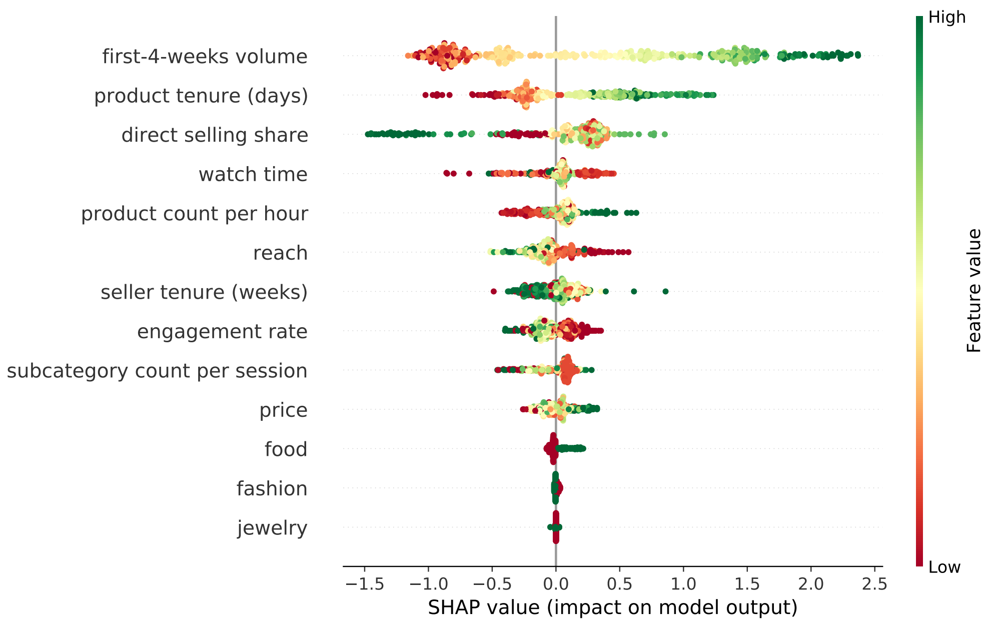
5.2.3 Prediction Results for Different Feature Sets

We investigate the incremental predictive power of different sets of features related to our three research questions. In Table 6, we show the predictive power of the following model specifications

Figure 5: Features ranked in order of importance for predicting survival (0% volume growth rate) based on (a) mean (|SHAP value|) and (b) the SHAP value for all sellers



(a)



(b)

with different feature sets: 1) baseline, which includes only the seller tenure and category information; 2) baseline + KPIs (i.e., the three industry-specific KPIs); 3) baseline + KPIs + the direct selling share; and 4) the full model: baseline + KPIs + the direct selling share + marketing mix variables.

For each model specification, Table 6 reports the model's performance on the test set. Specifically, we are interested in the model's accuracy, F1 score, and AUC. All three performance measures improve with the additions of the industry-specific KPIs, direct selling share, and marketing mix variables. The KPIs have the highest incremental predictive power, followed by the direct selling share and then the marketing mix variables. The results help answer our three research questions: all three sets of variables are useful for predicting seller survival.

Table 6: Model accuracy with different feature sets

	Accuracy	Precision	Recall	F1	AUC
Baseline	0.724 (0.003)	0.735 (0.001)	0.971 (0.004)	0.837 (0.002)	0.586 (0.011)
Baseline + KPIs	0.750 (0.007)	0.793 (0.003)	0.889 (0.007)	0.838 (0.005)	0.772 (0.008)
Baseline + KPIs + direct selling share	0.760 (0.008)	0.799 (0.004)	0.897 (0.007)	0.845 (0.005)	0.785 (0.008)
Baseline + KPIs + direct selling share + marketing mix	0.779 (0.009)	0.811 (0.006)	0.910 (0.006)	0.858 (0.006)	0.805 (0.009)

Note: Baseline includes seller tenure and seller categories. Results are averaged over 10-fold cross-validation iterations. Standard errors are provided in parentheses.

5.3 Robustness

We conduct a series of robustness checks including using sales rather than transaction volume to define relevant variables, applying logit models to survival analysis, defining direct selling share in an alternative way, and using alternative time windows for predictors and survival measures.

Sales. In the main analysis, we constructed many variables, including two of the success measures and the direct selling share, based on the seller's transaction volume. In e-commerce, however, another important measure is the seller's sales (revenue), so we conduct a robustness check in which we replace all transaction volume variables (including the growth rate and direct selling share) with sales variables (e.g., the sales growth rate instead of the volume growth rate). The result tables (Table A2-A3), included in appendix C.1, show that using sales instead of the transaction volume does not change the main insights.

Alternative analysis for seller survival. In the main analysis, we used the Cox proportion hazards model to study survival, and we repeat the survival analyses using a logit model for a robustness check. Unlike the Cox proportional hazards model, the logit model only considers if a seller survived but cannot accommodate survival duration. We include two survival thresholds: volume growth rates of 0% and 20%. The former threshold is consistent with the previous models and indicates that the seller was out of business in the last 4 weeks; the latter indicates that the seller's volume has dropped drastically, and the seller is unlikely to survive for much longer. The results of the logit model for both survival thresholds are consistent with our main model for all three research questions. We provide the results in Tables A4, appendix C.2.

Alternative definition of direct selling share. We define the direct selling share based on a seller's all transactions in 20 weeks. This approach is different from the construction of other predictors, such as industry KPIs and assortment decision variables, which are based on the seller's performance in the first 4 weeks. We repeat the analysis restraining all "direct selling orders" into the first 4 weeks, which is consistent with other predictors. However, we don't restrict any "indirect selling orders" into any time framework. It is because that livestreaming's advertising effect may last longer. For instance, a consumer might watch a session in the fourth week and make a purchase in the seventh week. Table A5 in appendix C.3 reports the result with the alternative definition of the direct selling share, and we find the main insights do not change.

Alternative time windows for predictors and survival measures. In the main analysis, we construct predictors and controls, including seller tenure and size, KPIs, and assortment decisions, based on the first 4 weeks' observations, and we define a seller's survival based on the last 4 week's performance. We repeat the analyses using predictors and survival measures with redefined time windows. We use observations from the first three and five weeks of each seller to reconstruct those predictors and controls. Correspondingly, we use each seller's performance from the last three and five weeks to redefine survival measures. We find that all results are consistent with our results in the main analysis. For the sake of paper length, we only provide the result for the unified prediction framework in Table A6 and A7, appendix C.4.

6 Conclusion

We study factors that predict the survival and success of sellers with new livestream shopping channels. We collect data from 3,568 sellers in the fashion, food, and jewelry categories on Taobao Live. About 27% did not survive for 20 weeks (the duration of our sample period) after the first livestreaming session. Given the difficulty of surviving surviving and succeeding as a seller in the livestream shopping industry, it is crucial to understand which factors are most strongly associated with survival and success.

We focus on three categories of factors: the channel strategy (within-channel direct selling effect vs. cross-channel spillover effect), industry-specific KPIs, and marketing mix variables. Several interesting findings emerge. First, survival and success are more likely when a larger share of the seller's transaction volume comes from the "cross-channel spillover effect effect" (purchases made via the seller's online store) rather than from the "within-channel direct selling effect" (purchases made via the livestream). Second, the transaction volume (the e-commerce KPI) is a positive predictor for seller survival, while the watch time (the entertainment KPI) is a negative predictor. For the social networks KPIs, the reach positively predicts seller success, while the engagement rate negatively predicts it. Thus, sellers might find it beneficial by focusing on spreading livestreaming sessions to a larger crowd, i.e., enhancing the cross-channel spillover effect, instead of on creating content that will keep viewers hooked for as long as possible or simulating an overly interactive environment, i.e., strengthening the direct selling effect. Third, sellers who primarily sell mature products are more likely to succeed than those who sell new products. Finally, to compare the predictive power of the features we studied, we use XGBoost and interpret the results using the SHAP method. Averaged across all sellers, we find that the most important features are the first-4-weeks transaction volume (positive predictor), product tenure (positive predictor), and the direct selling share (negative predictor).

Our results have implications for multiple stakeholders, including investors, livestream shopping platforms, and sellers. Investors can use our predictive model to screen profitable sellers that just launched a livestreaming channel. Our findings may help sellers design better channel and marketing mix strategies. The lead indicators we discover can also be used as surrogates (Athey et al., 2019; Yang et al., 2020) for long run success when sellers design marketing and operation strategies. Livestream shopping platforms might leverage our insights to improve their policies and recommendations as well as identify key sellers to support, in order to increase the seller survival rate.

Our paper is subject to several limitations that invite future research. First, we provide descriptive insights and predictive analytics, not causal inferences. Future research may investigate whether any of the lead indicators have a causal impact on survival and success.

Second, our data come from only one livestream shopping company, Taobao Live, which is connected with the large e-commerce platform Taobao. Future research can test the generalizability of our findings by collecting data from alternative livestream shopping platforms, such as Facebook and Tiktok, on which the social network and entertainment aspects are more salient than the e-commerce aspect.

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Appendix A Clustering Model

We conduct a clustering analysis of sellers' trajectories by implementing the three-step procedure proposed by Leffondré et al. (2004). According to Sylvestre et al. (2014), the procedure involves (1) calculating 24 measures (in Table A1) that describe the features of the trajectories, (2) using factor analysis to select a subset of the 24 measures, (3) using cluster analysis to identify clusters of trajectories, and (4) classifying each individual trajectory into one of the clusters.

Table A1: 24 Measures Used in Trajectory Clustering Analysis

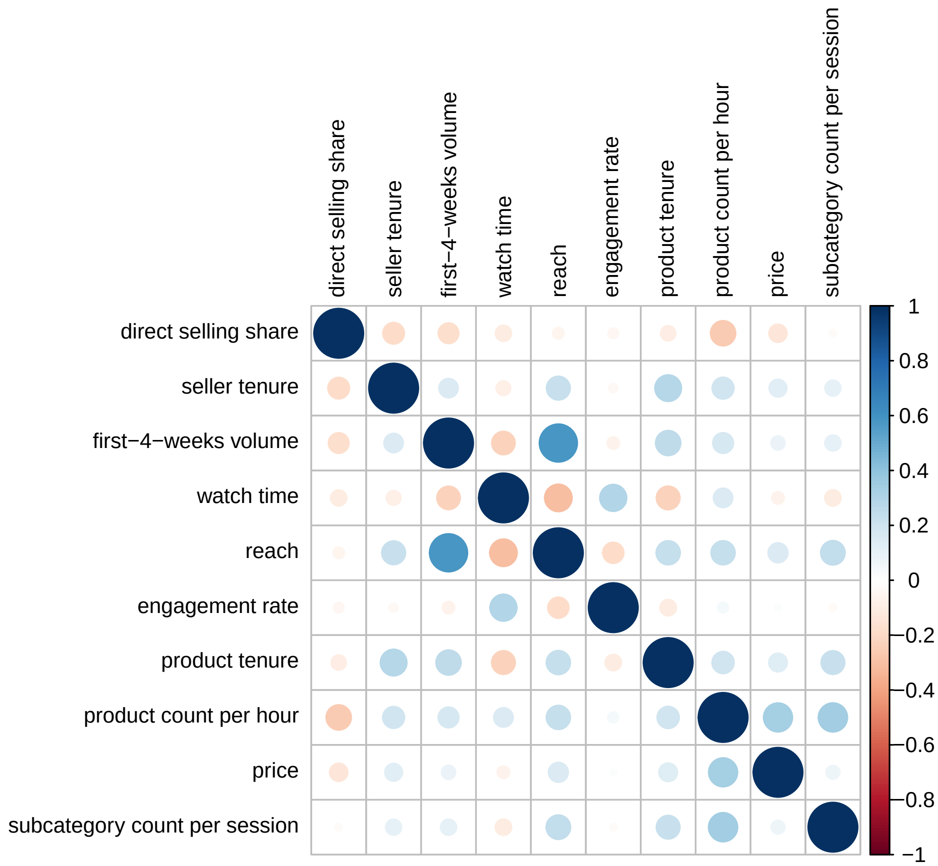
1. Range
2. Mean-over-time
3. Standard deviation (SD)
4. Coefficient of variation (CV)
5. Change
6. Mean change per unit time
7. Change relative to the first score
8. Change relative to the mean over time
9. Slope of the linear model
10. R^2: Proportion of variance explained by the linear model
11. Maximum of the first differences
12. SD of the first differences
13. SD of the first differences per time unit
14. Mean of the absolute first differences
15. Maximum of the absolute first differences
16. Ratio of the maximum absolute difference to the mean-over-time
17. Ratio of the maximum absolute first difference to the slope
18. Ratio of the SD of the first differences to the slope
19. Mean of the second differences
20. Mean of the absolute second differences
21. Maximum of the absolute second differences
22. Ration of the maximum absolute second difference to the mean-over-time
23. Ratio of the maximum absolute second difference to mean absolute first difference
24. Ratio of the mean absolute second difference to the mean absolute first difference

For each seller, we calculate the weekly transaction volume for the 20 weeks in the sample period and the 24 measures that describe the feature of the 20-weeks transaction volume trajectory. We then use cluster analysis to identify the clusters of trajectories based on the selected subset of measures using factor analysis. Five clusters emerge from the analysis; clusters 1, 2, 3, 4, and 5 have 422, 909, 1,630, 459, and 148 sellers, respectively. Figure 1 shows the average trend in the weekly transaction volume for each cluster.

Appendix B Correlation Plot

Figure 6 shows the correlation plot of the independent variables used in our main analysis. All variables except the *directsellingshare* are log-transformed.

Figure 6: Correlation Plot



Appendix C Robustness Check

C.1 Alternative Measures Based On Sales

Tables A2-A3 show the results on the association of seller success with various factors and the evaluation of prediction model with variables defined based on sales instead of transaction volume.

Table A2: Association of seller success with direct selling share, industry-specific KPIs and product tenure: based on sales measure

	Dependent variable:		
	hazard rate	last-4-weeks sales	sales growth rate
	Cox Prop. Hazards	*OLS*	*OLS*
	(1)	(2)	(3)
direct selling share	0.799***	−1.577***	−0.512***
	(0.133)	(0.223)	(0.083)
first-4-weeks sales	−0.119***	0.632***	−0.193***
	(0.013)	(0.023)	(0.008)
watch time	0.191***	−0.317***	−0.108***
	(0.058)	(0.104)	(0.039)
reach	−0.189***	0.413***	0.110***
	(0.040)	(0.055)	(0.021)
engagement rate	0.021	−0.071**	−0.018
	(0.019)	(0.033)	(0.012)
product tenure	−0.336***	0.618***	0.125***
	(0.040)	(0.059)	(0.022)
product count per hour	−0.104*	0.118	−0.025
	(0.057)	(0.084)	(0.031)
price	0.060*	−0.022	0.058***
	(0.032)	(0.056)	(0.021)
subcategory count per session	0.033	−0.651***	−0.171**
	(0.152)	(0.204)	(0.076)
seller tenure	−0.024	0.038	−0.004
	(0.019)	(0.036)	(0.013)
Category FE	Yes	Yes	Yes
Observations	3,568	3,568	3,568
R^2	0.131	0.403	0.146
Adjusted R^2		0.401	0.143
Max. Possible R^2	0.937		
Log Likelihood	−4,675.603		

Notes: The table reports the correlations between seller success and factors including direct selling share, industry-specific KPIs and product tenure. Note that the interpretation of the Cox proportional hazards model is different from that of the other two regressions: a positive coefficient indicates a higher hazard (and lower chance of survival). All variables except direct selling share are log-transformed.
Significance level: *p<0.1; **p<0.05; ***p<0.01

Table A3: Evaluation of the trained model on test data: based on sales measures

Survival threshold	Accuracy	Precision	Recall	F1	AUC
0%	0.780 (0.007)	0.801 (0.005)	0.931 (0.005)	0.861 (0.005)	0.804 (0.007)
20%	0.649 (0.007)	0.654 (0.006)	0.737 (0.009)	0.693 (0.006)	0.695 (0.006)

Note: Results are averaged over 10-fold cross-validation iterations. Standard errors are provided in parentheses.

C.2 Alternative Analysis for Seller Survival (Logit Model)

Table A4 shows the results of the surivival analyses using a logit model. Two survival thresholds holds, volume growth rates of 0% and 20%, are used to construct the binary survival variable.

Table A4: Association of seller survival with direct selling share, industry-specific KPIs and product tenure: logit models

	Dependent variable:	
	survival (0%)	survival (20%)
	logistic	
	(1)	(2)
direct selling share	-0.482^{***}	-0.358^{***}
	(0.146)	(0.128)
first-4-weeks volume	0.439^{***}	0.124^{***}
	(0.024)	(0.018)
watch time	-0.080	-0.113^{**}
	(0.065)	(0.056)
reach	-0.053	0.046
	(0.039)	(0.031)
engagement rate	-0.061^{***}	-0.048^{***}
	(0.020)	(0.018)
product tenure	0.307^{***}	0.261^{***}
	(0.040)	(0.033)
product count per hour	0.113^{**}	0.067
	(0.057)	(0.046)
price	0.035	-0.013
	(0.035)	(0.030)
subcategory count per session	-0.170	-0.227^{**}
	(0.140)	(0.111)
seller tenure	-0.006	0.035^{*}
	(0.021)	(0.019)
Category FE	Yes	Yes
Observations	3,568	3,568
Log Likelihood	$-1,681.800$	$-2,289.757$

Notes: The table reports the correlations between seller survival and factors including direct selling share, industry-specific KPIs and product tenure. All variables except direct selling share are log-transformed.

Significance level: *p<0.1; **p<0.05; ***p<0.01

C.3 Alternative Definition of Direct Selling Share

Table A5 reports the result with the alternative definition of direct selling share, and we find the main insights do not change

Table A5: Association of seller success with direct selling share, industry-specific KPIs and product tenure: alternative direct selling share measure

	Dependent variable:		
	hazard rate	last-4-weeks volume	volume growth rate
	Cox Prop. Hazards	*OLS*	*OLS*
	(1)	(2)	(3)
direct selling share	0.949***	−1.142***	−0.444***
	(0.125)	(0.120)	(0.047)
first-4-weeks volume	−0.436***	0.783***	−0.068***
	(0.036)	(0.025)	(0.010)
watch time	0.085	−0.116	−0.054*
	(0.078)	(0.075)	(0.029)
reach	−0.123**	0.235***	0.078***
	(0.059)	(0.042)	(0.016)
engagement rate	0.030	−0.015	−0.020**
	(0.024)	(0.024)	(0.009)
product tenure	−0.278***	0.289***	0.066***
	(0.054)	(0.042)	(0.017)
product count per hour	−0.113	0.055	−0.005
	(0.076)	(0.059)	(0.023)
price	0.024	−0.071*	−0.014
	(0.046)	(0.041)	(0.016)
subcategory count per session	−0.023	−0.374**	−0.069
	(0.220)	(0.147)	(0.058)
seller tenure	−0.019	0.032	−0.001
	(0.026)	(0.027)	(0.010)
Category FE	Yes	Yes	Yes
Observations	2,120	2,120	2,120
R^2	0.233	0.591	0.079
Adjusted R^2		0.589	0.074
Max. Possible R^2	0.916		
Log Likelihood	−2,346.242		

Notes: The table reports the correlations between seller success and factors including direct selling share, industry-specific KPIs and product tenure. Note that the interpretation of the Cox proportional hazards model is different from that of the other two regressions: a positive coefficient indicates a higher hazard (and lower chance of survival). All variables except direct selling share are log-transformed.
Significance level: *p<0.1; **p<0.05; ***p<0.01

C.4 Alternative Time Windows for Predictors and Survival Measures

We repeat the analyses using predictors and survival measures with redefined time windows (first/last 3 and 5 weeks) and show the results in Tables A6 and A7.

Table A6: Evaluation of the trained model on the test data: predictors and survival measures based on first/last 3 weeks

Survival threshold	Accuracy	Precision	Recall	F1	AUC
0%	0.758 (0.007)	0.795 (0.005)	0.884 (0.008)	0.837 (0.005)	0.795 (0.007)
20%	0.650 (0.009)	0.658 (0.008)	0.688 (0.009)	0.672 (0.008)	0.701 (0.009)

Note: Results are averaged over 10-fold cross-validation iterations. Standard errors are provided in parentheses.

Table A7: Evaluation of the trained model on test data: predictors and survival measures based on first/last 5 weeks

Survival threshold	Accuracy	Precision	Recall	F1	AUC
0%	0.792 (0.007)	0.818 (0.004)	0.933 (0.006)	0.872 (0.004)	0.810 (0.009)
20%	0.661 (0.011)	0.677 (0.010)	0.746 (0.009)	0.710 (0.009)	0.705 (0.011)

Note: Results are averaged over 10-fold cross-validation iterations. Standard errors are provided in parentheses.

C.5 Prediction results of survival with 20% volume growth rate as the threshold

We present the prediction results using the survival definition with 20% volume growth rate as the threshold.

Table A8: Evaluation of the trained model on test data: survival threshold 20%

Survival threshold	Accuracy	Precision	Recall	F1	AUC
20%	0.650 (0.009)	0.664 (0.009)	0.712 (0.009)	0.687 (0.008)	0.696 (0.009)

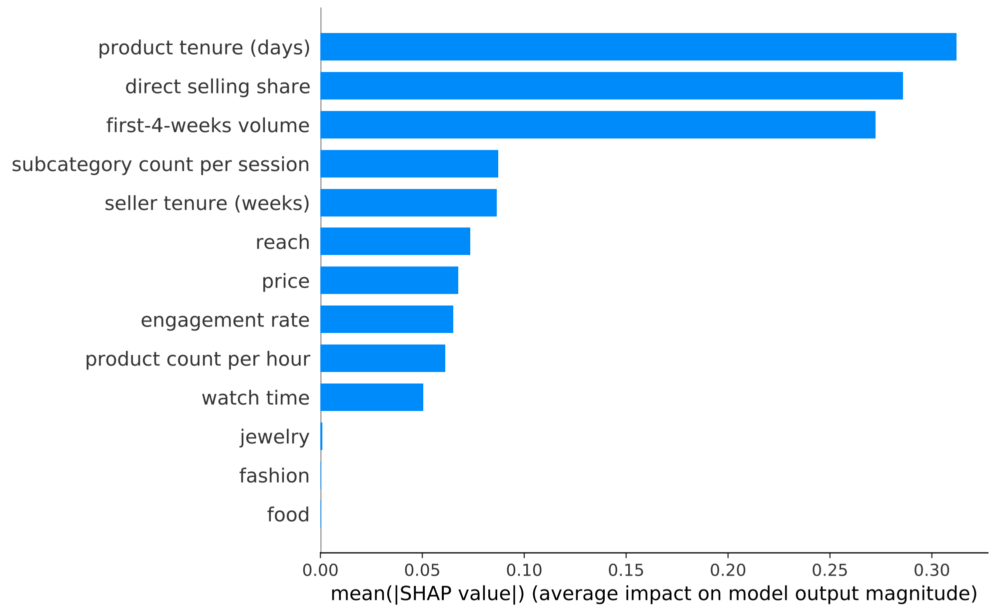
Note: Results are averaged over 10-fold cross-validation iterations. Standard errors are provided in parentheses.

Table A9: Model accuracy with different feature sets: survival threshold 20%

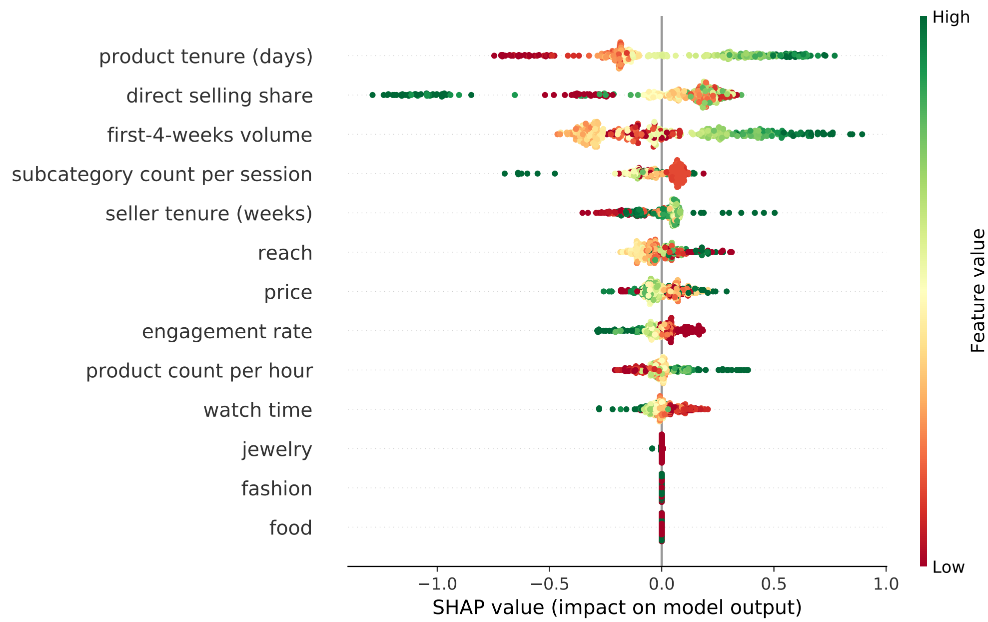
	Accuracy	Precision	Recall	F1	AUC
Baseline	0.550 (0.011)	0.566 (0.008)	0.711 (0.016)	0.630 (0.011)	0.562 (0.012)
Baseline + KPIs	0.611 (0.007)	0.634 (0.007)	0.661 (0.008)	0.647 (0.007)	0.649 (0.006)
Baseline + KPIs + direct selling share	0.638 (0.007)	0.646 (0.007)	0.729 (0.008)	0.685 (0.006)	0.680 (0.008)
Baseline + KPIs + direct selling share+ marketing mix	0.650 (0.009)	0.664 (0.009)	0.712 (0.009)	0.687 (0.008)	0.696 (0.009)

Note: Baseline includes seller tenure and seller categories. Results are averaged over 10-fold cross-validation iterations. Standard errors are provided in parentheses.

Figure 7: Features ranked in order of importance for predicting survival (20% volume growth rate) based on (a) mean (|SHAP value|) and (b) the SHAP value for all sellers



(a)



(b)