The Power of Livestream Shopping: Boosting Revenues and Catalyzing Spillovers*

Weiqing Zhang† Rice University

Zekun Liu‡ Indiana University

Xiao Liu§ New York University

Eitan Muller¶ New York University

Abstract

Livestream shopping has attracted significant attention in the e-commerce world, but its actual benefits for online sellers are still under debate. We investigate how adopting the livestream shopping channel affects seller performance by analyzing 2,851 online sellers who used this sales channel from September 2019 to June 2020. After applying multiple estimators to address a series of identification challenges, we find that adopting this channel boosts the sellers' total revenue by 105.9%. Notably, 46.2% of this revenue increase comes from the online store channel, indicating a positive cross-channel spillover effect from the livestream shopping to the online store channel. The adoption of the livestream shopping channel proves especially advantageous for small-scale sellers, enabling rapid expansion and increased competitiveness in the e-commerce marketplace. In addition, we find that the sellers' use of livestream shopping not only helps reduce product uncertainty through information provision but also strengthens the consumer-seller relationship. Moreover, despite the average price for the same product being 7.3% lower in the livestream shopping channel than in the online store channel, which may partially drive the overall revenue increase, the distinctive attribute of livestream shopping—enhanced visibility of price promotions—does not explain the cross-channel spillover effect.

Keywords: multichannel, livestream shopping, small business owner, uncertainty reduction, consumer-seller relationship, promotion visibility

*The paper was previously circulated under the title "Doubling Revenues by Adopting Livestream Shopping: A Synthetic DiD Approach". This work is supported by Henry Assael PhD Student-Faculty Joint Research Grant. We are grateful to Alibaba for providing the data. Xiao Liu worked as a visiting scholar at Alibaba.

†wz60@rice.edu

‡zl73@indiana.edu

§xliu@stern.nyu.edu

¶em101@stern.nyu.edu

1 Introduction

Small business owners often turn to online shopping platforms such as eBay and Taobao to launch their ventures, drawn by these platforms' affordability and flexibility. However, critics frequently point out online shopping platforms' shortcomings in providing sufficient product information and helping sellers build connections to consumers.[1][2] This challenge is especially acute for small businesses, whose brands and products are less recognized by consumers. Opening offline channels, such as brick-and-mortar stores and showrooms, in addition to online channels, emerges as a solution to this problem. Yet, for many small businesses, this solution is impractical because of its high cost.[3]

In recent years, small business owners have found a new ally in livestream shopping, an innovative e-commerce model that uses video streaming to showcase products live. This trend, which started in China in 2016, has quickly caught the attention of global e-commerce giants such as Amazon and eBay, spreading rapidly across the world.[4][5]By 2026, the livestream shopping market in the United States is projected to hit $68 billion.[6] Notably, livestream shopping has gained significant traction among small business owners. In 2021, small online store owners on Taobao conducted 70% of their livestream sessions on Taobao Live, China's leading livestream shopping platform.

Despite the growing popularity of livestream shopping, the specifics of its benefits for online sellers remain largely unexplored. Our paper fills this gap by causally quantifying the benefits of adopting the livestream shopping channel and investigating its underlying mechanisms. Our work conceptually ties to the nascent literature on multichannel marketing, which primarily focuses on distinguishing between complementary and substitute relationships among various channels. Yet, studies specifically examining livestream shopping as a distinct channel are rare. This scarcity is often due to the early association of livestream shopping with influencer marketing, where livestreamers were not typically online store or brand owners, leading to the classification of livestream shopping as a promotion strategy.[7] We aim to narrow this gap by analyzing Alibaba's ecosystem, which includes Taobao as the online shopping platform and Taobao Live for livestream

[1] Source: https://www.prefixbox.com/blog/online-shopping-problems/

[2] Source: https://shorturl.at/THXQB

[3] Source: https://www.evantagestore.com/blog/32/Key-Differences-between-Online-and-Offline-Selling/

[4] Source: https://www.amazon.com/live

[5] Source: https://www.ebayinc.com/stories/news/ebay-launches-live-shopping-for-collectibles/

[6] Source: https://shorturl.at/cprGL

[7] Previous research on livestream shopping has largely concentrated on influencer marketing (e.g., Gu et al., 2022). However, in 2021, it was store owners or sellers, not influencers, who hosted 70% of livestream sessions, prompting our investigation into this overlooked aspect of seller-hosted livestream shopping.

shopping, where sellers operating on Taobao also manage their livestream channels on Taobao Live. Moreover, we investigate if this emerging channel offers particular benefits to small business owners, aligning with the observed trend.

In addition to uncovering the value of the livestream shopping channel, we delve into *how* it could benefit the existing online store channel through three potential mechanisms. First, the livestream shopping channel may act as an informative marketing communication tool, offering details about product attributes and quality, to reduce consumer uncertainty. This function mirrors that of certain traditional offline channels (e.g., Bell et al., 2018). We refer to this effect as the *uncertainty reduction* effect. Second, the livestream shopping channel can also act as a bridge connecting consumers to sellers. Livestreaming technologies, by virtue of their ability to traverse geographical boundaries, allow offering content that is not only highly engaging and entertaining but also adept at fostering feelings of affection and warmth among audiences (e.g., Liu et al., 2022). Such characteristics of livestreams empower consumers to discover new sellers and to re-engage with familiar ones, thereby facilitating the establishment of trustworthy and positive connections. This phenomenon is beyond the "billboard effect" identified in extant literature (e.g., Wang and Goldfarb, 2017), highlighting the dual role of livestreams in both initiating consumer awareness of sellers and sustaining ongoing relationships between them. We refer to this as the *consumer-seller relationship* effect. Third, livestream shopping uniquely enhances the visibility of price promotions by prominently displaying them at the center of the screen, in contrast to the online store channel where promotions (such as discount codes, coupons or rebates) are often displayed less prominently.[8] Livestreams can make these promotions more visible, prompting consumers to seek and apply the promotional codes in the online store channel, thus increasing their likelihood of shopping there. We call this effect the *promotion visibility* effect, a third potential mechanism that could make the livestream shopping channel complementary to the online store channel. We empirically examine these three mechanisms to understand how livestream shopping benefits sellers' online stores.

We collect data from Alibaba's online shopping ecosystem, covering $2,851$ sellers who had operated their online stores on Taobao before February 2019. These sellers come from three categories: fashion essentials, food, and jewelry. From September 2019 to June 2020, they gradually started adopting the livestream shopping channel on Taobao Live. We track the revenue for each seller in the online store channel before these sellers' adoption of livestream shopping and in both channels

[8] In our context, consumers need to manually apply promotional codes on the platform (See Liu, 2022). Please refer to Section 7 for details.

(the online store and livestream shopping channels) after its adoption. Additionally, we observe transactions from a representative group of consumers. Using this dataset, we aim to causally determine the impact of adopting the livestream shopping channel on seller performance and uncover the underlying mechanisms.

To identify the treatment effect, we adapt to the staggered adoption and tackle a range of identification challenges by employing the synthetic difference-in-differences (SynDiD) estimator, as proposed by Arkhangelsky et al. (2021) and Berman and Israeli (2022). We also conduct additional analyses, including the consumer-level ones, to rule out endogeneity caused by unobserved confounders and to demonstrate the robustness of the results. To investigate the three potential mechanisms, we conduct analyses at both the product and seller levels. Specifically, to see if livestreams offer detailed product information and reduce consumer uncertainty about product attributes, we explore whether products with more attributes that livestreams are able to highlight benefit more significantly. To examine the consumer-seller relationship mechanism, we investigate whether products not showcased in livestreams (and therefore not benefiting from the *uncertainty reduction* effect) still gain from the seller's adoption of the livestream shopping channel. To assess whether the increased visibility of promotions in livestreams influences the customers' behavior of applying the same promotional codes in the online store channel, we analyze changes in the transaction prices for the same product both within and across channels.

Several findings emerge from our analyses. First, we outline the key findings regarding the effect of adopting the livestream shopping channel on seller performance.

- **Revenue Increase.** Adopting the livestream shopping channel leads to an increase in sellers' total revenue by 105.9%, equating to a 2,937 CNY increase over six weeks for a median-sized seller in our dataset.[9]
- **Spillover.** The fact that 46.2% of this revenue increase originates in the sellers' online store channel means the livestream shopping channel generates a positive spillover and complements the online store channel effectively.
- **Empowerment of Small-scale Sellers.** Small-scale sellers experience a disproportionate advantage. This finding highlights the potential of livestream shopping to enhance these sellers' competitiveness.

Next, we summarize the findings from our analysis of the three potential mechanisms.

[9] The Chinese yuan (CNY) is the official currency of China. As of June 1, 2024, the exchange rate from the US dollar (USD) to CNY stands at 7.2.

- **Uncertainty Reduction Effect.** Our analysis indicates the role of livestreams in providing information and reducing consumer uncertainty about product attributes. Specifically, we show that products with more attributes to showcase, such as the fit-and-feel attribute of apparel or the freshness attribute of fresh food, gain more from livestream introductions compared with other products, such as accessories and snacks.
- **Consumer-seller Relationship Effect.** We provide evidence that livestreams may help build stronger consumer-seller relationships, as sales in the online store channel increase even for products not featured in livestreams.
- **Promotion Visibility Effect.** Our analysis highlights the role of the enhanced promotion visibility of the channel by showing that the average transaction price for the same product is 7.3% lower in the livestream shopping channel than in the online store channel. However, the transaction price in a seller's online store channel remains unchanged after the seller adopts livestream shopping. This finding indicates that increased promotion visibility does not lead consumers to apply the promotional codes more in the online store channel. Thus, this result does not explain the positive spillover effect.

Our findings highlight the role of the livestream shopping channel in e-commerce and have managerial implications for various stakeholders. On the one hand, our results are relevant for online store owners. Understanding the impact of adopting the livestream shopping channel helps online sellers make informed decisions. Additionally, we identify two mechanisms for the positive spillover effect from the livestream shopping channel to the online store channel: the *uncertainty reduction* and the *consumer-seller relationship* effects. These results can help direct sellers specializing in different product categories toward the most appropriate mechanism for their daily operations. On the other hand, our results are relevant for e-commerce platforms, as they emphasize the importance of motivating online sellers to become livestreamers, thus invigorating the e-commerce ecosystem.

We organize the rest of the paper as follows. Section 2 reviews the related literature. Section 3 introduces the institutional background, and Section 4 describes the data. We outline the empirical strategy in Section 5, and in Section 6 we report the results about the impact of adopting the livestream shopping channel. In Section 7, we discuss the potential mechanisms. And, finally, in Section 8, we present our conclusions, discuss the practical insights and limitations of our results, and offer suggestions for future research.

2 Literature Review

Our paper contributes to four streams of literature: multichannel marketing, modernization of retail in emerging markets, information communication on digital platforms, and livestream shopping.

Firstly, our paper contributes to the multichannel marketing literature, specifically, on whether and how a new channel complements the online channel. A canonical paper, Avery et al. (2012), introduces a conceptual framework illustrating how the adoption of an offline channel can complement the online channel. Building on this framework, recent research has examined various offline channels and explored the underlying reasons for their complementary role. For instance, Wang and Goldfarb (2017) identify the billboard effect of opening a brick-and-mortar store, suggesting that the offline channel plays an informative role in communicating the existence of a brand. Bell et al. (2018) demonstrate how online retailers employ showrooms to provide information about product attributes. In addition, researchers have also analyzed the mobile channel's uniqueness and its complementary nature to the online channel. Ghose et al. (2013) suggest that search costs and geographical proximity contribute to the uniqueness of mobile app shopping and therefore its complementarity to the online channel. Narang and Shankar (2019) investigate the buying and returning behaviors of users of mobile shopping apps, finding that these users tend to purchase more than those who shop in online stores. Gu and Kannan (2021) show that a user's adoption of a focal retailer's mobile app may negatively affect the consumer's purchases in a competitive marketing environment. The literature extends to the synergies between the online channel and other channels such as tablet shopping (Xu et al., 2017), pop-up stores (Zhang et al., 2019), and voice AI shopping (Wang et al., 2020; Sun et al., 2024). Our work adds to this body of literature by empirically investigating the impact of adopting livestream shopping, an innovative e-commerce model. We find that the livestream shopping channel benefits online sellers by strengthening consumer-seller relationships and reducing consumer uncertainty about product attributes. Our results suggest that sellers who specialize in different product categories can use the most suitable channel of the two mechanisms to inform their operational strategies and reap the livestream shopping channel's benefits.

Secondly, our paper expands the literature on retail modernization in emerging markets by examining the potential role of livestream shopping as an equalizer in the retail and e-commerce world. Bronnenberg and Ellickson (2015) analyze the widespread trend toward retail modernization in emerging markets, including the rise of online retail. Anderson et al. (2022) conceptualize modernization as the adoption of the physical structures and operational practices of organized retail chains; the authors use field experiments to underline the beneficial impact of modernization in emerging markets. Our study positions livestream shopping as a new facet of retail modernization, especially relevant in the context of the booming e-commerce sector in emerging markets. Goldmanis et al. (2010) suggest that the advent of e-commerce might disadvantage small, high-cost retailers. In contrast, our analysis indicates that livestream shopping, within the e-commerce landscape, could serve to level the playing field by offering particular advantages to small business owners.

Thirdly, our paper is closely related to the discussion on how online platforms can communicate seller information, including the seller's existence, traits, quality, and product attributes. Researchers have examined the effectiveness of various marketing communication tools from the seller's perspective, such as pricing (Gerstner, 1985; Mamadehussene, 2019), advertising (Sahni and Nair, 2020; Sahni, 2016), customer relationship management (Ou et al., 2014), high-quality images (Zhang et al., 2021), and seller profiles and portraits (Troncoso and Luo, 2023). Platforms also play a crucial role in facilitating the dissemination of information about sellers through visualization media (Hong and Pavlou, 2014), reviews and feedback (Pavlou and Dimoka, 2006), certification and reputation systems (Hui et al., 2016, 2022), and the mandatory disclosure of social information (Rong et al., 2022). Our work extends these studies by investigating how livestream shopping serves as a medium for communicating seller and product information to consumers, and by assessing its impact on seller performance.

Lastly, our paper contributes to the nascent literature on livestream shopping, which has primarily focused on its impact within the realm of influencer marketing. Studies in this area have examined how factors such as influencer popularity, emotion, and persuasiveness (Gu et al., 2022; Lin et al., 2021; Li and Han, 2024), negotiations between brands and influencers (Gui et al., 2022), and the content of livestreams (Cheng et al., 2019; Wang et al., 2022) affect the effectiveness of livestream shopping. Unlike works that focus on the influencer marketing domain, our study examines livestream shopping in the multichannel context, where online sellers manage their own livestreams. The studies most closely related to ours include the following. Cong et al. (2021) investigates the price elasticity of demand for live content before and after livestreams in a creator economy setting. Liu (2022) examines the optimal coupon targeting strategy during livestream sessions through batch deep reinforcement learning. Liu et al. (2022) look into the factors determining seller survival and success following the adoption of the livestream shopping channel. Our contribution lies in causally quantifying the impact of adopting the livestream shopping channel in the multichannel context and uncovering the mechanisms in which livestream shopping complements the online store channel.

3 Institutional Background

Our study focuses on Taobao, the leading online marketplace in China, capturing 40% of the market share.[10] Distinct from Tmall, another Alibaba subsidiary catering to established brands, Taobao is famous for its openness and affordability, attracting millions of small-scale entrepreneurs. The merchants in our dataset span three categories: fashion essentials, food, and jewelry. Predominantly, these merchants either manufacture their products or collaborate closely with manufacturers to offer bespoke items, and use Taobao to market their unique brand offerings. While a minority of shops act as retailers showcasing various third-party brands, these shops typically cultivate a distinctive brand identity that resonates with consumers. For example, stores similar to Zumiez present a curated mix of brands under a cohesive theme (in this case, "organized chaos," mirroring the adolescent lifestyle). Such an approach suggests these sellers prefer to align closely with brands that mirror their established image.

In 2016, Alibaba launched Taobao Live, its livestream shopping platform, with the goal of offering a novel online shopping experience. Over the years, Taobao Live has evolved from a platform primarily featuring influencers to one dominated by sellers themselves, as outlined in Liu et al. (2022). This evolution means that rather than competing for airtime in an influencer's broadcast—which might feature a variety of brands and products—sellers with storefronts on Taobao now use Taobao Live to host their own livestream sessions. This shift allows them to exclusively showcase and discuss products from their own stores. This seller-centric approach offers several advantages. Firstly, it is more cost-effective, since securing a slot in a popular influencer's livestream can be prohibitively expensive, costing up to millions of CNY.[11] Secondly, sellers can present more precise and comprehensive information about their products and brands. They can thus make the most of the interactive and engaging nature of livestream shopping.

Figure 1 illustrates the user interface of a typical Taobao Live livestream session hosted in the seller-centric environment. In this scenario, as sellers showcase a product (a package of mixed nuts in this example), potential consumers have the opportunity to engage with the seller through likes,

[10] Source: https://www.statista.com/chart/22519/biggest-b2c-e-commerce-platforms-china/
[11] Source: https://36kr.com/p/1504362860512389

shares, and subscriptions. Additionally, consumers can interact directly with the sellers by posting questions or comments in the comment box. This box appears on the bottom left of the screen and is visible to the sellers and all consumers. This setup facilitates real-time communication, allowing the sellers to respond to specific comments. The top left corner features a link to the seller's Taobao online store, emphasizing the seller-centric nature of the platform. Consumers can access a product list through the item pocket, with detailed information about the current product highlighted at the top, followed by details on previously showcased products. Should a consumer decide to purchase an item through the item pocket, the sale is attributed to the livestream shopping channel, distinguishing it from purchases made through the seller's online store channel. This differentiation enables the analysis of transactions originating in distinct channels. Notably, the selection of products featured in a seller's livestreams represents a subset of the broader range of products available in the seller's online store. This means that all products introduced during a seller's livestreams are also accessible in the seller's online store.

Figure 1: An example of a livestream session on Taobao Live

The integration of Taobao and Taobao Live offers an opportunity to examine sellers' strategies across multiple channels, particularly highlighting the significance of the livestream shopping channel. This channel stands out due to its unique characteristics that differentiate it from traditional marketing approaches. For example, it shares certain similarities with home shopping networks (e.g., QVC), such as the format of presenting products to consumers. However, in shopping networks, the video content may be partly pre-recorded, is introduced by anchors rather than sellers, and lacks interactive components. In contrast, livestream shopping on platforms such as Taobao Live is predominantly live, fostering real-time engagement between the seller and potential consumers. The direct interaction environment of livestream shopping distinguishes it from passive, influencer-driven promotional methods and conventional commercials. One may argue that, in contrast to online and physical stores where buyers independently seek out product information, livestream shopping involves a less flexible scenario where sellers usually dictate the products showcased, as in traditional commercials. Yet, livestream shopping allows immediate consumer feedback and interaction, enabling real-time adjustments to the products presented. Therefore, livestream shopping is a uniquely interactive and dynamic channel, offering a more engaged and responsive shopping experience than traditional commercials.

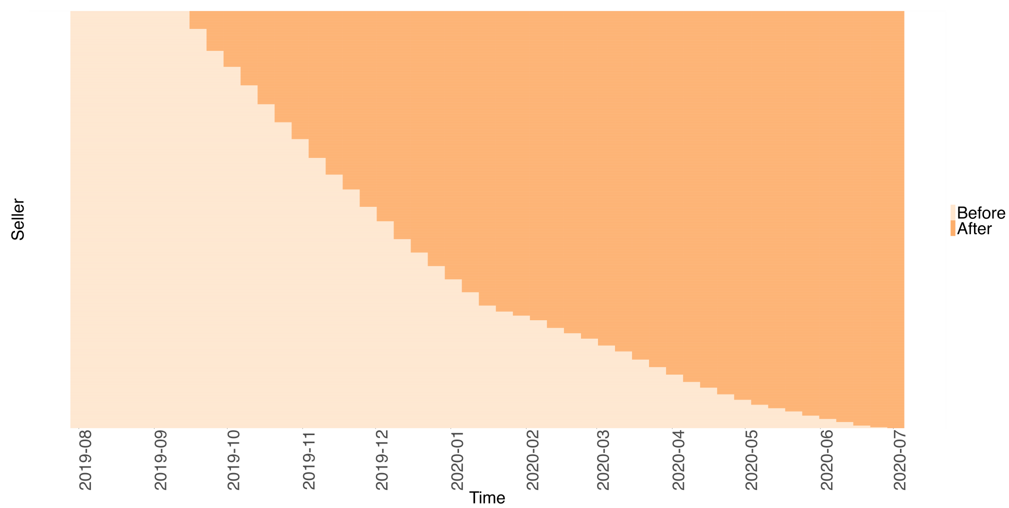
4 Data

Our data come from Alibaba's e-commerce platforms, Taobao and Taobao Live. The dataset we use comprises 3,643 sellers observed from August 2019 to June 2020. These sellers adopted the livestream shopping channel in a staggered fashion from September 2019 to June 2020, and all of them had been online sellers on Taobao before August 2019. For each seller, we track sales (revenue), quantity sold, and the number of transactions in the online store channel before and after the seller's adoption of the livestream shopping channel, and in the livestream shopping channel after its adoption. We aggregate the data at the biweekly panel level.[12] All sellers in our data eventually adopted the livestream shopping channel. Therefore, we rely on the staggered fashion of their adoption of this channel and treat the sellers as control units during the period before their adoption of the livestream shopping channel, similarly to the approach in Manchanda et al. (2015). Figure 2 illustrates the dynamics of the adoption of the livestream shopping channel. We further select sellers who had been running their online stores since February 2019, six months prior to the beginning of our observation period. We thus ensure that our sample includes those sellers who are committed to their online store channel on the platform. We obtain a sample of 2,851 sellers, which we use for analyzing the treatment effect of adopting the livestream shopping channel. We

[12]We have conducted a robustness check and verified that the weekly panel yields the same results.

also perform a robustness check using the entire sample. Moreover, given that our observation period includes the COVID-19 outbreak, we conduct another robustness check by excluding the observations after December 2019. Both robustness checks, presented in Appendix A, show that our findings remain qualitatively consistent.

Figure 2: Treatment Variation Plot



We report the seller-panel level summary statistics in Table 1. The distributions of variables tend to be left-skewed, because most sellers in our sample are small business owners. Therefore, we perform a robustness check that excludes the top 1% of sellers by average sales (shown in Appendix A) and find that all results display qualitatively similar patterns. Table 2 presents the category distribution (fashion essentials, food, and jewelry) of the 2,851 sellers in our dataset.

Table 1: Seller Panel Summary Statistics

Variable	N	Mean	SD	Min	Max
Panel A: Online Store Channel					
Quantity Sold	57,020	1,817	15,682	0	1,736,053
Number of Transactions	57,020	683	4,760	0	190,725
Sales (CNY)	57,020	86,760	399,399	0	9,866,777
Panel B: Livestream Shopping Channel					
Quantity Sold	28,948	1,085	13,718	0	816,793
Number of Transactions	28,948	101	1,012	0	80,346
Sales (CNY)	28,948	13,654	78,862	0	3,145,321

Note: The table reports the seller panel summary statistics for the online store channel (Panel A) and the livestream shopping channel (Panel B). Panel A is based on data from 20 time periods for 2,851 sellers. Panel B is based on data from the period after the adoption of the livestream shopping channel by these sellers.

Table 2: Seller Distribution Across Categories

Category	Frequency	Percentage
Fashion Essentials	1,946	68.3
Food	643	22.6
Jewelry	262	9.2
Total	2,851	100

Note: The table reports the seller distribution across the categories in our sample.

In addition to sales data, we observe details about the livestream sessions conducted by each seller. In the six weeks following their initial adoption of the livestream shopping channel, 11.7% of the sellers in our sample conducted only one livestream session. Across the sessions conducted by the 2,851 sellers in our sample, the average and median numbers of unique viewers are 919 and 160, respectively. The average and median conversion rates, i.e., the percentages of unique consumers who watched the livestream session and made a purchase during it, are 1.42% and 0.28%, respectively.

In addition to seller-level data, we collect a random sample of consumer-level data. The data are limited to 1,308 sellers and 5,060,816 consumers (4.4% of these sellers' total number of consumers) due to the company's privacy measures, which restrict our data access and prevent a comprehensive analysis across all sellers and consumers. Within the available sample, 3.2% are overlapping consumers who purchased from multiple sellers. We observe whether and when a consumer watched livestreams on the platform. Further, we track every transaction made by these consumers on both channels. However, the company's data policy prevents us from obtaining consumer-level demographic details. We use the consumer-level dataset to recover product information, including the prices of the same product sold through both the online store channel and the livestream shopping channel over time. In total, there are $339,347$ products in our sample. Table 3 provides the summary statistics of product prices at the product-panel level for both channels.

Table 3: Product Price (CNY) by Channel at the Product-Biweekly Level

Channel	N	Mean	SD	Median
Online Store	735,844	410.66	37722.89	45.04
Livestream Shopping	33,559	143.35	606.45	37.32

Note: The table reports the summary statistics of product prices at the product-panel level for the online store and the livestream shopping channels.

To provide additional support to our seller-level analyses, we construct a sample of existing consumers to investigate changes in consumer behavior after the consumers watch livestreams. An existing consumer is defined as someone who had made at least one purchase from a seller before the seller's adoption of the livestream shopping channel. Employing this selection criterion yields a sample of 237,156 consumers across 626 sellers. Similar to how we treat the data at the seller level, we aggregate consumer transactions at the biweekly panel level. We present the summary statistics in Table 4.

Table 4: Consumer Panel Summary Statistics

Variable	N	Mean	SD	Min	Max
Panel A: Online Store Channel					
Purchase Quantity	4,743,120	0.54	46.56	0	52,680
Purchase Frequency	4,743,120	0.17	1.19	0	542
Purchase Amount (CNY)	4,743,120	22.03	702.50	0	594,989
Panel B: Livestream Shopping Channel					
Purchase Quantity	164,135	1.14	49.47	0	9,394
Purchase Frequency	164,135	0.16	2.31	0	344
Purchase Amount (CNY)	164,135	26.59	672.09	0	61,687

Note: The table reports the consumer panel summary statistics for the online store channel (Panel A) and the livestream shopping channel (Panel B). Panel A is based on data from 20 time periods for 237,156 consumers. Panel B is based on observations after consumers watched their first livestreams. Purchase quantity refers to the total number of products purchased during a time period. Purchase frequency refers to the number of transactions made within that period. Purchase amount refers to the total monetary value of all transactions within that period.

5 Empirical Strategy

In this section, we outline our empirical strategy for assessing how adopting the livestream shopping channel affects seller performance. First, we discuss identification challenges in our empirical context. Then, we introduce the estimators and discuss how they can address the challenges.

5.1 Identification Challenges

Our objective is to assess the impact of adopting the livestream shopping channel on seller performance. We analyze data from sellers who adopted the channel at different times. This staggered adoption enables us to use the sellers who have not adopted this channel as a control group (Manchanda et al., 2015). However, we do not observe any sellers who never adopt the livestream shopping channel during our study period. As a result, we estimate the effect of the adoption as the average treatment effect on the treated (ATT) rather than the average treatment effect (ATE). This is because we cannot evaluate if the sellers who did not adopt the channel (and are thus not present in our dataset) are systematically different from the sellers we observe. If the sellers in our dataset are more likely to benefit from the adoption of the livestream shopping channel, then the ATT might be greater than the ATE. However, this scenario should not be a major concern, given the widespread popularity of livestream shopping and resources for channel management, which make the adoption of this channel a common step for sellers on the platform.[13] Therefore, given a substantial percentage of the sellers are likely to adopt the livestream shopping channel eventually in practice, our ATT estimate remains relevant for various stakeholders, including sellers and the platform. Moreover, even in a hypothetical scenario where sellers were randomly assigned to adopt this channel, those sellers opposed to its adoption would face a noncompliance issue, making the ATE estimate potentially less informative.

To identify the ATT, we must navigate the following hurdles. Firstly, the method we use must be capable of calculating a time-variant treatment impact. Specifically, given the staggered nature of the adoption of the livestream shopping channel, the estimator must adjust for varied treatment effects across sellers who adopt this channel at different time periods.

Secondly, traditional methods such as the two-way fixed effect difference-in-differences (TWFE) model typically assume that treated and control groups exhibit parallel trends. However, this assumption may not hold in our context because of the staggered nature of the channel adoption.

Thirdly, the sellers' staggered adoption of the livestream shopping channel suggests that the decision to adopt this channel may be strategic. Sellers who believe the livestream shopping channel suits their needs better might adopt it earlier. Although this scenario may not be prevalent in our context, given that most small-scale sellers lack access to strategic planning resources at early stages,[14] our estimation technique should account for the strategic nature of the livestream shopping channel adoption.

Lastly, it is possible that sellers take concurrent, yet unobserved, actions (such as implementing an inventory optimization tool) in addition to adopting the livestream shopping channel. Furthermore, the adoption of this channel could bring platform-driven advantages, such as enhanced search rankings.

[13]Source: https://zhuanlan.zhihu.com/p/88369126

[14]Source: https://shorturl.at/3qts6

5.2 Empirical Methods

5.2.1 TWFE Estimator

We begin with the TWFE model, which is extensively used in marketing research. Considering that all sellers in our dataset eventually adopted the livestream shopping channel, we follow Manchanda et al. (2015), truncate the data in April 2020, and categorize all sellers who adopted this channel after this date as control units. The TWFE model is specified as follows:

$$y_{it} = \alpha_i + \tau_t + \beta^{TWFE} D_{it} + \epsilon_{it}, \tag{1}$$

where y_{it} represents the logged revenue of seller i at time t; α_i and τ_t represent the seller and time fixed effects, respectively; D_{it} indicates whether seller i has adopted the livestream shopping channel at time t; ϵ_{it} is the idiosyncratic error term; and β^{TWFE} estimates the ATT. Although we use the TWFE model as the baseline method, it cannot accommodate any of the identification challenges mentioned above.

5.2.2 SynDiD Estimator

To accommodate as many of the challenges as possible, we employ the synthetic difference-in-differences (SynDiD) method introduced by Arkhangelsky et al. (2021). This estimator merges the strengths of the TWFE and the synthetic control methods. Like the TWFE method, the SynDiD method remains unaffected by additive shifts at the unit level and supports inference in large panels. Additionally, akin to the synthetic control method, the SynDiD method recalibrates pre-treatment period outcomes and control unit outcomes to generate synthetic units, thus not relying on the strict assumption of parallel trends.

Given that the sellers in our dataset adopt the livestream shopping channel in a staggered fashion, we follow Berman and Israeli (2022) to conduct the estimation for each cohort, and then aggregate the estimates to obtain the average treatment effect. To perform the estimate, we construct a balanced panel for each cohort g. We obtain the cohort-specific estimator, β_g, by solving the following optimization problem:

$$(\hat{\beta}_g, \hat{\theta}) = \arg\min_{\beta_g, \theta} \left\{ \sum_{i \in N_g} \sum_{t=\mu(g)}^{\nu(g)} \left(y_{it} - \alpha_i - \tau_t - \beta_g D_{it}\right) \hat{\omega}_i \hat{\lambda}_t \right\}, \tag{2}$$

where θ contains the seller and time fixed effects, i.e., $\theta = (\alpha_i, \tau_t)$; N_g is the set of sellers of cohort g; D_{it} indicates whether seller i has adopted the livestream shopping channel at time t; and β_g is the cohort-specific treatment effect. The average treatment effect, β^{SynDiD}, is defined as the average of the cohort-specific treatment effects across all cohorts, i.e., $\beta^{SynDiD} = \frac{1}{G}\sum_g \beta_g$, where G is the total number of cohorts. Moreover, $\mu(g)$ and $\nu(g)$ denote the pre- and post-adoption period for a cohort g. In our main analysis, we consider the performance for each cohort during 3 biweekly time periods before and after the adoption of the livestream shopping channel. Thus, for the cohort that adopts the livestream shopping channel at $t = 10$, $\mu(g) = 7$ and $\nu(g) = 12$. We conduct a robustness check using 4 biweekly periods before and after the adoption of the livestream shopping channel. The results, presented in Appendix A, remain qualitatively unchanged. The SynDiD method introduces two sets of weights: unit weights, $\hat{\omega}_i$, and time period weights, $\hat{\lambda}_t$. These two sets of weights match the trend of seller outcomes of the two groups and balance the outcome of each control seller in the post-adoption periods to be the weighted average outcome of the pre-adoption periods, respectively.[15]

The SynDiD method addresses the initial three challenges of identification as outlined in Section 5.1. Firstly, it operates as a cohort-based estimator, being able to accommodate heterogeneous treatment effects across various cohorts and adapt well to the staggered nature of adoption. Secondly, it allows for the creation of optimal synthetic units, similar to the synthetic control approach, thus easing the requirements of the parallel trend assumption. Thirdly, with the incorporation of the two types of weights, the SynDiD estimator can provide a consistent estimate of the treatment effect even when the adoption decision is correlated with the seller-level time trend (i.e., a seller's strategic planning on adoption at a specific time), as long as the combined number of control sellers and pre-adoption periods is sufficiently large (Arkhangelsky et al., 2021; Berman and Israeli, 2022). This is the case in our context (see Appendix B for the number of sellers in the treatment and control groups for each cohort). Thus, the estimator addresses most of the identification challenges, and we use it as the main model to interpret our results.[16]

5.3 Unobserved Confounders

The presence of unobserved confounders, which is the last challenge mentioned in Section 5.1, could hinder the accurate estimation of the impact of adopting the livestream shopping channel

[15] Section OA1.1 in the Online Appendix presents a detailed discussion of SynDiD.

[16] Additionally, we explore an alternative estimator, staggered DiD, which can partially address certain challenges. We discuss the method and results of this estimator in Section OA1.2 of the Online Appendix.

on seller performance. Firstly, sellers might simultaneously adopt the livestream shopping channel and make other strategy adjustments, such as refining inventory management. Although we cannot directly observe these adjustments, they could influence seller performance and, as a result, skew the estimated treatment effect. In addition, upon adopting the livestream shopping channel, sellers might benefit from preferential treatment by the platform, such as improved visibility through superior search rankings, leading to increased traffic in their online storefronts. Consequently, the observed increase in revenue for the online store might stem from this enhanced visibility rather than the adoption of the livestream shopping channel itself. To address these potential issues of unobserved confounders, we undertake the following additional analyses.

5.3.1 Consumer-level Analysis

We use the sample of existing consumers and perform multiple analyses to address the concerns of unobserved confounders. In the context of our study, every seller already had a presence on Taobao before adopting the livestream shopping channel. Hence, some consumers purchased from these sellers' online storefronts before these sellers' adoption of the new channel. We categorize these consumers as existing consumers. The consumer-level dataset we have includes not only their purchase history but also whether and when they watched a specific seller's livestreams. By comparing the changes in behavior of the existing consumers who watched the livestreams ("watchers") with those of the existing consumers who did not watch the livestreams ("non-watchers"), we aim to overcome challenges related to unobserved confounders for two main reasons. Firstly, if the introduction of the livestream shopping feature is the primary factor influencing seller performance, rather than concurrent actions, then the changes in watchers' purchasing behavior should be more significant than non-watchers'. In contrast, it is unlikely that concurrent changes would affect the purchasing habits of the two categories of existing consumers in distinct ways. Secondly, although our dataset does not include the platform's search rankings or impressions, any changes to search rankings on Taobao (which is the platform for the online store channel) should impact all consumers equally rather than being tailored to individual behaviors. This is because, during the observational period, Taobao stated that search rankings were primarily influenced by product attributes rather than personalized recommendations.[17] Thus, if our analysis at the consumer level indicates that the changes in watchers' purchasing patterns diverge from non-watchers', we can attribute such discrepancies to the influence of livestream viewing rather than to any advantageous

[17] Source: https://zhuanlan.zhihu.com/p/77039873

search rankings.

This consumer-level analysis faces a challenge due to the absence of randomization between watchers and non-watchers. Essentially, there could be systematic differences between these groups due to both observable and unobservable factors. A recent paper (see Li and Han, 2024) demonstrates that consumers spend more after watching livestreams on the same platform, Taobao; the authors leverage the randomness of consumers' entry times into livestreams as the identification strategy. Although this result supports our argument, we cannot apply the same approach because we do not have granular information about consumers' interactions with livestreams. We address this challenge as follows. For observable differences, we apply propensity score matching to pair non-watchers with watchers who share similar characteristics. This method is commonly used in marketing research for reducing bias from observable differences among consumer groups (e.g., Rubin and Waterman, 2006). To calculate the propensity scores, we use the purchasing data (i.e., amount spent, frequency of purchases, and total number of transactions) before the sellers' adoption of livestream shopping as indicators of a consumer's likelihood to engage with livestreams.

In addition, watchers and non-watchers might also differ due to unobservable factors. For example, a consumer's inherent demand for specific products could lead them to become a watcher and make purchases. To tackle this issue, we employ the interactive fixed effect counterfactual estimator (IFEct, Liu et al. 2024). This estimator is designed to handle unobservables that change over time at the individual level. The IFEct method incorporates an interactive term between these two dimensions. It thus offers a more nuanced control for potential selection biases, especially those specific to individual-level time-varying factors, such as a consumer's particular interest in a seller's offerings at a given time period.

We denote by $Y_{cit}(1)$ and $Y_{cit}(0)$ the potential outcomes for consumer c of seller i in period t, when $D_{cit} = 1$ and $D_{cit} = 0$, respectively. Here D_{cit} indicates the treatment status, i.e., whether consumer c has watched the livestreams held by seller i by time t. The IFEct method assumes that the untreated potential outcomes take the following functional form:

$$Y_{cit}(0) = \delta_{ci} + \tau_t + \iota_{ci}' f_t + \epsilon_{cit}, \tag{3}$$

where δ_{ci} represents the consumer-seller pair fixed effect, τ_t denotes the time fixed effect, f_t is a vector of unobserved common factors in time, and ι_{ci} is a vector of individual unknown factors. The interaction term, $\iota_{ci}' f_t$, then incorporates an unobserved time-variant individual effect that can be decomposed into a multiplicative form. In other words, the interaction term can capture the unobserved, intertemporal variations distinguishing watchers from non-watchers, such as differences in their individual purchasing needs. For the estimation, the key is to obtain the counterfactual outcome $Y_{cit}(0)$ for the treated observations.[18]

5.3.2 Occasional versus Frequent Livestream Sellers

In addition to the consumer-level analysis, which may be criticized for relying on the functional form assumption to alleviate the self-selection concern, we also present supplementary analysis at the seller level. This additional perspective allows us to examine whether the unobserved confounders can explain any changes in seller performance. Specifically, we investigate the differential impact of adopting the livestream shopping channel on sellers who engage in only one livestream session versus those who conduct multiple sessions. Unlike traditional physical retail environments and showrooms, livestream shopping is accessible to consumers solely while sellers host livestream sessions. Logically, it follows that the sellers conducting multiple livestream sessions (i.e., frequent livestream sellers) are likely to see a greater increase in revenue from adopting the livestream shopping channel compared with those who livestream only once (i.e., occasional livestream sellers), all else being equal. Conversely, if concurrent but unobserved actions, such as the use of inventory management tools, play a major role in influencing seller performance, it is reasonable to anticipate that these performance changes would be observed for both occasional and frequent livestream sellers. This is because these background actions are not expected to exclusively impact frequent livestream sellers. Similarly, if the platform prioritizes sellers that adopt the livestream shopping channel in terms of search rankings, we would expect performance changes for both occasional and frequent livestream sellers. To conduct this comparative analysis, we apply our seller-level estimators to the two groups of sellers separately.[19]

This analysis has limitations, particularly as it might be compromised in situations where a seller uses livestream sessions to gather feedback and then adjust their strategies, such as optimizing inventory management, after a few sessions. Furthermore, although the platform asserts that search rankings are based solely on product attributes, this result will be compromised if the platform prioritizes frequent livestream sellers. However, this analysis together with the consumer-level analysis should partially alleviate the concern that the boosted performance of the sellers is only

[18] We present more details and the estimation procedure in Section OA1.4 of the Online Appendix.

[19] In Section OA2 of the Online Appendix, we conduct a series of robustness checks to extend the comparison to occasional and frequent livestream sellers based on different definitions, and the results remain unchanged.

due to unobservables rather than the adoption of the livestream shopping channel.

6 Results

6.1 The Impact of Adopting the Livestream Shopping Channel on Seller Performance

6.1.1 Total and Online Store Channel Revenue

We use the TWFE and SynDiD estimator to identify the ATT of adopting the livestream shopping channel on seller performance.

Table 5 presents the findings from the TWFE and SynDiD analyses. All results are positive and significant, indicating that adopting the livestream shopping channel leads to an increase in a seller's overall revenue. For the remainder of the paper, we will focus on the SynDiD result, as it more effectively addresses the identification challenges highlighted in Section 5.1. The reported coefficient of 0.722 indicates that adopting the livestream shopping channel results in a 105.9% increase in a seller's total revenue (calculated as $\exp(0.722) - 1$). This represents a biweekly revenue boost of 979 CNY, resulting in a total increase of $2,937$ CNY over six weeks for a median seller.

Table 5: The Impact of Adopting the Livestream Shopping Channel on Seller Revenue

	TWFE	SynDiD
Total Rev.	1.049***	0.722***
	(0.151)	(0.058)
Δ Pct	185.5%	105.9%
Online Store Rev.	0.736***	0.398***
	(0.144)	(0.057)
Δ Pct	108.8%	48.9%
Contribution %	58.7%	46.2%
Seller FE	✓	✓
Time FE	✓	✓
Observations	57,020	57,020

Notes: The table reports the average treatment effect of adopting the livestream shopping channel on the seller's total revenue and online store revenue. The results are based on $2,851$ sellers over 20 time periods. For the SynDiD method, we set the post-treatment periods to 6 weeks (3 biweekly time periods). FE means fixed effects. Significance level: *p<0.1; **p<0.05; ***p<0.01

Next, we examine the impact of adopting the livestream shopping channel on a seller's revenue deriving from the online store channel. The SynDiD estimator yields an estimate of 0.398, indicating that a seller's revenue from the online store channel experiences a 48.9% increase (calculated as $\exp(0.398) - 1$) following the adoption of the livestream shopping channel. This equates to an additional 453 CNY in revenue biweekly for a median seller in our sample. The observed revenue boost within the online store channel highlights the presence of a positive cross-channel spillover effect. It thus demonstrates that the adoption of the livestream shopping channel can enhance revenue streams across both channels. Given that a seller's total revenue is derived exclusively from the online store channel prior to that seller's adoption of the livestream shopping channel, comparing the total revenue increase with the revenue increase derived from the online store channel allows us to conclude that 46.2% of the total revenue increase comes from the online store channel.

6.1.2 Discussion on Unobserved Confounders

Up to this point, we have identified the impact of adopting the livestream shopping channel on seller revenue. To eliminate the influence of potential unobserved confounders (refer to Section 5.1), we carry out two distinct analyses. Firstly, we perform analyses at the consumer level to assess changes in purchasing behavior between watchers and non-watchers. Other simultaneous actions by sellers or potential advantages in search ranking provided by the platform are unlikely to impact these two consumer groups differently. Therefore, any observed changes in watchers' purchasing behavior can be attributed to the sellers' adoption of the livestream shopping channel. Secondly, we compare the effects of the adoption of this channel on sellers who livestream frequently with the effects on sellers who livestream occasionally. Should the adoption prove to be advantageous for seller revenue, we anticipate a more pronounced effect for frequent livestream sellers than for occasional ones.

Consumer-level Analysis

We use the consumer-level data to mitigate the issue of endogeneity stemming from unobserved confounding variables. For each seller, we identify existing customers who have made at least one purchase prior to the seller's adoption of the livestream shopping channel. We divide these customers into two groups: watchers (treated group), who start watching the seller's livestreams upon the seller's adoption of this channel,[20] and non-watchers (control group), who do not engage with the seller's livestreams.

[20] In this analysis, we include only those watchers who have watched the livestreams within the first period following the seller's adoption of the livestream shopping channel.

We posit that, by comparing watchers with non-watchers, we can provide supporting evidence that the increase in revenue at the seller level after the seller's adoption of the livestream shopping channel is not entirely attributable to any concurrent but unobserved actions by the seller and any preferential treatments such as enhanced search rankings from the platform. Therefore, if watching livestreams positively influences the purchasing behaviors of watchers while exerting no impact on non-watchers, it would imply that the concurrent actions and preferential treatments cannot exclusively explain the observed positive effect on seller revenue.

Watchers and non-watchers might differ systematically in both observable and unobservable factors, because pure randomization is lacking. Hence, we use propensity score matching to identify non-watchers who resemble watchers in terms of observable characteristics. We perform a balance check of the covariates before and after the matching process. Table A6 in Appendix C.1 demonstrates that after matching, the covariates are well-balanced and show no significant differences in observable factors between the two groups. After the matching process, the dataset includes 7,354 consumers, with each group containing 3,677 individuals.[21]

To address the differences in unobservable factors between the two consumer groups, we use the IFEct estimator. We use all available observations from consumers three periods before and three periods after the sellers' adoption of the livestream shopping channel, yielding a total of 44,124 observations.

Table 6 presents the results. These findings demonstrate statistically significant and positive average treatment effects, indicating that even existing consumers tend to increase their spending and purchase frequency after watching livestreams. This result aligns with the findings in Li and Han (2024), who employ a different identification strategy for a similar consumer-level analysis in the same empirical context. Importantly, this result supports the argument that the observed positive changes in seller performance are not merely the result of unobserved confounders. One should note the treatment effect observed at the consumer level may not fully reflect the extent of the effect at the seller level, because only a partial sample of consumers is available to us. Despite this limitation, we demonstrate that adopting the livestream shopping channel can enhance seller performance, even in the presence of other potential contributing factors.

[21] The reported numbers are the numbers of consumer-seller pairs. Given that only 9 consumers in the sample watched multiple sellers' livestreams, we use the term "consumers" for simplicity.

Table 6: The Effect of Watching Livestreams on Consumer Purchase Amount and Frequency

	Total		Online Store	
	Amount	Frequency	Amount	Frequency
Method: IFEct				
After Watching Livestreams	0.539*** (0.035)	0.122*** (0.007)	0.267*** (0.031)	0.049*** (0.007)
Observations	44,124	44,124	44,124	44,124

Notes: The table presents the average treatment effect of adopting the livestream shopping channel on the total and online store spending amounts and purchase frequencies (biweekly) of existing consumers. The data include 7,354 seller-consumer pairs, matched based on their purchase frequency and amount, using data from 6 weeks (3 time periods) prior to the sellers' adoption of the livestream channel. Panel B displays the estimation results using the IFEct method, based on 7,354 consumers over 6 time periods. Significance level: *p<0.1; **p<0.05; ***p<0.01

Occasional versus Frequent Livestream Sellers

In our sample, 11.7% of sellers engaged in livestreaming only once during the six weeks following their initial adoption of this channel. We classify them as occasional livestream sellers. We analyze the treatment effects on seller performance by comparing occasional livestream sellers with frequent livestream sellers (i.e., those who offered livestreams more than once in the same period). We use propensity score matching to identify frequent livestream sellers that are similar to occasional livestream sellers, based on pre-adoption seller metrics such as positive feedback rate and seller rating. Table A7 in Appendix C.2 details the covariate balance check following this matching process. Then, we estimate the ATT of the adoption of the livestream shopping channel for each group and report the results in Table 7. Frequent livestream sellers experience notable increases in both total revenue and online store channel revenue post-adoption, with surges of 141.6% (calculated as $\exp(0.882)-1$) and 70.9% (calculated as $\exp(0.536)-1$), respectively. Conversely, the impact on revenue for occasional livestream sellers is not statistically significant, indicating that these sellers do not see the same benefits from the adoption of this channel. The findings provide necessary, albeit not sufficient, support for dismissing the explanation that concurrent actions by sellers are the cause of the observed increase in seller performance. This is based on the premise that it is unlikely for concurrent actions to have a disparate impact on the two groups of sellers.

Table 7: The Impact of Adopting the Livestream Shopping Channel on Occasional and Frequent Livestream Sellers

	TWFE		SynDiD	
	Occasional	Frequent	Occasional	Frequent
Total Rev.	−0.209	0.982***	−0.241	0.882***
	(0.191)	(0.279)	(0.154)	(0.171)
Online Store Rev.	−0.226	0.646**	−0.252	0.536**
	(0.190)	(0.265)	(0.153)	(0.168)
Seller FE	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
Observations	6,640	6,640	6,640	6,640

Notes: The table reports the average treatment effect of adopting the livestream shopping channel on the revenue of occasional and frequent livestream sellers. The two types of sellers are matched based on seller-level characteristics. The results are based on 332 occasional livestream sellers and 332 frequent livestream sellers over 20 time periods. FE means fixed effects. Significance level: *p<0.1; **p<0.05; ***p<0.01

6.2 Heterogeneous Effects of the Adoption

Given the evidence supporting the positive impact of adopting the livestream shopping channel, we now explore whether the benefits uniformly apply to all sellers. The seller-centric livestream shopping platform is designed to empower small business owners by providing them with a direct channel to engage with consumers. Given that these sellers likely lack alternative self-promotion and product introduction methods, anecdotal evidence suggests that livestream shopping can have substantial advantages for these sellers, potentially leveling the playing field in today's e-commerce landscape.[22] In this section, we examine the heterogeneous impact of the adoption on sellers of different sizes.

We use two metrics as proxies for seller size: seller credibility rating and subscriber count. On Taobao, a seller's credibility rating mainly derives from the historical transaction volume; the subscriber count reflects a seller's popularity and scale. We use a median split of the two proxies to categorize sellers as either large or small.

Panels A and B in Table 8 present the findings using the two proxies. For both proxies, the outcomes suggest that the effects of adopting the livestream shopping channel are more significant for smaller sellers. For instance, when we use seller credibility rating as a proxy for seller size, we find that the ATT of total revenue for large-scale sellers is 0.494, which is notably lower than

[22] Source: https://shorturl.at/jFGY2

the ATT of 1.592 for small-scale sellers. Thus, the livestream shopping channel may help level the playing field in the e-commerce marketplace, offering small business owners a chance to expand and compete with larger sellers.

Table 8: The Heterogeneous Impact of Adopting the Livestream Shopping Channel on Seller Performance

Panel A: Seller Size–Seller Credibility Rating

	TWFE		SynDiD	
	Large	Small	Large	Small
Total Rev.	0.494***	1.592***	0.249***	1.202***
	(0.137)	(0.184)	(0.070)	(0.090)
Online Store Rev.	0.232*	1.226***	-0.013	0.817**
	(0.134)	(0.173)	(0.069)	(0.087)
Seller FE	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
Observations	28,540	28,480	28,540	28,480

Panel B: Seller Size–Subscriber Count

	TWFE		SynDiD	
	Large	Small	Large	Small
Total Rev.	0.467***	1.634***	0.247***	1.231***
	(0.141)	(0.177)	(0.070)	(0.090)
Online Store Rev.	0.200	1.273***	-0.020	0.849**
	(0.139)	(0.164)	(0.070)	(0.087)
Seller FE	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
Observations	28,540	28,480	28,540	28,480

Notes: The table reports the heterogeneous treatment effect of adopting the livestream shopping channel on seller revenue. Panels A and B present the results using seller credibility rating and subscriber count, respectively, as proxies for seller size. FE means fixed effects. Significance level: *p<0.1; **p<0.05; ***p<0.01

7 Mechanism

Our findings demonstrate that a seller's adoption of the livestream shopping channel significantly increases both their total revenue and online store revenue. This finding suggests a positive cross-channel spillover effect. In this section, we investigate the mechanism behind this spillover. Specifically, we examine how integrating the livestream shopping channel can benefit sellers with preexisting online stores. We explore three potential mechanisms responsible for this effect.

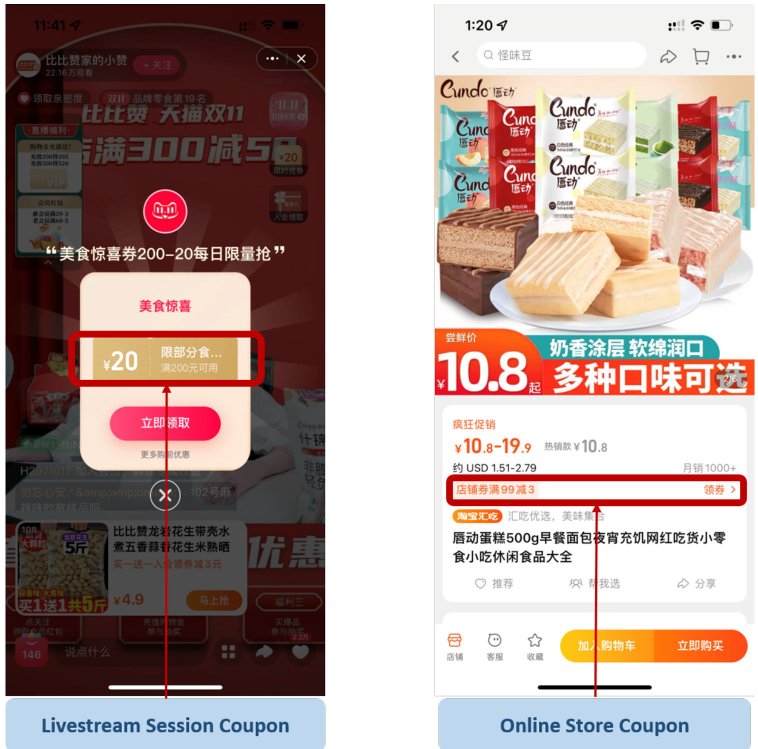
Firstly, sellers can use livestreams to convey product details to consumers. The capability for real-time interaction within livestream shopping platforms potentially makes them more captivating and efficient in providing information than traditional physical stores or showrooms. Consequently, livestream shopping has the *uncertainty reduction* effect: it enhances consumers' comprehension of product attributes. This improved understanding diminishes the ambiguity buyers may have about the products, encouraging increased purchases across both the livestream shopping and the online store channels.

Secondly, livestreams act as a bridge connecting consumers and sellers. Livestreams may offer consumers the opportunity to discover new sellers, revisit and engage with known sellers, and become attracted to charismatic and popular sellers. Unlike the *uncertainty reduction* effect, which focuses on providing information about products, this mechanism centers on the formation of connections between consumers and sellers. As these connections strengthen, consumers are more likely to commit to purchases across both the livestream shopping and the online store channels. We label this as the *consumer-seller relationship* effect.

Lastly, livestream shopping stands out for its prominent display of promotions. The sellers who use livestreams frequently highlight offers such as low prices, coupons, rebates, raffles, and free gifts (Liu, 2022). Although similar promotions may be available in a seller's online store, they are often less noticeable, leading consumers to overlook them and potentially pay more for a product than they would pay in the same seller's livestream shopping channel. Livestream shopping thus plays a crucial role in educating and reminding consumers about these promotions, even those available in the seller's online store. A comparison of coupon promotions in livestreams versus online store channels (Figure 3) reveals that in livestreams, coupons are prominently displayed on the screen, whereas in online stores, coupons must be manually applied from a less obvious location before checkout. The increased visibility of promotions through livestreams encourages consumers to actively look for and apply promotional codes in online stores, potentially boosting revenue for sellers thanks to the appeal of lower prices and increased demand across both channels. We refer to this as the *promotion visibility* effect.

Consequently, an important question emerges: What drives the positive cross-channel spillover effect? We proceed to examine these three aforementioned mechanisms.

Figure 3: Coupons in Livestreams versus Online Stores



7.1 Uncertainty Reduction

To explore whether the livestream shopping channel facilitates the *uncertainty reduction* effect, we compare the treatment effects of introducing products in livestreams across different product subcategories. If the mechanism is valid, we would anticipate a more pronounced treatment effect for products that benefit more from the additional information provided through livestreams.

To test our hypothesis, we analyze two sets of product subcategories. Firstly, within the realm of fashion essentials, we assess whether apparel benefits more from the introduction in livestreams compared with accessories. Our reasoning is that livestreams are particularly adept at reducing uncertainty for apparel products. In this interactive setting, sellers can effectively showcase the texture, style, and design of apparel, and use live modeling to highlight size and fit. On the other hand, the information conveyed about accessories through livestreams tends to be more limited, as these items generally have fewer fit-and-feel attributes. While the interactive nature of livestream shopping channels should also improve consumers' understanding of accessories, it particularly enhances the appreciation of products requiring a deeper understanding of fit and feel. This argument is supported by existing literature (e.g., Wang and Goldfarb, 2017).

Furthermore, within the food category, we investigate the effect of showcasing fresh food versus snacks in livestreams. In our context, snacks are generally packaged food items, whereas fresh food includes produce, meat, and seafood items. This distinction allows the sellers who use livestreams to not only discuss common aspects such as taste and nutrition that apply to all food products, but also highlight the particular attribute of freshness, which is exclusive to fresh food. Freshness is a critical factor for consumers considering the purchase of fresh food online.[23] Livestream shopping alleviates this concern by offering strong evidence of this important quality attribute through product displays. Consequently, we anticipate a more pronounced average treatment effect of livestream introductions on fresh food than on snacks, driven by the enhanced assurance of quality that livestream shopping facilitates.

We apply the product-level difference-in-differences model to products across different subcategories, using the following econometric form:

$$y_{lt} = \gamma_l + \tau_t + \kappa D_{lt} + \epsilon_{lt}, \tag{4}$$

where y_{lt} is product l's logged sales at time t; γ_l and τ_t are the product and time fixed effects, respectively; D_{lt} is an indicator equaling 1 if the product has been introduced in livestreams, and 0 otherwise; and κ is the coefficient of interest, measuring the product-level average treatment effect of livestream introductions.[24]

Panels A and B of Table 9 present the findings for the two sets of product subcategory comparisons. Panel A indicates that both apparel and accessories gain from being showcased in livestreams. Nonetheless, there is a significant difference in the average treatment effects between these two product subcategories. Specifically, compared with accessory products, apparel products see a notably greater benefit from livestream introductions, as evidenced by the effects on their total sales ($1.540 > 0.452$) and sales through the online store channel ($1.467 > 0.357$). A similar pattern emerges in the comparison of fresh food versus snacks in Panel B, with fresh-food products experiencing a far greater advantage. These outcomes provide supportive evidence that livestreams serve an essential role in providing information and reducing consumer uncertainty regarding product attributes.

One caveat of the product-level difference-in-differences analysis is the potential systematic difference between products featured in livestreams and those not featured. For example, sellers

[23]Source: https://www.supermarketnews.com/online-retail/produce-no-easy-pickin-s-online-grocery

[24]We do not include the seller fixed effects because all product IDs are specific within sellers, and thus product fixed effects will absorb seller fixed effects.

might opt to showcase on livestreams those products that are already popular or trending in the online store channel in order to capitalize on their popularity. However, no definitive evidence suggests such phenomena would impact these different subcategories of products differently. Since the primary goal of this analysis is to compare effects across product subcategories, and considering the substantial differences in effect sizes, we maintain that the premise remains valid: the benefit of showcasing a product in livestreams varies by product subcategories.

Table 9: The Impact of Livestream Introductions on Product-level Revenue by Product Subcategories

Panel A: Fashion Essentials	Apparel		Accessory	
	Total	Store	Total	Store
After Livestream Introduction (κ)	1.540*** (0.161)	1.467*** (0.158)	0.452*** (0.100)	0.357*** (0.101)
Product FE	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
R^2	0.263	0.263	0.319	0.316
Observations	5,319,700	5,319,700	330,740	330,740

Panel B: Food	Fresh Food		Snacks	
	Total	Store	Total	Store
After Livestream Introduction (κ)	1.011*** (0.170)	0.930*** (0.166)	0.383*** (0.080)	0.341*** (0.081)
Product FE	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
R^2	0.390	0.392	0.472	0.474
Observations	93,280	93,280	68,140	68,140

Notes: The table reports the impact of livestream introductions on product-level revenues for products of different subcategories. Panel A presents the results for apparel and accessory products over 20 time periods. Panel B presents the results for fresh-food and snack products over 20 time periods. FE means fixed effects. Significance level: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

7.2 Consumer-seller relationship

In addition to examining the *uncertainty reduction* effect, we examine whether livestream shopping might also foster connections between consumers and sellers, therefore boosting sellers' demand. We highlight that the connection facilitated by livestreams can manifest in several ways. Firstly, livestreams can introduce consumers to new sellers by raising their awareness about these sellers and their products. Secondly, livestreams can serve to remind consumers of their previous interactions with the sellers. Thirdly, through livestreams, consumers may develop positive affects as well as stronger trust toward sellers. This, in turn, strengthens the consumer-seller relationship, potentially leading to increased purchases across channels. We refer to this comprehensive impact as the *consumer-seller relationship* effect and explore whether it contributes to explaining the identified positive cross-channel spillover.

Due to the platform's privacy requirements, we cannot directly observe the interactions between the consumers and sellers in our data. Therefore, we propose an indirect method to test this mechanism. When sellers adopt livestream shopping, they independently decide which products to showcase during their livestreams. Consequently, some products in their online store may never be featured in these livestreams. We argue that products not featured in livestreams—termed non-focal products—are not likely to benefit from the *uncertainty reduction* effect. Hence, if non-focal products also experience sales benefits following the seller's adoption of livestream shopping, this suggests that livestream shopping may enhance the consumer-seller relationship beyond merely providing product-level information.

We conduct an event study to examine whether the sales performance of a non-focal product changes after the seller's adoption of the livestream shopping channel. We run the following regression:

$$y_{lt} = \gamma_l + \tau_t + \omega \cdot Post_{lt} + \epsilon_{lt}, \tag{5}$$

where y_{lt} is product l's logged sales at time t; γ_l and τ_t are the product and time fixed effects, respectively; $Post_{lt}$ is an indicator equaling 1 if the seller of product l has adopted the livestream shopping channel, and 0 otherwise; and ω is the coefficient of interest. In our empirical context, we do not have instances of the same products offered by different sellers. This is probably because our dataset is largely composed of small business owners, who often operate and promote their own unique brands.

We show the results in Table 10. The positive and significant coefficient indicates that even products not featured in livestream sessions experience a sales increase. This phenomenon suggests that the livestream shopping channel not only boosts the sales of featured products but also strengthens seller-consumer connections, thereby enhancing the sales performance across the seller's entire product lineup.

This approach has several limitations. The event study, while insightful, is not causal, as other factors may change over time. In Appendix D we provide an additional analysis at the seller level to further provide evidence for this mechanism. In addition, without direct observation of livestream content, we are unable to distinctly categorize the types of consumer-seller relationships formed. For example, it remains unclear whether a seller's improved revenue performance is due to consumers' enjoyment of the livestream content, the seller's charisma, or the livestreams' effectiveness in establishing brand recall. We acknowledge this limitation and suggest it as an avenue for future research.

Table 10: Event Study for Products Not Featured during Livestreams

	Dependent variable:
	Total Rev.
Post	0.298*** (0.088)
Product FE	✓
Time FE	✓
R^2	0.25174
Observations	1,922,720

Notes: The table reports the change for total revenue of products not featured during livestreams after the seller's adoption of the livestream shopping channel. FE means fixed effects. Significance level: *p<0.1; **p<0.05; ***p<0.01

7.3 Promotion Visibility

We have demonstrated that both the *uncertainty reduction* and the *consumer-seller relationship* effects contribute to explaining the positive spillover from the adoption of the livestream shopping channel. An additional mechanism that might drive increases in both a seller's overall and online store revenues is the visibility of price promotions during livestreams. This visibility may motivate consumers to actively seek out these promotions and apply the promotional codes in the online store channel as well. This mechanism could also explain why even products not featured in a seller's livestreams can have increased sales (Table 10), potentially challenging our argument regarding the *consumer-seller relationship* effect. We undertake the following analyses to further examine this mechanism.

In our context, the sellers have the option to use two distinct types of promotions. They can issue promotions applicable to all customers, typically consistent across both the livestream shopping and online store channels. In addition, the sellers may offer personalized price promotions, which are more commonly found in the livestream shopping channel (see Liu, 2022). However, personalized promotions are less common among the sellers in our sample, who are mostly small business owners, due to the complexity of planning and executing such promotions. Unfortunately, our dataset lacks specific promotion information, preventing us from distinguishing between these two types. Thus, we rely on the transaction price (i.e., paid price) for the following analyses.

First, we verify the improved visibility of price promotions in the livestream shopping channel by examining if the price of the same product varies between the livestream and online store channels. We investigate this through the following regression:

$$p_{lt} = \gamma_l + \tau_t + \rho live_{lt} + \epsilon_{lt}, \tag{6}$$

where p_{lt} is the logged price of product l at time t; γ_l and τ_t are the product and time fixed effects, respectively; and $live_{lt}$ is an indicator that equals 1 if the transaction is through the livestream shopping channel, and 0 otherwise. Finally, ρ is the variable of interest, which measures whether the same product's transaction prices differ across channels.

Table 11 reports the result. Our analysis indicates that the transaction price for a product is on average 7.3% lower when it is sold through the livestream shopping channel than through the online store channel. This result potentially provides supporting evidence that the enhanced visibility of price promotions in livestream shopping affects the price consumers pay, resulting in lower prices compared with those in the online store channel. One limitation of this analysis is that we do not observe the specific promotion details. While it is less common for small business owners in our context to vary promotions across channels, we cannot entirely dismiss the possibility that sellers may offer greater promotions in the livestream shopping channel.

Table 11: Product Price Study Across Channels

	Product Price
Livestream Channel (ρ)	-0.076^{***}
	(0.016)
Product FE	✓
Time FE	✓
R^2	0.973
Observations	769,403

Notes: This table reports the results of differences in product price across different channels. The results are based on product-channel-level price observations over 20 time periods. The analysis includes 270,189 products. The result is not based on a balanced panel because some products do not have transaction records in all 20 periods. FE means fixed effects. Significance level: *p<0.1; **p<0.05; ***p<0.01

Next, we investigate whether the increased visibility of price promotions in the livestream shopping channel leads to more active consumer engagement in searching for promotions and applying promotional codes, thereby boosting revenue in the online store channel. We employ a product-level difference-in-differences analysis to determine if there is a significant change in a product's price within the online store channel following the seller's adoption of the livestream shopping channel. Should consumers indeed become more proactive in seeking out price promotions and using promotional codes in the online store channel, we would anticipate a decrease in the transaction price for the same product. We implement the following difference-in-differences regression:

$$p_{ilt} = \gamma_l + \tau_t + \phi D_{it} + \epsilon_{ilt}, \tag{7}$$

where p_{ilt} is the logged price of product l sold by seller i at time t; γ_l and τ_t are the product and time fixed effects, respectively; D_{it} is an indicator representing whether seller i has adopted the livestream channel; and ϕ measures if the same product's transaction price in the online store changes after the seller's adoption of the livestream shopping channel.

Table 12 shows the result is insignificant, which suggests that a product's transaction price in the online store channel remains unchanged following the seller's adoption of the livestream shopping channel. This outcome suggests that the enhanced visibility of promotions in the livestream shopping channel may not necessarily lead consumers to actively apply the promotional codes in the online store channel. Therefore, this mechanism might not account for the positive spillover observed following a seller's adoption of the livestream shopping channel.

Table 12: Product Price for Online Store Channel

	Product Price
After Introduction	-0.011
	(0.009)
Product FE	✓
Time FE	✓
R^2	0.97508
Observations	735,844

Notes: This table reports the average treatment effect of adopting the livestream shopping channel on the product price in the online channel. The price analysis includes 266,378 products and is conditional on transactions. The result is not based on a balanced panel because some products do not have transactions in all 20 periods. FE means fixed effects. Significance level: *p<0.1; **p<0.05; ***p<0.01

In summary, our findings indicate that livestream shopping serves to (1) provide consumers with product information, thereby reducing their uncertainty regarding products, and (2) strengthen the connection between consumers and sellers. Both mechanisms play a role in explaining the positive cross-channel spillover effect. Regarding the enhanced visibility of promotions within the livestream shopping channel, while the transaction price tends to be lower in this channel, there is insufficient evidence to corroborate that this mechanism contributes to the cross-channel spillover.

Investigating the aforementioned mechanisms provides deeper insights into the evolving e-commerce landscape. The livestream shopping channel supports sellers through both the *uncertainty reduction* and the *consumer-seller relationship* effects. Therefore, this channel is a more inclusive option than traditional physical retail outlets, such as showrooms and stores. Consequently, it caters to a wide range of sellers, including those dealing with different product categories, because the sellers see potential advantages in adopting the livestream shopping channel through multiple mechanisms.

8 Conclusion

The rise of livestream shopping has attracted enormous attention among online sellers. Although online platforms strive to build an e-commerce ecosystem that supports both the traditional online marketplace and the livestream shopping marketplace, investigations into the effects of adopting the livestream shopping channel on online sellers remain limited. In this paper, we use Alibaba's e-commerce ecosystem, which enables Taobao's online sellers to seamlessly transition into the livestream shopping channel on Taobao Live, to causally examine the impact of adopting the livestream shopping channel on seller performance.

We discover that adopting the livestream shopping channel boosts the sellers' total revenue by an average of 105.9%. Furthermore, we observe a positive cross-channel spillover effect on the sellers' online stores, with 46.2% of the total revenue increase originating in the online store channel. Our investigation into the mechanisms behind the cross-channel spillover effect reveals that livestreams particularly benefit products with more product attributes to display. This finding validates the *uncertainty reduction* effect of the livestream shopping channel, showcasing its ability to provide product information to consumers. Additionally, our analysis indicates that sellers who specialize in different product subcategories experience similar revenue increases in the online store channel. This finding suggests that even a seller's products not featured in their livestreams benefit from the seller's adoption of this channel. This evidence hints at the *consumer-seller relationship* effect, where livestreams potentially strengthen the consumer-seller relationship. However, while the enhanced visibility of promotions in the livestream shopping channel might result in lower transaction prices within the channel, it does not account for the observed positive cross-channel spillover at the seller level.

Our results offer practical insights for both online sellers and platforms. Firstly, we supply a benchmark estimate to aid online sellers in assessing their decisions to adopt livestream shopping. Additionally, by understanding the two distinct mechanisms through which livestream shopping benefits sellers, they can make informed choices to enhance their performance. For instance, an apparel seller might focus more on highlighting product attributes, whereas an accessory seller could prioritize building consumer-seller relationships. For platforms, our findings affirm the benefits of creating a seller-centric environment through livestream shopping and offer an evaluation of this emerging e-commerce ecosystem.

Our research comes with limitations that leave room for future research opportunities. Since we lack cost information, our findings primarily address revenue impacts. The costs of adopting the livestream shopping channel, including equipment setup and employee labor, differ across sellers. Thus, we refrain from offering tailored recommendations for individual sellers. In addition, our research context centers on Taobao and Taobao Live, making our insights potentially applicable to similar online shopping platforms (such as Amazon and eBay), which also host millions of sellers. However, in recent years, digital platforms without an e-commerce foundation, such as Facebook, have ventured into livestream shopping. We encourage further studies of these platforms to investigate whether collaborations with other online marketplaces yield comparable results.

Acknowledgement

Funding and Competing Interests: This work is supported by a PhD Student-Faculty Joint Research Grant. We are grateful to Alibaba for providing the data. One author worked as a visiting scholar at Alibaba.

References

Anderson, Stephen J, Leonardo Iacovone, Shreya Kankanhalli, and Sridhar Narayanan, "Modernizing Retailers in an Emerging Market: Investigating Externally Focused and Internally Focused Approaches," *Journal of Marketing Research*, 2022, *59* (3), 472–496.

Arkhangelsky, Dmitry, Susan Athey, David A Hirshberg, Guido W Imbens, and Stefan Wager, "Synthetic difference-in-differences," *American Economic Review*, 2021, *111* (12), 4088–4118.

Avery, Jill, Thomas J Steenburgh, John Deighton, and Mary Caravella, "Adding bricks to clicks: Predicting the patterns of cross-channel elasticities over time," *Journal of Marketing*, 2012, *76* (3), 96–111.

Bell, David R, Santiago Gallino, and Antonio Moreno, "Offline showrooms in omnichannel retail: Demand and operational benefits," *Management Science*, 2018, *64* (4), 1629–1651.

Berman, Ron and Ayelet Israeli, "The Value of Descriptive Analytics: Evidence from Online Retailers," *Marketing Science*, 2022.

Bronnenberg, Bart J and Paul B Ellickson, "Adolescence and the path to maturity in global retail," *Journal of Economic Perspectives*, 2015, *29* (4), 113–134.

Cheng, Chen, Yuheng Hu, Yingda Lu, and Yili Hong, "Everyone can be a star: Understanding the role of live video streaming in online retail," *Available at SSRN 3422615*, 2019.

Cong, Ziwei, Jia Liu, and Puneet Manchanda, "The Role of" Live" in Livestreaming Markets: Evidence Using Orthogonal Random Forest," *arXiv preprint arXiv:2107.01629*, 2021.

Gerstner, Eitan, "Do higher prices signal higher quality?," *Journal of Marketing Research*, 1985, *22* (2), 209–215.

Ghose, Anindya, Avi Goldfarb, and Sang Pil Han, "How is the mobile Internet different? Search costs and local activities," *Information Systems Research*, 2013, *24* (3), 613–631.

Goldmanis, Maris, Ali Hortaçsu, Chad Syverson, and Önsel Emre, "E-commerce and the Market Structure of Retail Industries," *The Economic Journal*, 2010, *120* (545), 651–682.

Gu, Xian and PK Kannan, "The dark side of mobile app adoption: Examining the impact on customers' multichannel purchase," *Journal of Marketing Research*, 2021, *58* (2), 246–264.

_, Xiaoxi Zhang, and PK Kannan, "Growing Sales with Influencers in Livestreaming Commerce," *working paper*, 2022.

Gui, Luyi, Xi Lin, and Yixin Lu, "Managing Sales via Livestream Commerce," *Available at SSRN*, 2022.

Hong, Yili and Paul A Pavlou, "Product fit uncertainty in online markets: Nature, effects, and antecedents," *Information Systems Research*, 2014, *25* (2), 328–344.

Hui, Xiang, Maryam Saeedi, Zeqian Shen, and Neel Sundaresan, "Reputation and regulations: Evidence from eBay," *Management Science*, 2016, *62* (12), 3604–3616.

_, Zekun Liu, and Weiqing Zhang, "From High Bar to Uneven Bars: The Impact of Information Granularity in Quality Certification," *Available at SSRN 3731169*, 2022.

Li, Xing and Ruobing Han, "Streaming Consumers in Livestreaming E-commerce: Identifying Lifts from Sales Pitches," *working paper*, 2024.

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

Liu, Licheng, Ye Wang, and Yiqing Xu, "A practical guide to counterfactual estimators for causal inference with time-series cross-sectional data," *American Journal of Political Science*, 2024, *68* (1), 160–176.

Liu, Xiao, "Dynamic coupon targeting using batch deep reinforcement learning: An application to livestream shopping," *Forthcoming, Marketing Science*, 2022.

Liu, Zekun, Weiqing Zhang, Xiao Liu, Eitan Muller, and Feiyu Xiong, "Success and Survival in Livestream Shopping," *Available at SSRN 4028092*, 2022.

Mamadehussene, Samir, "Price-matching guarantees as a direct signal of low prices," *Journal of Marketing Research*, 2019, *56* (2), 245–258.

Manchanda, Puneet, Grant Packard, and Adithya Pattabhiramaiah, "Social dollars: The economic impact of customer participation in a firm-sponsored online customer community," *Marketing Science*, 2015, *34* (3), 367–387.

Narang, Unnati and Venkatesh Shankar, “Mobile app introduction and online and offline purchases and product returns,” *Marketing Science*, 2019, *38* (5), 756–772.

Ou, Carol Xiaojuan, Paul A Pavlou, and Robert M Davison, “Swift guanxi in online marketplaces: The role of computer-mediated communication technologies,” *MIS quarterly*, 2014, *38* (1), 209–230.

Pavlou, Paul A and Angelika Dimoka, “The nature and role of feedback text comments in online marketplaces: Implications for trust building, price premiums, and seller differentiation,” *Information systems research*, 2006, *17* (4), 392–414.

Rong, Ke, Di Zhou, Xinwei Shi, and Wei Huang, “Social Information Disclosure of Friends in Common in an E-commerce Platform Ecosystem: An Online Experiment,” *Production and Operations Management*, 2022, *31* (3), 984–1005.

Rubin, Donald B and Richard P Waterman, “Estimating the causal effects of marketing interventions using propensity score methodology,” *Statistical Science*, 2006, pp. 206–222.

Sahni, Navdeep S, “Advertising spillovers: Evidence from online field experiments and implications for returns on advertising,” *Journal of Marketing Research*, 2016, *53* (4), 459–478.

_ **and Harikesh S Nair**, “Does advertising serve as a signal? Evidence from a field experiment in mobile search,” *The Review of Economic Studies*, 2020, *87* (3), 1529–1564.

Sun, Chenshuo, Zijun June Shi, Xiao Liu, Anindya Ghose, Xueying Li, and Feiyu Xiong, “The effect of voice ai on consumer purchase and search behavior,” *NYU Stern School of Business*, 2024.

Troncoso, Isamar and Lan Luo, “Look the part? the role of profile pictures in online labor markets,” *Marketing Science*, 2023, *42* (6), 1080–1100.

Wang, Kitty and Avi Goldfarb, “Can offline stores drive online sales?,” *Journal of Marketing Research*, 2017, *54* (5), 706–719.

Wang, Lingli, Nina Huang, Yili Hong, Luning Liu, Xunhua Guo, and Guoqing Chen, “Effects of voice-based AI in customer service: Evidence from a natural experiment,” 2020.

Wang, Zining, Yanwen Wang, Shuai Yang, and Hongju Liu, “Sales Impacts of Live-streaming Video Ads,” *working paper*, 2022.

Xu, Kaiquan, Jason Chan, Anindya Ghose, and Sang Pil Han, "Battle of the channels: The impact of tablets on digital commerce," *Management Science*, 2017, *63* (5), 1469–1492.

Zhang, Dennis J, Hengchen Dai, Lingxiu Dong, Qian Wu, Lifan Guo, and Xiaofei Liu, "The value of pop-up stores on retailing platforms: Evidence from a field experiment with Alibaba," *Management Science*, 2019, *65* (11), 5142–5151.

Zhang, Shunyuan, Dokyun Lee, Param Vir Singh, and Kannan Srinivasan, "What makes a good image? Airbnb demand analytics leveraging interpretable image features," *Management Science*, 2021.

Appendix A Robustness

A.1 Seller-level ATT

A.1.1 Analyses Using Different Sets of Sellers

In the main analyses, we selected sellers who had been operating their online stores for at least 6 months before the beginning of our study period, to identify sellers highly committed to operating their online storefronts. This selection resulted in $2,851$ sellers. For robustness, we re-conduct the analysis using the full set of sellers (i.e., $3,643$). Table A1 reports the average treatment effect on the sellers' total and online store channel revenue. All results are qualitatively similar to those in the main analysis.

Table A1: The Impact of Adopting the Livestream Shopping Channel on Seller Performance (Full Set)

	Method	
	TWFE	SynDiD
Total Rev.	1.100***	0.682***
	(0.154)	(0.053)
Online Store Rev.	0.776***	0.358***
	(0.148)	(0.052)
Seller FE	✓	✓
Time FE	✓	✓
Observations	72,860	72,860

Notes: The table reports the average treatment effect of adopting the livestream shopping channel on the sellers' total revenue and online store revenue biweekly. The results are based on $3,643$ sellers over 20 time periods. For the SynDiD method, we set the post-treatment periods to 6 weeks (3 biweekly time periods). FE means fixed effects.

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

In addition, we conduct a robustness check removing the top-performing 1% of the sellers (based on their average biweekly sales) in the main analyses. This approach may alleviate the concern regarding the skewness of seller size. Table A2 reports the results, and all are qualitatively similar to the ones in the main analyses.

Table A2: The Impact of Adopting the Livestream Shopping Channel on Seller Performance (Top 1% Sellers Removed)

	Method	
	TWFE	SynDiD
Total Rev.	1.117***	0.773***
	(0.157)	(0.062)
Online Store Rev.	0.795***	0.438***
	(0.149)	(0.060)
Seller FE	✓	✓
Time FE	✓	✓
Observations	51,320	51,320

Notes: The table reports the average treatment effect of adopting the livestream shopping channel on the sellers' total revenue and online store revenue biweekly. The results are based on $2,566$ sellers over 20 time periods. For the SynDiD method, we set the post-treatment periods to 6 weeks (3 biweekly time periods). FE means fixed effects.

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

A.1.2 Analysis Using Non-COVID-19 Time Periods

To make sure that the average treatment effect is not contaminated by the COVID-19 pandemic, we conduct a robustness check using only the data before December 2019. We obtain 10 biweekly time periods of observations for each seller. Table A3 reports the results, which are qualitatively similar to those in the main analysis.

Table A3: The Impact of Adopting the Livestream Shopping Channel on Seller Performance (Using Data Before December 2019)

	Methods:	
	TWFE	SynDiD
Total Rev.	0.828***	0.649***
	(0.120)	(0.082)
Online Store Rev.	0.499***	0.302***
	(0.115)	(0.080)
Seller FE	✓	✓
Time FE	✓	✓
Observations	28,510	28,510

Notes: The table reports the average treatment effect of adopting the livestream shopping channel on the sellers' total revenue and online store revenue biweekly. The results are based on 2,851 sellers over 10 time periods. For the SynDiD method, we set the post-treatment periods to 6 weeks (3 biweekly time periods). FE means fixed effects.

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

A.1.3 Analysis Using An 8-Week Window

We perform the SynDiD analysis to identify the average treatment effect of adopting the livestream shopping channel using a different length of pre- and post-treatment periods. Specifically, we study how seller performance changes 8 weeks (or 4 biweekly time periods) before and after the adoption of the livestream shopping channel. The analyses apply exclusively to sellers who adopted the livestream shopping channel after September 19, 2019 (8 weeks after the earliest observational period), resulting in $2,635$ sellers. Table A4 reports the average treatment effect of the sellers' total and online store channel revenue. All results are qualitatively similar to those obtained using 6-week periods before and after the adoption of the livestream shopping channel.

Table A4: The Impact of Adopting the Livestream Shopping Channel on Seller Performance (Using an 8-Week Window)

	Methods:	
	TWFE	SynDiD
Total Rev.	1.025***	0.691***
	(0.146)	(0.063)
Online Store Rev.	0.719***	0.367***
	(0.140)	(0.061)
Seller FE	✓	✓
Time FE	✓	✓
Observations	52,700	52,700

Notes: The table reports the average treatment effect of adopting the livestream shopping channel on the sellers' total revenue and online store revenue biweekly. The results are based on $2,635$ sellers over 20 time periods. For the SynDiD method, we set the treatment periods to 8 weeks (4 biweekly time periods). FE means fixed effects.

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

Appendix B Number of Sellers in Each Cohort

We use Table A5 to report the number of sellers in the treatment and control groups for each cohort. The number of sellers in the control group exceeds that in the treatment group for each cohort, which is sufficient for the Synthetic DiD estimator. We define each cohort on a biweekly basis. Cohort 1 includes the earliest adopters in our data, with their adoption date starting on September 6, 2019.

Table A5: Number of Sellers in Each Cohort

Cohort	Treatment	Control
1	216	2,635
2	246	2,389
3	242	2,147
4	222	1,925
5	234	1,691
6	219	1,472
7	217	1,255
8	170	1,085
9	174	911
10	123	788
11	61	727
12	84	643
13	85	558
14	92	466
15	104	362

Notes: The table reports the number of sellers in the treatment and control groups for each cohort.

Appendix C Balance Check on Propensity Score Matching

C.1 Balance Check on Watchers and Non-watchers

We conduct propensity score matching on a seller's existing customers to match watchers and non-watchers based on observable characteristics. The covariates include purchase frequency, amount, and quantity for the 6 weeks (or 3 biweekly periods) before the seller's adoption of the livestream shopping channel. Table A6 presents the balance check for watchers and non-watchers, both before and after matching. Following matching, the differences in covariates between the two consumer groups are not statistically significant at the 10% level.

Table A6: Balance Check Before and After Matching (Watchers versus Non-watchers)

	Before		After	
	Mean Difference	p-value	Mean Difference	p-value
Purchase Frequency 1	0.159	$8.750e-12$	0.002	0.707
Purchase Frequency 2	0.144	$8.738e-10$	0.005	0.316
Purchase Frequency 3	0.105	$1.509e-16$	-0.005	0.372
Purchase Amount 1	0.580	$1.096e-12$	-0.002	0.939
Purchase Amount 2	0.550	$4.189e-10$	0.001	0.971
Purchase Amount 3	0.398	$1.532e-18$	-0.014	0.528
Purchase Quantity 1	0.187	$1.92e-11$	0.002	0.778
Purchase Quantity 2	0.179	$3.763e-11$	0.009	0.203
Purchase Quantity 3	0.129	$6.842e-17$	0.0002	0.970

Notes: The table reports the mean difference and p-value of covariates between watchers and non-watchers before and after matching. Covariates used for matching comprise seller (exact match), purchase frequency, purchase amount, and purchase quantity based on 1, 2, and 3 biweekly time periods before each seller's adoption time. Since watchers and non-watchers are matched exactly based on seller, seller fixed effects are incorporated when computing the mean difference and p-value. All variables are log-transformed.

C.2 Balance Check on Occasional and Frequent Livestream Sellers

We conduct propensity score matching to identify frequent livestream sellers that are similar to occasional livestream sellers. The covariates comprise pre-adoption seller metrics: positive feedback rate, seller credibility rating, number of subscribers, and average product price. Table A7 shows the balance check before and after matching. After matching, the differences in covariates between the two groups of sellers are not statistically significant at the 10% level.

Table A7: Balance Check Before and After Matching (Occasional versus Frequent Livestream Sellers)

	Before		After	
	Mean Difference	p-value	Mean Difference	p-value
Positive Feedback Rate	0.012	0.548	−0.014	0.586
Seller Credibility Rating	0.077	0.693	0.052	0.840
Number of Subscribers	0.117	0.564	−0.059	0.826
Average Product Price	0.224	0.014	0.014	0.900

Notes: The table reports the mean difference and p-value of covariates between occasional and frequent livestream sellers before and after matching. The covariates used for matching comprise positive feedback rate, seller credibility rating, number of subscribers, and average product price. All variables except for positive feedback rate are log-transformed.

Appendix D Additional Evidence for the Consumer-seller Relationship Effect

In addition to the event study in Section 7.2, we provide evidence for the *consumer-seller relationship* effect.

First, we revisit the product-level difference-in-differences results presented in Table 9. Even though livestreams might have a limited ability to reduce product uncertainty for accessories and snacks, we still observe a significant increase in these products' sales after their sellers adopted the livestream shopping channel. This phenomenon indicates an increase in consumer purchases of these items, suggesting that the mechanism of *uncertainty reduction* might not exclusively account for the observed sales surge. Therefore, if accessory and snack products do not benefit from the uncertainty reduction effect at all, we propose that the sales increase for these products could result from the enhanced seller-consumer relationship due to the adoption of the livestream shopping channel. However, there is a caveat: although being showcased in livestreams may not significantly reduce product uncertainty for certain subcategories of products, they can still provide some information, such as caloric and nutritional details for snacks. Consequently, it is arguable that the positive (albeit smaller) average treatment effect for accessories and snacks is not solely due to the strengthened consumer-seller relationship.

To address this concern, we investigate whether the adoption of the livestream shopping channel affects sellers specializing in different product subcategories differently. Given that we have demonstrated how different product subcategories experience varying benefits from livestreams, analyzing whether the performance of sellers specializing in different product subcategories follows a similar pattern and can further shed light on this mechanism.

Recall that the sellers in our sample are from three categories. Although there are no sellers specializing in multiple categories, the sellers might offer products from a variety of subcategories. For example, a fashion essentials seller might offer both apparel products and accessories. Therefore, we determine the proportion of each product subcategory sold by each seller using our consumer-level data. We define a seller as specialized in a particular product subcategory (for example, apparel) if 70% of their sales volume is from products in that subcategory.[25]

Panels A and B in Table A8 present the results of two comparative analyses: one between apparel and accessory sellers, and the other between fresh-food and snack sellers. In Section 7.1,

[25] We have also applied thresholds of 50% and 60%, and the findings remain qualitatively consistent.

we have shown that products such as apparel and fresh food derive greater benefits from being showcased in livestreams. However, at the seller level, we find that sellers specializing in different subcategories of products experience similar benefits in the online store channel from their adoption of the livestream shopping channel. For example, the magnitude of effects for sellers who specialize in accessories even exceeds that for those who specialize in apparel, although the difference is insignificant.

This finding suggests that the cross-channel spillover observed for sellers specializing in accessories and snacks might partly result from the increased sales of products not featured in these sellers' livestream shopping channel. Since the uncertainty associated with products not featured in a seller's livestreams remains largely unchanged, the observed increase in these products' sales deriving from the seller's online stores is likely attributable to an enhanced seller-consumer connection.

This analysis has certain limitations. First, since we have access to only a subset of consumer transaction data, our definition of sellers' specializations is based on this limited information, which could result in inaccurate categorization. However, there is no evidence to suggest that this limitation will disproportionately bias the representation of certain subcategories of products in which sellers specialize. Second, similar to the event study in Section 7.2, our approach is indirect, centering on whether non-focal products benefit from sellers' adoption of livestream shopping. Without direct observation of the livestream content and consumer-seller interactions, we cannot determine the specific types of consumer-seller relationships formed. Therefore, we use this analysis as suggestive evidence to demonstrate that livestream shopping can stimulate more sales beyond the information provision mechanism.

Table A8: The Impact of Adopting the Livestream Shopping Channel on Seller-level Revenue by Seller Specialization

Panel A: Fashion Essentials

	TWFE		SynDiD	
	Apparel	Accessory	Apparel	Accessory
Total Rev.	0.943***	1.009***	0.624***	0.871***
	(0.248)	(0.312)	(0.163)	(0.246)
Online Store Rev.	0.645**	0.719**	0.273*	0.573**
	(0.240)	(0.297)	(0.159)	(0.240)
Contribution %	57.8%	60.4%	36.2%	55.6%
Seller FE	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
Observations	8,280	2,760	8,280	2,760

Panel B: Food

	TWFE		SynDiD	
	Fresh Food	Snacks	Fresh Food	Snacks
Total Rev.	1.027***	0.562*	0.675***	0.463**
	(0.259)	(0.303)	(0.154)	(0.233)
Online Store Rev.	0.828***	0.483	0.475***	0.388*
	(0.153)	(0.298)	(0.150)	(0.227)
Contribution %	71.9%	82.3%	63.1%	80.5%
Seller FE	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
Observations	7,080	2,300	7,080	2,300

Notes: The table reports the average treatment effect of adopting the livestream shopping channel on total revenue and online store revenue for sellers specialized in different product subcategories. Panel A presents the results for 414 apparel sellers and 138 accessory sellers over 20 time periods. Panel B presents the results for 354 fresh-food sellers and 115 snack sellers over 20 time periods. Contribution % = $(\exp(coef\_online\_store) - 1) / (\exp(coef\_total) - 1)$. FE means fixed effects. Significance level: *p<0.1; **p<0.05; ***p<0.01.