The Power of Livestream Shopping: Boosting Revenue and Catalyzing Spillover *

Weiqing Zhang†
New York University

Zekun Liu‡
New York University

Xiao Liu §
New York University

Eitan Muller¶
New York University & Reichman University (IDC)

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 adopted livestream shopping from September 2019 to June 2020. Applying multiple estimators to address a series of identification challenges, we find that adopting this channel boosts 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 from the livestream shopping to the online store channel. This adoption proves especially advantageous for small-scale sellers, enabling rapid expansion and competitiveness in the e-commerce marketplace. Our further investigation into the positive cross-channel spillover reveals that livestream shopping not only helps reduce product uncertainty through information provision but also strengthens the consumer-seller connection. Moreover, despite the average price for the same product being 7.3% lower in the livestream shopping 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.

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†wz1571@stern.nyu.edu
‡zl3126@stern.nyu.edu
§xliu@stern.nyu.edu
¶em101@stern.nyu.edu

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1 Introduction

Small business owners often turn to online shopping platforms like eBay and Taobao to launch their ventures, drawn by their affordability and flexibility. However, critics frequently point out these 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, emerges as a solution to bridge these gaps alongside the online presence. Yet, for many small businesses, the high costs render this solution impractical.[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 like Amazon and eBay, spreading rapidly across the world.[4] By 2026, the livestream shopping market in the United States is projected to hit $68 billion.[5] Notably, livestream shopping has gained significant traction among small business owners. In 2021, small online store owners on Taobao conducted 70% of the 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 the 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 its early association with influencer marketing, where livestreamers were not typically online store or brand owners, leading to its classification as a promotion strategy.[6] We aim to narrow this gap by analyzing Alibaba's ecosystem, which includes Taobao as the online shopping platform and Taobao Live for livestream shopping, where sellers operating on Taobao also manage their livestream channels on Taobao Live. Moreover, we investigate if this emerging channel offers

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

[2] Source:https://www.brookfieldproperties.com/en/our-businesses/retail/blog/the-billboard-effect.html

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

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

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

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

particular benefits to small business owners, aligning with the trend observed in practice.

In addition to uncovering the value of the livestream shopping channel, we delve into *how* livestream shopping 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. Furthermore, 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, offer content that is not only highly engaging and entertaining but also adept at fostering feelings of affection and warmth among audiences. Such characteristics of livestreams empower consumers not only to discover new sellers but also 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 not just initiating consumer awareness of sellers but also in sustaining ongoing relationships between them. We refer to this effect as the *consumer-seller connection* effect. Moreover, 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 are often hidden in less noticeable page areas. Viewing livestreams can make these promotions more visible, prompting consumers to seek and apply similar ones 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 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 the adoption and in both channels (the online store and livestream shopping channels) after the adoption. Additionally, we observe transactions from a representative group of consumers. Using this data, 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 timeline and tackle a range of identification challenges by employing the synthetic difference-in-differences (SynDiD) estimator, as Arkhangelsky et al. (2021) and Berman and Israeli (2022) proposed. We also conduct additional analyses, including the consumer-level ones, to rule out endogeneity because of 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 connection mechanism, we investigate the existence of a cross-product cross-channel spillover effect; that is, we study 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 behavior of applying promotions 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 of sellers' total revenue by 105.9%, equating to a 2,937 CNY increase over six weeks for a median-sized seller in our dataset.[7]
- **Spillover.** 46.2% of this revenue increase originates from the sellers' online store channel. Therefore, 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, highlighting the potential of livestream shopping to enhance their competitiveness.

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

- **Uncertainty Reduction Effect.** We provide analysis that indicates the role of livestreams in providing information and reducing consumer uncertainty about product attributes by showing 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 to other products, like accessories and snacks.

[7] CNY is the official currency of China. As of March 1st, 2024, the exchange rate from the US dollar (USD) to CNY stands at 7.2.

- **Consumer-seller Connection Effect.** We show evidence to suggest that livestreams may help build stronger consumer-seller connections by observing that sales in the online store channel increase even for products not featured in livestreams.
- **Promotion Visibility Effect.** We provide analysis that reflects the role of channel's enhanced promotion visibility by showing that 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 the online store channel remains unchanged post-adoption, indicating that increased promotion visibility does not lead consumers to apply similar promotions more in the online store channel, thus not explaining the positive spillover effect.

Our findings highlight the role of the livestream shopping channel in e-commerce and provide managerial insights for various stakeholders. For online sellers, we assess the impact of adopting the livestream shopping channel, helping them to make informed decisions. Additionally, identifying two mechanisms for the positive spillover, the *uncertainty reduction* and the *consumer-seller connection* effects, directs sellers specializing in different product categories towards the most appropriate mechanism for their daily operations. For platforms, our results 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 follows with a description of the data. We outline the empirical strategy in Section 5 and present the results on the impact of adoption in Section 6. In Section 7, we discuss the potential mechanisms. And, finally, in Section 8, we conclude by offering practical insights, limitations, and suggestions for future research.

2 Literature Review

Our paper contributes to four streams of literature, including 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 the 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. Beyond offline channels, 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 mobile shopping's uniqueness and therefore complementarity to the online channel. Narang and Shankar (2019) investigate mobile shopping app adopters' buying and returning behaviors, finding that app users tend to purchase more than those who shop online. The literature extends to the synergies between the online channel and other channels like 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. Moreover, we find that the livestream shopping channel benefits online sellers by strengthening consumer-seller connections and reducing consumer uncertainty about product attributes. Our results suggest that sellers who specialize in different product categories can use the most proper mechanism to inform their operational strategies and fully take advantage of the 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 towards retail modernization in emerging markets, including the rise of online retail. Anderson et al. (2022) conceptualize modernization as the adoption of the physical and operational practices characteristic of organized retail chains, underlining its beneficial impact in emerging markets through field experiments. 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. Whereas Goldmanis et al. (2010) suggest that the advent of e-commerce might disadvantage small, high-cost retailers, our analysis indicates that livestream shopping, within the e-commerce landscape, could serve to level the playing field, 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, quality, and product attributes. Researchers have examined the effectiveness of various marketing communication tools from the seller's perspective, such as pricing (Zhuang et al., 2021), advertising (Sahni and Nair, 2020a,b), customer relationship management (Ou et al., 2014), high-quality images (Zhang et al., 2021), and seller profiles and portraits (Troncoso and Luo, 2020). 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 its impact on seller performance.

Lastly, our paper contributes to the nascent literature on livestream shopping, which has primarily focused on its influence within the realm of influencer marketing. Studies in this area have examined how factors such as influencer popularity (Gu et al., 2022), negotiations between brands and influencers (Gui et al., 2022), and the content of livestreams (Cheng et al., 2019; Wang et al., 2022) influence the effectiveness of livestream shopping. Unlike works that focus on the influencer marketing domain, our study examine livestream shopping in the multichannel context, where online sellers manage their own livestreams. The studies most closely related to ours include Cong et al. (2021), which investigates the price elasticity of demand for live content before and after livestreams in a creator economy setting; Liu (2022), which examines the optimal coupon targeting strategy during livestream sessions through batch deep reinforcement learning; and Liu et al. (2022), which looks 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.[8] 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, using 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

[8]Source: https://www.statista.com/chart/22519/biggest-b2c-e-commerce-platforms-china/

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) study on its success. 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 in CNY.[9] Secondly, sellers can present more precise and comprehensive information about their products and brands, making the most of the interactive and engaging nature of livestream shopping.

Figure 1 illustrates the user interface (UI) 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—potential consumers have the opportunity to engage through likes, shares, and subscriptions with the sellers. Additionally, consumers can interact directly with the sellers by posting questions or comments in the comment box, which 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 sellers' 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 sellers' online store channel. This differentiation enables the analysis of transactions originating from distinct channels. It is important to recognize that 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 livestreams are also accessible in the same seller's online store.

[9] Source: https://36kr.com/p/1504362860512389

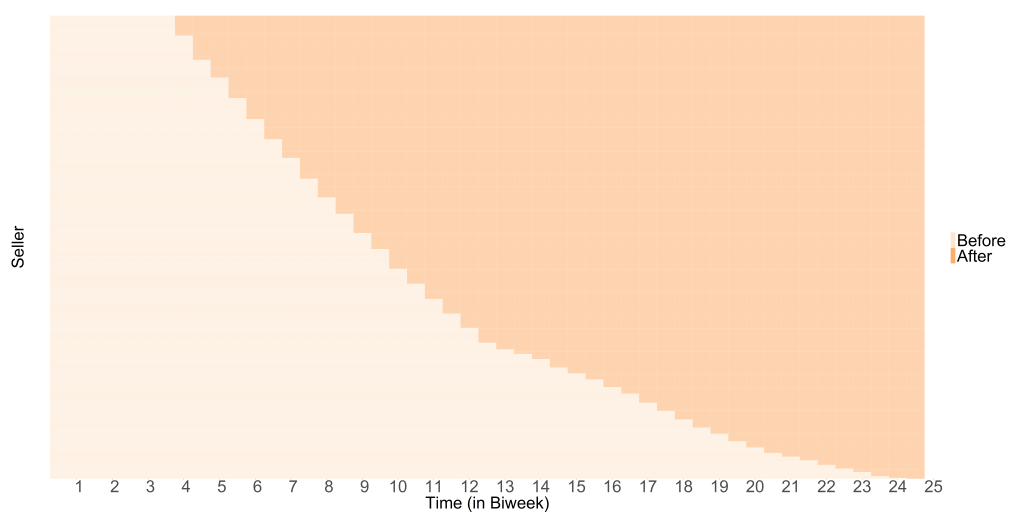
Figure 1: An example of a livestream session on Taobao Live

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 like QVC, such as the format of presenting products to consumers. However, unlike these networks, where content may be partly pre-recorded, introduced by anchors rather than sellers, and lacks interactive components, livestream shopping on platforms like Taobao Live is predominantly live, fostering real-time engagement between sellers 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, which makes it analogous to traditional commercials. Yet, its ability to allow immediate consumer feedback and interaction, enabling real-time adjustments to the products presented, marks livestream shopping as a uniquely interactive and dynamic channel, offering a more engaged and responsive shopping experience than what is typically observed in traditional commercials.

4 Data

Our data comes from Alibaba's e-commerce platforms, Taobao and Taobao Live, and includes 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 adoption, and in the livestream shopping channel post-adoption. We aggregate the data at the biweekly panel level. As all sellers in our data eventually adopted the livestream shopping channel, we rely on the staggered fashion of their adoptions and treat sellers as control units during periods before their adoptions, similarly to the approach in Manchanda et al. (2015). Figure 2 illustrates the adoption dynamics of the livestream shopping channel. We further select sellers who had been running their online stores since February 2019, six months prior to our observation period. This selection criteria ensures that we include those sellers who are committed to their online store channel on the platform, resulting in a sample of 2,851 sellers, for analyzing the treatment effect of adopting the livestream shopping channel. We 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 observations after December 2019. Both robustness checks are in Appendix A, with all findings remaining qualitatively consistent.

Figure 2: Treatment Variation Plot



We report the seller-panel level summary statistics in Table 1. Since most sellers in our sample are small business owners, the distributions of variables tend to be left-skewed. Therefore, we perform a robustness check that excludes the top 1% of sellers by average sales 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 and the livestream shopping channel in Panels A and B, respectively. Panel A is based on the 20 periods data for 2,851 sellers, and Panel B is based on the periods after adoption for 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 categories.

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

Beyond seller-level data, we randomly collect a sample of consumer-level data. The data is limited to 1,308 sellers and 5,060,816 consumers (4.4% of their total number of consumers) due to the company's privacy measures, which restrict our access and prevent a comprehensive analysis across all sellers and consumers. Within this dataset, 3.2% are overlapping consumers who have purchased from multiple sellers. We observe whether and when a consumer watches 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 this data 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. Table 3 provides the summary statistics of product prices at the product-panel level for both channels.

Table 3: Product Price (CNY) 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 behaviors after watching livestreams. An existing consumer is defined as someone who has 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 the data at the seller level, we aggregate consumer transactions at the biweekly panel level and 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 and the livestream channel in Panels A and B, respectively. Panel A is based on data from 20 periods for 237,156 consumers, and Panel B is based on observations after consumers watched their first livestreams.

5 Empirical Strategy

In this section, we outline our empirical strategy for assessing how adopting livestream shopping channels affects seller performance. We start by discussing identification challenges in our empirical context. Following this, 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 livestream shopping channels. We analyze data from sellers who adopted the livestream shopping channel at different times. This staggered adoption enables us to use those who have not adopted as a control group (Manchanda et al., 2015). There is a caveat in this setting: we do not observe any sellers who never adopted the livestream shopping channel. As a result, we estimate the effect of adoption as the average treatment effect on the treated (ATT) rather than the average treatment effect (ATE), because we cannot evaluate if those who did not adopt (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 adoption, then the ATT might be greater than the ATE. However, this should not be a major concern, given the widespread popularity of livestream shopping channels and the availability of numerous resources for channel management, making adoption a common step for sellers on the platform.[10] Therefore, with a substantial portion of sellers likely to adopt the channel eventually, 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 the channel, those opposed to adoption would face a noncompliance issue, making the ATE estimate potentially less informative.

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

Secondly, traditional methods like 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 adoption nature.

Thirdly, the sellers' staggered adoption of the livestream shopping channel suggests that the

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

decision to adopt may be strategic. Sellers who believe the livestream shopping channel suits their needs better might adopt earlier. This implies that the decision to adopt is potentially endogenous, necessitating that our estimation technique accounts for the strategic nature of 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 could bring platform-driven advantages, like enhanced search rankings.

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 eventually adopted the livestream shopping channel, we follow the same spirit in Manchanda et al. (2015), truncating the data in April 2020 and categorizing all sellers who adopted 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, and ϵ_{it} is the idiosyncratic error term. β^{TWFE} estimates the ATT. We use the TWFE model as the baseline method, however, 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 both the TWFE and the synthetic control methods. Like the TWFE method, it remains unaffected by additive shifts at the unit level and supports inference in large panels. Additionally, akin to the synthetic control method, it recalibrates pre-treatment period outcomes and control unit data to generate synthetic units, thus not relying on the strict assumption of parallel trends.

Since sellers adopt the livestream shopping channel in a staggered fashion, we follow Berman and Israeli (2022) to conduct the estimation for each cohort, then aggregate them to obtain the average treatment effect. To perform the estimator, we construct a balanced panel for each cohort g. The cohort-specific estimator, β_g, is obtained by solving the following optimization problem,

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

where θ contains the seller and time fixed effects, i.e., $\theta = (\alpha_i, \tau_t)$, and 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, β_g is the cohort-specific treatment effect, and 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. $\mu(g)$ 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 3 biweeks before and after the adoption. 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 biweeks before and after the adoption and find all results, presented in Appendix A, remain qualitatively unchanged. SynDiD introduces two sets of weights: unit weights, $\hat{\omega}_i$, and time period weights, $\hat{\lambda}_t$. These two sets of weights are selected to match the trend of seller outcomes of the two groups and to balance each control seller's outcome in the post-adoption periods to be the weighted average outcome, respectively.[11]

SynDiD addresses the initial three challenges of identification as outlined in Section 5.1. Firstly, it operates as a cohort-based estimator, enabling it to accommodate heterogeneous treatment effects across various cohorts and adapt well to the staggered nature of adoptions. 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. Third, with the incorporation of the two types of weights, SynDiD can provide a consistent estimate of the treatment effect even when the adoption decision is correlated with seller-level time trend, as long as the combination of the number of control sellers and pre-adoption periods is sufficiently large (Arkhangelsky et al., 2021; Berman and Israeli, 2022), which is the case in our context (see Appendix B for the number of sellers in the treatment and control group for each cohort). Thus, the estimator addresses most of the identification challenges, and we use it as the main model to interpret our results.[12]

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

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

5.2.3 Instrumental Variables Estimator

The SynDiD estimator is consistent even when the adoption decision correlates with seller-level time trend, which largely addresses the identification challenge of the strategic adoption. In addition, we provide an alternative approach, the instrumental variables (IV) estimator, to address this strategic adoption issue.

The instrumental variables are based on the changing popularity of the livestream shopping channel among sellers over time. We construct two types of IVs. First, for every seller in each time period, we compute the proportion of sellers who have adopted livestream shopping within the same category (e.g., fashion essentials, food, etc.) as the focal seller. We refer to this IV as the *category instrument*. Second, for every seller in each time period, we calculate the proportion of sellers who have adopted livestream shopping within the same geographic location (i.e., the same province) as the focal seller. We refer to this IV as the *geographic location instrument*. The concept of developing these two types of IVs are similar to previous marketing literature (e.g., Berman and Israeli, 2022).

Both the *category* and *geographic location* instruments capture the popularity of the livestream channel, and could positively correlate with sellers' adoption decisions. However, as both instruments measure the industry-level popularity trend, they should not correlate with a specific seller's revenue. Thus, we consider these two IVs as exogenous shifters of adoption timing, which do not relate to seller performance. We then use the three-step estimation procedure proposed by Wooldridge (2019) to obtain the treatment effect.[13] A caveat of this estimator is that the exogenous adoption shifters can influence the seller's decision to adopt only until the period of adoption. Consequently, the ATT is estimated using observations from only up to one period post-adoption. Due to this limitation, we position this method as a secondary support to the SynDiD estimator.

5.3 Unobserved Confounders

The presence of unobserved confounders, which is the last challenge in Section 5.1, could undermine the ability to accurately estimate the impact of adopting the livestream shopping channel. Firstly, sellers might accompany the adoption of the livestream shopping channel with other strategy adjustments, such as refining inventory management. Although these adjustments are not directly observed, they could influence seller performance and, as a result, skew the estimated treatment

[13] Section OA1.3 of the Online Appendix provides a detailed discussion and outlines the procedure.

effect. In addition, upon adopting livestream shopping, sellers might benefit from preferential treatment by the platform, such as improved visibility through superior search engine placements, 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 itself. To address these potential issues of unobserved confounders, we undertake the following additional analyses.

5.3.1 Consumer-level Analyses

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 they adopted the livestream shopping channel. Hence, a portion of the consumers had previously made purchases from these sellers' online storefronts before the new channel was adopted. These individuals are categorized as existing consumers. For these existing consumers, our dataset includes not only their purchase history but also whether they have watched a specific seller's livestream within a given time period. By comparing the changes in behavior of those who watched the livestreams to that of those who did not, 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 other concurrent actions, then the changes in the purchasing behavior of watchers should be significant than that of non-watchers. In contrast, it is unlikely that other changes happening at the same time would affect the purchasing habits of watchers and non-watchers in distinct ways. Secondly, while our dataset does not explicitly capture the platform's search rankings or impressions, any modifications to search rankings on Taobao, the platform for the online store channel, should affect all consumers equally and not be tailored to individual consumer behaviors.[14] Thus, if our analysis at the consumer level indicates that the changes in purchasing patterns of those who watch livestreams diverge from those who do not, we can attribute such discrepancies to the influence of livestream viewing rather than to any advantageous search rankings.

This consumer-level analysis faces a challenge due to the absence of random assignment between watchers and non-watchers. Essentially, this means there could be systematic differences between these groups due to both observables and unobservables. To address observable differences, we apply

[14] Source: The platform claims that rankings are mainly influenced by product attributes. https://zhuanlan.zhihu.com/p/77039873

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 before the sellers' adoption of livestream shopping, including metrics such as the amount spent, the frequency of purchases, and the total number of transactions, as indicators of a consumer's likelihood to engage with livestreams.

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 two strategies. Firstly, we apply the Heckman correction method to manage the problem of self-selection. Secondly, we use the interactive fixed effect counterfactual estimator (IFEct, Liu et al. 2024), which is designed to handle unobservables that change over time at the individual level.

Heckman Correction Approach The Heckman Correction method has been extensively applied in marketing research to address issues of selection bias (e.g., Manchanda et al., 2015). The key is to identify exogenous variations that affect a consumer's choice to become a watcher. To achieve this, we collect a dataset from the Baidu News Index, which tracks the media popularity trends of keywords related to livestream shopping over time. We suggest that fluctuations in this index can act as external motivators, nudging consumers to engage with livestreams. Therefore, increased media coverage on livestream shopping correlates with a higher likelihood for consumers to become watchers, satisfying the relevance condition of an instrumental variable. Meanwhile, this aggregate index should remain unlinked to individual-specific behaviors, such as specific personal needs, thereby satisfying the exclusion restriction.

In the first stage, we estimate a probit model to analyze the likelihood of consumers choosing to watch livestreams by the following specification:

$$Pr(Watch_{cit} = 1) = \Phi(\alpha + \gamma LoggedNewsIndex_t) \tag{3}$$

where $Watch_{cit}$ indicates whether consumer c watched livestreams offered by seller i at time t. We use all observations up to the first observation after the seller launched the livestream shopping channel. $LoggedNewsIndex_t$ is the logged Baidu News Index at time t. The observed variations are attributed to changes over time in the Baidu News Index.

Then we derive the inverse Mills ratio from the first stage and plug it into the difference-in-differences model,

$$y_{cit} = \delta_{ci} + \tau_t + \gamma D_{cit} + \sigma \lambda_{cit} + \epsilon_{cit}, \tag{4}$$

where y_{cit} is the logged outcome variable, i.e., purchase amount and frequency, for consumer c's purchase from seller i at time t. δ_{ci} is the consumer-seller pair fixed effect, and τ_t is the time fixed effect. D_{cit} indicates whether consumer c has watched livestreams offered by seller i at time t, γ is the variable of interest which measures the consumer-level average treatment effect of watching livestreams, λ_{cit} is the inverse Mills ratio calculated from the first stage.

IFEct Approach In addition to the Heckman correction approach, we introduce an alternative estimator, interactive fixed effect counterfactual estimator (IFEct, Liu et al., 2024), to address the concern that unobservable factors might influence consumers' decisions to become watchers. The IFEct method incorporates an interactive term between these two dimensions, offering a more nuanced control for potential selection biases, especially those that are specific to individual-level time-varying factors, such as a consumer's particular interest in a seller's offerings at a given moment.

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, where D_{cit} indicates the treatment status, i.e., whether consumer c has watched the livestreams held by seller i by time t. IFEct assumes that the untreated potential outcomes take the following functional form:

$$Y_{cit}(0) = \delta_{ci} + \tau_t + \iota'_{ci} f_t + \epsilon_{cit}, \tag{5}$$

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, and ι_{ci} is a vector of unknown factor loadings. The interaction term 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.[15]

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

5.3.2 Occasional versus Frequent Livestream Sellers

Besides the consumer-level analyses, we also provide supporting evidence from the seller level to examine whether sellers' concurrent actions may explain their performance changes, if there are any. Specifically, we investigate the differential impact of adopting the livestream shopping channel on sellers who engage in livestream sessions once versus those who conduct multiple sessions. Unlike traditional physical retail environments and showrooms, the livestream shopping platform is accessible to consumers solely during the times sellers host livestream sessions. Logically, it follows that sellers conducting multiple livestream sessions (i.e., frequent livestream sellers) are likely to see a greater increase in revenue from adopting livestream shopping compared to those who livestream only once (i.e., occasional livestream sellers), all else being equal. Conversely, if concurrent but unobserved actions, such as the utilization of inventory management tools, play a major role in influencing sellers' 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. To conduct this comparative analysis, we apply our seller-level estimators to each seller group separately.[16]

This analysis has limitations. While comparing occasional and frequent livestream sellers helps address the concern that concurrent actions by sellers might drive performance changes, it does not completely eliminate the possibility of other factors affecting the performance of all sellers who adopt the livestream shopping channel, such as enhanced search rankings provided by the platform. Moreover, this analysis might be compromised in situations where sellers may use livestream sessions as a conduit for feedback, subsequently adjusting their strategies (e.g. optimizing inventory management) only after a few sessions. Therefore, we view this analysis as offering supplementary support to our consumer-level analyses, helping mitigate unobserved confounders.

[16]We also conduct a series of robustness checks to extend the comparison to occasional and frequent livestream sellers based on different definitions in Section OA2 of the Online Appendix and show the results remain unchanged.

6 Results

6.1 The Impact of Adopting the Livestream Shopping Channel

6.1.1 Total and Online Store Channel Revenue

We use the TWFE, SynDiD, and IV estimators 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 positive and significant results indicate 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). Significance level: *p<0.1; **p<0.05; ***p<0.01

We next examine the impact on revenue specifically from the online store channel after adopting the livestream shopping channel. The SynDiD analysis 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 livestreaming. This equates to an additional 453 CNY in revenue biweekly for a median seller. The observed revenue boost within the online store channel highlights the presence of a positive cross-channel spillover effect, demonstrating that the adoption of the livestream shopping channel can enhance revenue streams across both channels. Given that a seller's total revenue originated exclusively from the online store channel prior to adopting livestream shopping, comparing the total revenue increase with that of the online store channel allows us to conclude that 46.2% of the total revenue increase comes from the online store channel.

We also include results from the IV (Instrumental Variables) estimator in Table 6. As discussed in Section 5.2.3, this approach addresses the challenge of endogenous adoption timing. The positive and significant coefficients align with our findings from alternative estimators. However, the IV method, limited to observations up until a seller's adoption, produces substantially higher estimates than SynDiD. Therefore, we treat the IV estimator's results as supplementary evidence supporting the conclusions drawn from other estimators.

Table 6: The Impact of Adopting the Livestream Shopping Channel on Seller Revenue (IV)

	Total Rev.	Online Store Rev.
After Adoption	1.032***	0.700***
	(0.147)	(0.147)
Seller FE	✓	✓
Time FE	✓	✓
Observations	21,698	21,698

Notes: The table reports the average treatment effect of adopting the livestream shopping channel on sellers' total revenue and online store revenue, as estimated by the IV method. The effect is only for the period of the adoption only. Significance level: *p<0.1; **p<0.05; ***p<0.01.

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 confounding, as addressed in the last challenge in 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. Given that other simultaneous actions by sellers or potential advantages in search ranking provided by the platform are unlikely to impact these two consumer groups differently, any observed changes in the purchasing behavior of the watchers can be attributed to the sellers' adoption of the livestream shopping channel. Secondly, we compare the effects of adoption on sellers who livestream frequently with those who do so occasionally. Should the introduction of this channel prove to be advantageous for seller revenue, we anticipate a more pronounced effect for sellers who livestream frequently compared to those who do so occasionally.

Consumer-level Analyses We use data at the consumer level 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 adoption,[17] and non-watchers (control group), who do not engage with the livestreams.

We posit that by comparing watchers with non-watchers, we can establish a causal relationship between the adoption of the livestream channel and an increase in revenue at the seller level, regardless of (1) any concurrent but unobserved actions by the seller, and (2) 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 observed positive effect on seller revenue, stemming from the adoption of the livestream shopping channel, is causal.

Due to the lack of pure randomization, watchers and non-watchers might differ systematically in both observable and unobservable factors. Hence, we use propensity score matching to identify non-watchers who resemble the 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.[18]

To address the differences in unobservable factors between the two consumer groups, we use two methods: the Heckman correction and the IFEct estimator. The Heckman correction method is a two-step estimator that uses the exogenous variation from the Baidu News Index to predict the probability of consumers becoming watchers. Considering we classify a consumer as a watcher once they start viewing the seller's livestreams, and this variation no longer influences the consumer's decisions after becoming a watcher, we limit our analysis to observations up to the first period of becoming a watcher, which results in $29,416$ observations in total. Then, we derive the inverse

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

[18] To be accurate, the reported numbers are the numbers of consumer-seller pairs. Given that there are only 9 overlapping consumers, i.e., consumers who watched multiple sellers' livestreams, in the sample, we use the term 'consumers' for simplicity.

Mills ratio and run the regression in Eq 4. The IFEct estimator does not require the exogenous variation, so we use all available observations from consumers three periods before and after the adoption of the livestream shopping channel, yielding a total of $44,124$ observations.

Table 7 presents the first-stage result from the Heckman correction approach. Consistent with our expectations, there is a positive association between extensive media coverage and the probability of a consumer becoming a watcher. Subsequently, we investigate the potential changes in purchasing behaviors among consumers who have engaged with livestreams. Panels A and B of Table 8 present the estimates obtained from the Heckman correction approach and the IFEct estimator, respectively. These findings demonstrate statistically significant and positive average treatment effects, indicating that consumers tend to increase their spending and purchase frequency after watching livestreams. This suggests the adoption of the livestream shopping channel benefits seller performance. Importantly, this supports the argument that the observed positive changes in seller performance are not merely the result of unobserved confounders. It is important to note, however, that the treatment effect observed at the consumer level may not fully reflect the extent of the effect at the seller level due to the partial consumer sample available to us. Despite the limitation, we demonstrate that adopting this channel can enhance seller performance, even in the presence of other potential contributing factors.

Table 7: First Stage Results (The Heckman Correction)

	Watch
Baidu News Index	0.046^{***}
	(0.010)
Constant	-1.730^{***}
	(0.128)
Observations	29,416

Notes: The table reports the first stage result of the Heckman correction. Significance level: *p<0.1; **p<0.05; ***p<0.01

Table 8: The Effect of Livestreaming on Consumer Purchase Amount and Frequency

	Total		Online Store	
	Amount	Frequency	Amount	Frequency
Panel A: Heckman Correction				
After Watching Livestreams	0.877***	0.174***	0.609***	0.110***
	(0.042)	(0.009)	(0.041)	(0.009)
IMR	−3.463***	−0.604***	−3.289***	−0.606***
	(0.543)	(0.107)	(0.540)	(0.105)
Observations	29,416	29,416	29,416	29,416
Panel B: IFEct				
After Watching Livestreams	0.539***	0.122***	0.267***	0.049***
	(0.035)	(0.007)	(0.031)	(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 includes $7,354$ 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 A displays the estimation results with Heckman correction, based on $7,354$ consumers over 4 time periods. Panel B displays the estimation results using IFEct, 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

11.7% of sellers engaged in livestreaming only once during the six weeks following their initial adoption, and are classified here as occasional livestream sellers. We analyze the treatment effects on seller performance by comparing these occasional livestream sellers with the frequent livestream sellers. We use propensity score matching to identify frequent livestream sellers that are similar to those 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 9. For sellers who livestream frequently, there are notable increases in both total revenue and online store channel revenue post-adoption, with surges of 126.1% (calculated as $\exp(0.816) - 1$) and 58.6% (calculated as $\exp(0.461) - 1$), respectively. Conversely, the impact on revenue for sellers who only hosted a single livestream session was not statistically significant, indicating that occasional livestream sellers do not see the same benefits from adoption. The findings provide necessary, albeit not sufficient, support for dismissing the explanation that concurrent actions by sellers are the cause of the observed increases in seller performance. This is based on the premise that it is unlikely for the concurrent actions to have a disparate impact on the two groups of sellers.

Table 9: 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. Occasional and frequent livestream 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. 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 small business owners 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.[19] In this section, we examine the heterogeneous impact of the adoption on sellers of different sizes.

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

Panels A and B in Table 10 present the findings using the two proxies. For both proxies, the outcomes suggest that the adoption's effects are more significant for smaller sellers. For instance, when we use seller credibility rating as a proxy of seller size, we find that the ATT of total revenue

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

for large-scale sellers is 0.494, which is notably lower than the ATT of 1.592 for small-scale sellers. This highlights one potential advantage of the livestream shopping channel: it helps level the playing field in the e-commerce marketplace, offering small business owners a chance to expand and compete.

Table 10: The Differential Impact of Adopting the Livestream Shopping on Sellers

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, with Panels A and B presenting the results using seller credibility rating and subscriber count as proxies for seller size. Significance level: *p<0.1; **p<0.05; ***p<0.01

7 Mechanism

Our findings demonstrate that the adoption of the livestream shopping channel significantly increases both total revenue and online store revenue for sellers, suggesting a positive cross-channel spillover effect. In this section, we investigate the mechanism behind this spillover, specifically examining how integrating the livestream shopping channel can benefit sellers with pre-existing online stores. We explore three potential mechanisms responsible for this effect.

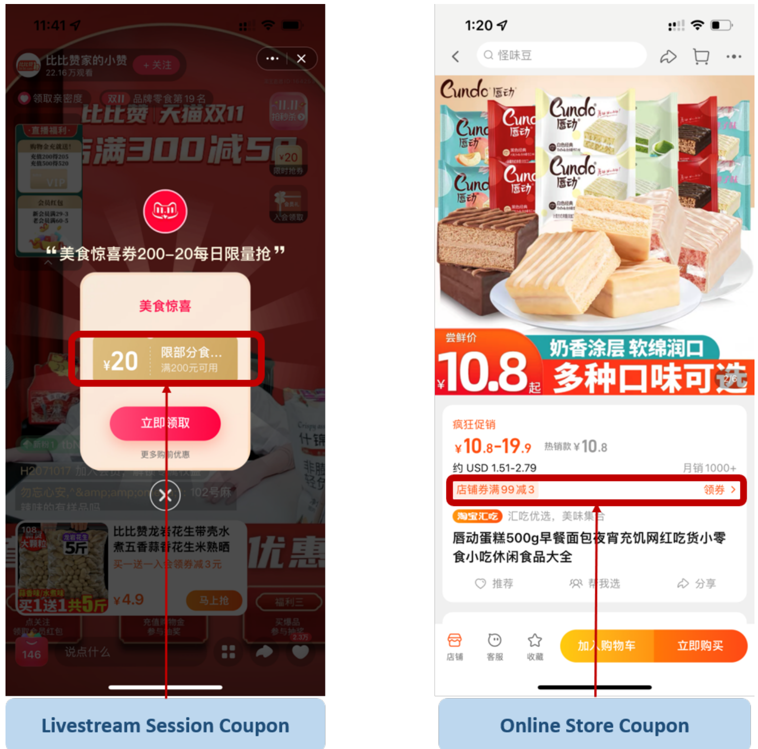
Firstly, sellers can use livestreams to convey product details to consumers. The capability for real-time interaction within livestream shopping platforms potentially makes them more captivating and efficient in providing information than traditional physical stores or showrooms. Consequently, livestream shopping possesses the *uncertainty reduction* effect, as 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 star sellers. Unlike the *uncertainty reduction* effect, which focuses on providing information about products, this mechanism centers around 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 connection* effect.

Lastly, livestream shopping stands out for its prominent display of promotions. Livestreamers frequently highlight offers such as low prices, coupons, rebates, raffles, and free gifts (Liu, 2022). Although similar promotions may be available in online stores, they are often less noticeable, leading consumers to overlook them and potentially pay more. Livestream shopping thus plays a crucial role in educating and reminding consumers about these promotions, even those available in online stores. 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 promotions in online stores, potentially boosting revenue for sellers from 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 livestream introductions 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 livestream introductions compared to 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, like apparel, in our context. This argument is supported by existing literature (e.g., Wang and Goldfarb, 2017).

Furthermore, within the food category, we investigate how fresh food compares to snacks in terms of the effect of livestream introductions. In our context, snacks are generally packaged food items, whereas fresh food includes produce, meat, and seafood items. This distinction allows livestreamers 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.[20] 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 compared to snacks, driven by the enhanced assurance in quality that livestream shopping facilitates.

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

$$y_{lt} = \gamma_l + \tau_t + \kappa D_{lt} + \epsilon_{lt}, \tag{6}$$

where y_{lt} is product l's logged sales at time t, and γ_l and τ_t are the product and time fixed effects. D_{lt} is an indicator equaling 1 if the product has been introduced in livestreams, and κ is the coefficient of interest, measuring the product-level average treatment effect of livestream introductions.[21]

Panels A and B of Table 11 present the findings for the two sets of product subcategory comparisons. In Panel A, the data indicates that both apparel and accessories gain from livestream introductions. Nonetheless, there is a significant difference in the average treatment effects between these two product subcategories. Specifically, apparel products see a notably greater benefit from livestream introductions than accessory products, 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 might opt to showcase on livestreams those products that are already popular or trending in the

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

[21]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.

online store channel in order to capitalize on their existing popularity. Although we recognize this limitation, we argue that 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—the benefit of livestream introductions varies by subcategories—remains valid.

Table 11: 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. Significance level: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

7.2 Consumer-seller Connection

Besides the *uncertainty reduction* effect, livestream shopping could 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. Additionally, livestreams can serve to remind consumers of previous interactions they have had with sellers. Moreover, through livestreams, consumers may develop positive affects as well as a stronger trust towards sellers. This, in turn, strengthens their relationship with the sellers, potentially leading to increased purchases across channels. We refer to this comprehensive impact as the *consumer-seller connection* effect and explore whether it contributes to explaining the identified positive cross-channel spillover.

First, we revisit the product-level difference-in-differences results presented in Table 11. For accessories and snacks, even though livestreams might have a limited ability to reduce product uncertainty, we still observe a significant sales increase after livestream introductions. 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 consumers forming connections with the sellers through livestreams. However, there is a caveat: although 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 connection.

To address this concern, we investigate whether adoption 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 can further shed some light on this mechanism.

Given that a seller might offer a variety of product subcategories, we determine the proportion of each product subcategory sold by each seller within 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.[22]

Panels A and B in Table 12 present the results of two comparative analyses: one between apparel and accessory sellers, and the other between fresh food and snack sellers. In the previous section, we show that products such as apparel and fresh food derive greater benefits from the livestream introductions. However, at the seller level, we find that sellers specializing in different subcategories of products experience similar benefits in the online store channel from adoption. This suggests that the cross-channel spillover observed for sellers specializing in accessories and snacks might

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

partly result from cross-product spillovers, where consumers increase their purchases of products not even featured in the livestream shopping channel. Since sellers are unlikely to discuss products not showcased in livestreams, this proves that the phenomenon stems from an enhanced connection between consumers and sellers.[23]

Table 12: The Impact of Adopting the Livestream Shopping Channel by Categories

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 %" = $(\exp(coef\_online\_store) - 1) / (\exp(coef\_total) - 1)$. Significance level: *p<0.1; **p<0.05; ***p<0.01.

This analysis has two limitations. First, as we only have access to a subset of consumer transaction data, our definition of sellers' specializations is based on this limited information, which could lead to inaccurate categorization. Nonetheless, there is no evidence suggesting that this will disproportionately bias the representation of certain subcategories of products sellers specialized in. Second, without direct observation of livestream content, we are unable to distinctly categorize the

[23] We conduct an additional event study to test whether the sales of products not featured in livestreams change. The results also suggest a cross-product spillover. We refer readers to Section OA3 of the Online Appendix.

types of consumer-seller connections formed. For example, it remains unclear whether a seller's improved revenue performance is due to consumers' enjoyment of the content, their attraction to the seller's charisma, or the livestreams' effectiveness in imprinting the seller's brand into consumers' memories for subsequent purchases. We acknowledge this limitation and suggest it as an avenue for future research.

7.3 Promotion Visibility

Thus far, we have demonstrated that both the *uncertainty reduction* and the *consumer-seller connection* effect 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, which may motivate consumers to actively look for and apply these promotions in the online store channel as well. This mechanism could also account for the similar scale of cross-channel spillovers observed among sellers specializing in different product subcategories (Table 12), potentially challenging our argument regarding the *consumer-seller connection* effect. We undertake the following analyses to further examine this mechanism.

In our context, sellers have the option to use two distinct types of promotions. The first type allows them to issue non-customized promotions applicable to all customers, typically consistent across both livestream shopping and online store channels. In addition, 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 sellers in our sample, who are mostly small business owners, due to the complexity of planning and executing such promotions. Unfortunately, our data does not have 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,

$$p_{lt} = \gamma_l + \tau_t + \rho live_{lt} + \epsilon_{lt}, \tag{7}$$

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

Table 13 reports the result. Our analysis indicates that the transaction price for aproduct is on average 7.3% lower when it is sold through the livestream shopping 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 to 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 impose greater promotions in the livestream shopping channel.

Table 13: Product Price Study Across Channel

	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 product price differences 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. 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 and applying price promotions, 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 introduction to livestream shopping. Should consumers indeed become more proactive in seeking out and using price promotions 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:

$$p_{ilt} = \gamma_l + \tau_t + \phi D_{it} + \epsilon_{ilt}, \tag{8}$$

where p_{ilt} is the logged price of product l sold by seller i at time t, and γ_l and τ_t are the product and time fixed effects. D_{it} is an indicator representing whether seller i has adopted the livestream channel or not. 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 14 shows the result. The insignificant result 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 similar promotions in the online store channel. Therefore, this mechanism might not account for the positive spillover observed following the adoption of the livestream shopping channel.

Table 14: 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. 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 of these 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 these 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 connection* effect, making it a more inclusive option than traditional physical retail outlets, such as showrooms and brick-and-mortar stores. Consequently, it caters to a wide range of sellers, including those dealing with different product categories, as they 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 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 from 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, suggesting that even products not featured in livestreams benefit from the adoption. This evidence hints at the *consumer-seller connection* effect, where livestreams potentially strengthen consumer-seller connections. However, while the livestream shopping channel's promotion visibility 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 connections. 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.

Like any research, ours comes with limitations that leave room for future research opportunities. Since we lack cost information, our findings primarily address revenue impacts. The costs of adoption, including equipment setup and employee labor, differ across sellers, so we refrain from offering tailored adoption 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 like Amazon and eBay, which also host millions of sellers. However, in recent years, platforms without an e-commerce foundation, such as Facebook, have ventured into livestream shopping. For these platforms, we encourage further studies to investigate whether collaborations with other online marketplaces yield comparable results.

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Appendix A Robustness

A.1 Seller-level ATT

A.1.1 Analyses Using Different Sets of Sellers

In the main analyses, we select sellers who had been operating their online stores for 6 months prior to the commencement of our observational data. This criterion was employed to identify sellers highly committed to operating their online storefronts. This selection results in $2,851$ sellers. For robustness, we reconduct the analysis using the full set of sellers ($3,643$ sellers). Table A1 reports the average treatment effect on 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 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).

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

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

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

A.1.2 Analysis Using Non-COVID 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 available before December 2019. This provided us with 10 periods (biweeks) of observations for each seller. Table A3 reports the results, which stay 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 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).

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 time periods) before and after the adoption. The analyses only apply to sellers who adopted livestreaming after September 19, 2019 (8 weeks after the earliest observational period), resulting in $2,635$ sellers. Table A4 reports the average treatment effect of sellers' total and online store channel revenue. All results are qualitatively similar to those obtained using 6-week periods before and after adoption.

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 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).

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 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 the 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 mean difference and p-value of covariates between watchers and non-watchers before and after the matching. Covariates used for matching include seller (exact match), purchase frequency, purchase amount, and purchase quantity based on 1, 2, and 3 biweeks 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 those occasional livestream sellers. The covariates include pre-adoption seller metrics, including the positive feedback rate, the seller credibility rating, the number of subscribers and the average product price. Table A7 shows the balance check before and after matching. After the 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 mean difference and p-value of covariates between occasional and frequent livestream sellers before and after the matching. Covariates used for matching includes positive feedback rate, seller credibility rating, number of subscribers and average product price. All variables except for positive feedback rate are log-transformed.