Agri-Food Products Live Streaming: Fad or A New Marketing Channel?

by Zhengliang Yang, Xiaoxue Du, Patrick Hatzenbuehler, Liang Lu, Thomas Reardon, and Guang Tian

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Abstract:

The continued persistence of the global COVID-19 pandemic has accelerated the increasing trends of agri-food businesses selling their products via E-commerce. One emerging element of this expansion of online marketing is the use of a new E-commerce tool, live streaming sales, among small and medium size agribusinesses globally. We are witnessing US entrepreneurs selling yogurt on Amazon Live, Singaporeans marketing fresh fish live through Facebook, and farmers in China selling fruits and vegetables live on Alibaba. The goal of this paper is to explore whether live streaming is a sustainable marketing channel for agri-food product retail. In this paper, we developed a fixed effects panel regression model that encompasses the key elements that explain variation in live streaming sales across firms. Specifically, the model accounts for the online market structural elements that divide the online marketplace into segments based on criteria related to official designations such as trademarks and their reputation among consumers. The model is estimated using a dataset composed of live streaming sales for hundreds of agri-food products from Alibaba. The empirical result suggests that market segmentation based on reputation is a key explanatory factor for explaining live streaming sales variation.

JEL Codes: Q110 Q120 Q130

1 Introduction

Use of live streaming e-commerce to sell food products has grown rapidly in recent years. Recent research has demonstrated that live streaming has great potential in reaching consumer audience and building trust in general (Wongkitrungrueng and Assarut, 2018; Chen et al., 2020), but little evidence exists regarding its feasibility for agri-food products. Due to the prominence of quality-related characteristics in food sales, it is plausibly the case that business and product reputation are a powerful signal to quality in live streaming sales as they have been observed to be in markets for other products (Nelson, 1970; Shapiro, 1982; Tirole, 1996; Winfree and McCluskey, 2005; Dequiedt, 2018) and and for agri-food products sold in other market channels such as in supermarkets (Standifird, 2001; Wu et al., 2011; Fan et al., 2016).

The aim of this paper is to determine whether business and product reputation can help explain variation in agri-food live streaming sales. Previous conclusions and facts provide reason to believe that agri-food products live streaming sales may follow the similar path as the non-agri-food products: interaction and video in the live streaming provide consumers the details of agri-food products and reduce consumers psychological distance, which allows consumers to better understand the products, thereby affecting their purchase intention. Interaction and video can help build trust of consumers by providing key information regarding the quality of agri-food products. However, several fundamental characteristics about agri-food marketing, such as product perishability, lead to challenges in using live streaming to inform consumers about products to the degree that they would make a purchase.

On the one hand, existing studies point out two types of consumer trust in the context of the live streaming: trust in product and in the streamer(Wongkitrungrueng and Assarut, 2018; Chen et al., 2020). The results by Chen et al. (2020) prove that trust in the streamer has more than twice the effect of product quality or trust in the product. In other words, live streaming could make consumers trust the streamer more than the trust in the product, which is not conducive to building product or company reputation. In addition, trust is subjective, which is affected by many factors in the context of live streaming, like the interaction frequency during the live streaming. Thus, it is difficult to establish whether consumers trust sellers based on their interactions with agri-food live streaming salespeople. However, the business or product reputation may likely be related to consumer trust.

Research findings from studies involving other types of experience goods may not applicable to agri-food products. For instance, Zhang et al. (2020) found that consumer experience is important for explaining sales of goods such as suitcases denim jackets, desk lamps, USB memory stick, etc., but these products are fundamentally different from agri-food products due to issues such as perishability and quality-factors being more prominent. Therefore, their conclusion shows that live streaming is beneficial for reducing psychological distance may not fully apply for agri-food products.

Determining the role of establishing business and product reputation in live streaming sales has important practical implications for small and medium sized agri-food companies. With lockdowns easing and shoppers returning to physical stores, the choice to adopt live streaming or not involves one of the fundamental issues of firms or individual development and marketing strategies in the post-epidemic era. Adoption of livestreaming may result in substantial costs. Without a thorough understanding of the mechanism for explaining effective live streaming sales, blindly following the trend and joining live streaming may carry substantial risks with uncertain benefits.

In this paper, we analyze sales of fresh fruits via live streaming on Taobao Live streaming as a case to study to determine the role of reputation and other business-related factors in explaining the variation in agri-food product live streaming sales. To establish whether reputation is a key factor, varying rules for selling the similar products on platforms with different brands were used to identify individual market segments. In order to improve the estimation accuracy, we used an instrumental variable approach to capture such market segmentation effects on sales in a first stage regression. Our results found that reputation is a key factor in explaining differences in live streaming revenue. This finding is important for small and medium-sized companies that want to adopt live streaming as a sales channel in the future.

The rest of paper proceeds as follows. Section 2 introduces the background of live streaming and Taobao. Section 3 presents our data sources, including a detailed description of the data processing and collecting process. Section 4 presents the empirical strategy and results. Section 5 discusses the key findings and some limitations. Concluding remarks close the paper.

2 Background

2.1 Live Streaming

Live streaming e-commerce is a type of e-commerce, it looks like TV shopping, but is different from traditional e-commerce like online shopping. It similar to TV shopping such as HSN (Home Shopping Network) or QVC (Quality, Value, Convenience), where users can watch live streaming videos, ask real-time questions and buy through third party e-commerce platform while the discounts and limited quantity are displayed on the screen. The difference between live streaming e-commerce and other forms of e-commerce is that live streaming offers a pseudo "in-store" shopping experience, in which consumers can interact with the streamer while watching the videos. Live streaming e-commerce become one of the important shopping channels during the epidemic by creating an offline shopping atmosphere.

Figure 1 gives an example of farmers sells apples via Taobao Live Streaming in China. Consumers type questions in the chat box to get information they need, like the shipping time, the taste of the apples etc. in live streaming. Some viewers require the streamer to try an apple in front of the screen as if they were tasting by themselves, in which they can learn more about the product before buying and help them make purchase decisions. Simultaneously, the streamer answer the consumer's questions and show the products detail such as packaging, eating suggestions or even storing tips to the consumers.

[Figure 1: Retailers sell apples in Taobao Live Streaming]

2.2 Taobao and its two type sellers

Taobao, a subsidiary of Alibaba, is a leading online shopping and agri-food products plantform in China, which is similar to Amazon and eBay. It has 755 million active users in Jun 2019 (Alizila, 2019) and GMV (gross merchandise volume) reaches 300 billion yuan ($46 billion) in 2020[1]. Its agricultural product transaction volume reached 200 billion yuan ($30.7 billion) in 2019[2]. Here are two main types of sellers in Taobao, one is Taobao Marketplace seller and the other is Taobao Mall seller (here we denote it as Tmall). These two kinds of sellers occupies 75% of the online agri-food products market share and have many similarities: product type, price, customer service, product quality etc. These sellers are also Taobao live streaming sellers.

Two features are worth highlighting to differentiate these two types of sellers. First is reputation. Taobao requires Tmall sellers either own a brand or sell branded products so Tmall sellers need to develop their own brands or become other brands' authorized sellers. Then sellers must pass the rigorous brand evaluation by the Taobao to be eligible for entering Tmall. The brand evaluation, which is a completely independent process, includes brand authorization procedures, brand influence etc. Even if some companies are in good operation conditions (like high profit margin), they are not eligible to enter Tmall due to insufficient brand influence. Taobao will also invite some sellers that they think have high brand influence to enter Tmall. In addition, Taobao will keep evaluating the Tmall sellers for their operation status annually, Tmall sellers cannot continue to operate if it fails the evaluation(Taobao, 2020a). However, Taobao Marketplace sellers do not need to go through all these processes. Brand influence has the tightened positively relationship with reputation

[1]https://www.statista.com/statistics/959633/china-taobao-gross-merchandise-volume/
[2]http://www.199it.com/archives/1099026.html

(Herbig and Milewicz, 1993, 1995; Kuenzel and Halliday, 2010). Therefore, such mechanism provides us with an ideal setting to explore the role of reputation.

The second difference are the entry barriers, which reflected in requirements and cost. Individuals or companies can register as Taobao Marketplace sellers for free, and they do not need to pay the platform operating costs. However, only companies that meet the specific requirement (for example, the registered capital of needs to reach 3 million yuan ($460,000)(Taobao, 2019b)) can register as Tmall sellers. Besides, Tmall sellers need to pay a huge amount of software service fees to Taobao platform(Taobao, 2019a).

Despite the differences in Taobao Marketplace Sellers and Tmall Sellers, their consumers are no different. This is because two types of sellers are completely open to all consumers and consumers are not charged if they want to shop in Tmall.

2.3 Taobao Live Streaming

Taobao Live Streaming is the top live streaming shopping platform in China. It was lunched by Alibaba Group in 2016, which has a 150% growth rate in transactions for three following years. Consumers can watch live streaming from Taobao Marketplace sellers and Tmall sellers through the Taobao mobile app or computers. Taobao Live Streaming transaction relies on the Taobao, where consumers purchase products on Taobao (such as filling in address information, viewing product history ratings, etc.) while they are watching the live streaming. It covers the vast majority of categories of products including agri-food products. There have been 1.4 million live streaming related to agri-food products, which drive 60,000 farmers to join the live streaming[3]. For Taobao Marketplace sellers and Tmall sellers, they can choose to sell the products in their live streaming rooms or entrust them to professional streamers.

[Figure 2: Selecting Agri-food Live Streaming Rooms in Taobao Live Streaming]

[3]https://www.cbndata.com/report/2219/detail?isReading=report&page=1

Taobao Live Streaming introduced many rules and innovated algorithms to ensure the content quality. First, in order to prevent the same user from registering multiple accounts to falsify live streaming data (for example, registering multiple accounts to purchase goods in the same live streaming room and create popularity), all registrations require ID card verification. The ID card information contains the name, birthday, photo, address and 18-digit unique code. This ensures the uniqueness of the registered account.

Second, Taobao Live Streaming developed a set of independent algorithms that can monitor live streaming with artificial intelligence technologies. For example, its video recognition algorithm can identify the prohibited content, and immediately impose penalties to the streamer. In addition, Taobao Live Streaming also has manual monitoring of streaming content. Finally, although Tmall sellers paid much higher fees than the Taobao Market Sellers, it does not mean that products from Tmall sellers would be shown up at consumer's phone at priority. It is because Taobao Live Streaming is an independent app with its own algorithm, which automatically recommends live content to viewers based on number of viewers, product popularity, and consumer preferences etc. Therefore, Tmall sellers will not have the advantage of being recommended in the live streaming.

3 Data

To explore the role of reputation in agri-food products live streaming, we collect Taobao live streaming data from a professional third-party database, sellers and products information from Taobao (including Taobao Marketplace sellers and Tmall sellers), respectively. Then we manually merge two data sets to construct our sample and get the panel data set. The first data set contains live streaming information of 10 fresh fruits with the highest total live streaming sales from June 1, 2020 to February 28, 2021. The second data set consist of live streaming sellers' and products information within the same period.

We focus on fresh fruits due to three reasons. First, fresh fruits are most likely to use live streaming to reduce uncertainty, which may have substitution effect on reputation. For example, fresh fruits like pear has much shorter shelf life than dry agri-food like nuts and they need live streaming to help selling as soon as possible. Second, fresh fruit producers (farmers) can directly participate in the sales without any processing. Compared to the agents, farmers can more directly participate in the sales process, answer consumer questions in more detail, and reduce consumer uncertainty.

Third, we found many missing values in other agri-food product categories (such as fresh vegetables, meat) due to database technical reasons. For example, there are only live streaming records from Tmall sellers in pork or aquatic products while no records for Taobao Marketplace sellers. Besides, the live streaming data on agri-food products from database concentrate on dry agri-food products (e.g., nuts), snacks(e.g., chips), instant food(e.g., noodles) etc., which are fundamentally different from fresh fruits. Therefore, we chose fresh fruits. Below we describe the key variables, data collection process and present summary statistics.

3.1 Live Streaming Data

We purchased the permission of the third-party database and get access to millions of daily live streaming records from June 1, 2020 to February 2021. The database start collecting revenue information on June 1, 2020 thus we set the same starting point in our sample.

Live streaming revenue refers to the sum of the products sold and the transaction price in live streaming from the beginning to the end. We focus on the live streaming revenue though it has multiple channels within observation period. The database shows the live streaming sales information directly, so we sorted the fresh fruit live streaming sales from June 1, 2020 to February 28, 2021 and selected top 10 different kinds of fresh fruits. Then we drop one specific record which are severely deviate from normal sales. The sales on that day is 6 million, while the average sales of that seller is 20[4]. As we suspect that record may

[4] In fact, the results stay the same even if we include this record in our sample

be due to the typo that caused exceeding normal sales.

Live streaming duration measures the time length (in hours) of live streaming on the certain day. It is the sum of live streaming hours of related products. For example, if the same apple product appears in the three live streaming room, then its duration should be the sum of time length of these three rooms. We drop records which have 0 live streaming hours in the selected period as it means the seller was not in live streaming on the certain day.

The thumbs up, which is similar to Twitter ”like” button, refers to the number of viewers who clicked the ”like” from the start to the end of the live streaming (multiple clicks on the ”likes” for the same account is invalid). We use it to measure the interaction between the audience and the streamer during the live streaming(Seo et al., 2019). This indicator can also indirectly measure the audience's acceptance and feedback of the product(Phua and Ahn, 2016).

3.2 Sellers and products information

Although the first data set provides us with comprehensive live streaming information, it lacks seller's and products information, which would lead to omitted bias estimation. For example, agri-food products' origins (like the Florida oranges) would be a powerful tool to signal the quality, which can affect consumer's decision making (Tirole, 1996). Therefore, we manually collected sellers and products information, mainly deposit, sellers' service ratings and product's origins to construct the second data set.

Deposit. It is the compensation paid by the seller to the consumer when the consumer's rights are damaged. For instance, consumers will receive the money paid by the sellers if consumers buy fake products. Taobao requires different deposits corresponding to seller type. For Tmall sellers, they need to pay a deposit base on the trademark registration status when entering: sellers whose trademarks are under censoring by the Bureau of Industry and Commerce need to pay a deposit of 100,000 yuan ($15,384), while the deposit for sellers holding registered trademarks is 50,000 yuan ($7,692)(Taobao, 2020b). Contrast to Tmall's high deposit, Taobao Marketplace sellers selling food products need to pay a minimum deposit of 1,000 yuan ($154) and it is not mandatory. Since we cannot directly observe the trademark registration status for Tmall sellers while live streaming, we manually search for the trademark registration status of each Tmall seller through an authoritative third-party websites[5]. For Taobao Marketplace sellers, we check the seller information page displayed on Taobao to find out their deposit.

Product origins. We use the origins to control for the effect from collective reputation(Winfree and McCluskey, 2005). The origin information includes provinces and counties. Some imported fruits (such as mangoes imported from Vietnam) do not include counties so we replace them with countries. We manually collected the origin of each product on the product detail page.

Service rating. It comes from the Taobao dynamic service rating (DSR), which is the dynamic score that shows consumers' satisfaction level with sellers' service including the response speed of customer service, the professionalism of answering questions etc. Tmall and Taobao Marketplace seller use the same calculation method and the service rating only depends on the product's positive rate of reviews. Since we are unable to obtain the history of dynamic service rating, we select the rating on February 28, 2021 as the final service rating.

Finally, we complete second data set by adding a dummy which indicates the seller's type (1= Tmall seller and 0 =Taobao Marketplace sellers). Since Taobao has mandatory and exclusive naming rule for Tmall sellers, Tmall seller's name must be suffixed with "flagship seller" or "specialty seller", while the Taobao Marketplace sellers cannot use such suffixed as part of their name(Taobao, 2013). For example, in the name of the "xx fruit flagship store", "xx" indicates seller's brand, and the "flagship store" indicates that it is a Tmall

[5] https://www.tianyancha.com/. Similar to Google, where we need to enter the company or brand name that we want to inquire, and the website will give us the registration status of trademark: cancelled or under censoring. From this we can determine the amount of deposit it needs to pay.

seller. Therefore, by identifying the shop name suffix, we established a seller type dummy.

3.3 Summary Statistics

Table 1 presents summary statistics after merging two data sets by seller's type. The full sample contains 9,505 live streaming records (1,536 from Taobao Marketplace sellers and 7,969 from Tmall sellers). We can observe a wild gap between Tmall sellers and Taobao Marketplace sellers on average revenue (9,186.0 versus 1,279.8) while other live streaming variables close to each other. Even though the Taobao Marketplace seller own larger group of audience on average (6.73 versus 6.47) and twice Thumbs up of Tmall sellers (13.08 versus 6.47), the average revenue of Tmall sellers is still close to 6 times that of Taobao Marketplace sellers. Tmall sellers are only higher than Taobao Marketplace seller on deposit and live streaming hours, but these do not explain why Tmall sellers have higher revenue than marketplace sellers.

For the fruit type, Tmall and Taobao Marketplace sellers focus on live streaming of apple (23.7%) and pear (13.8%) and dragon fruit(12.3%). Regarding to the sellers' information, the average service rating of Taobao Marketplace sellers (4.69) is 0.1 points higher than that of Tmall sellers (4.59). In addition, the average deposit of Tmall sellers is almost 10 times that of Taobao Marketplace sellers (83,491 versus 8,373).

4 Empirical strategy and results

4.1 OLS fixed effects panel regression model

First, we used an OLS fixed effects panel regression model as the baseline with a fruit type and origin fixed effects to estimate the effect of reputation in agri-food live streaming. The fruit type and origin fixed-effects enables us to alleviate bias and endogeneity problems caused by unobservable fresh fruit type and origin characteristics. For example, the taste of apples will not change in a short period, even if the brands are different, there will be no obvious differences in the taste of the same kind of apples. Different types of fruits have different tastes, which is a subjective experience and will affect sales but cannot be observed. Besides, agri-food products within same origins may share collective reputation(Winfree and McCluskey, 2005). We cannot observe such reputation impact on sales, which will not change in a short time.

Unfortunately, we cannot add fixed effects at seller's level because no Taobao Marketplace sellers enter the Tmall or vice versa during our observation period. If we add the fixed effect at sellers level, then there will be no variation in Tmall indicator. Equation (1) illustrate the our baseline model.

$$y_{ijt} = \beta_0 + \beta_1 * Tmall_i + \beta * C'_{ijt} + \mu_j + \epsilon_{ijt} \tag{1}$$

where y_{ijt} is the live streaming revenue of the seller i's fruit type j at time t; $Tmall_i$ is the seller type indicator, which equals to 1 if it is the Tmall seller otherwise 0 to capture the product reputation. We learned from section 2 that all sellers on Tmall need to go through a strict and independent third-party brand influence evaluation and products should have "some brand influence" [6]. Those who fail the evaluation will be refused to join Tmall. In addition, the Tmall sellers must pass the brand influence assessment annually, and Taobao will shut down companies do not meet the requirement. Therefore, whether the product sold by Tmall sellers can be a measurement of brand. We believe products that pass the Taobao brand evaluation process have a certain degree of influence, which we can regard it as a measurement of product reputation.

C'_{ijt} denote the live streaming control variable vector, which includes $Price_{ijt}$, $ThumbsUp_{ijt}$ and $LiveDuration_{ijt}$. They are the average transaction price, thumbs up and live streaming duration and for seller $i's$ live streaming product j at time t. We choose price as control as

[6] The evaluation process commonly conducted by Taobao but detail evaluation standard is non-public information. We learned from Taobao online forums (an online forum for sellers to exchange experiences, similar to Reddit) that many sellers can not pass the brand evaluation due to low brand influence.

it is the basic product information. The rest of variables are used to control the live streaming, live streaming time length ($LiveDuration_{ijt}$) and interactions ($ThumbsUp_{ijt}$)(see Li and Peng, 2021). $ServiceRating_i$ is used for controlling time-invariant seller's service effects (e.g. customer service may not change in the selected period but still affect the purchase intention). μ_j is the fruit type and origin fixed effect (here we construct the interactions to capture this effect); β_0 is a constant term, and ϵ_{ijt} is an error term.

Table 2 presents the regression results for the baseline OLS model. We ran four regression equations, each of them contains the fixed effect of fruit type and origin interaction, and each regression added one more control variable than the previous one. We put the regression results with increasing control variables in Table 2. From column (1) to column (4) represents number of control variables in regression equation. Overall, we can observe whether entering Tmall will significantly ($p < 0.01$) and positively(+) affect live streaming revenue across all columns: Tmall sellers will earn more from 4,788 yuan ($736) to 5,632 yuan ($866) on average than Taobao sellers holding other variables unchanged.

We can draw some other conclusions from Table 2. First, even if we keep adding more controls (1 to 4 controls), the result with all controls (column 4) is much higher than the mean revenue of Taobao Marketplace sellers in Table 1 (5,632 yuan versus 1,279 yuan), which shows that whether to enter Tmall or not has a great impact on revenue. Although the estimates of Tmall effect continue to change, its changes are within a range of one unit of standard error, which shows $Tmall$ and revenue have stable relations. Second, the R^2 improves greatly (over 10%) from only price as controls (column 1) to add live streaming as controls (column 2). It indicates that live streaming control variables are necessary because such effects would be absorbed by $Tmall$ without live streaming controls. Third, the R^2 increases from 0.05 (column 1) to 0.20 (column 4), which suggested the constantly improving of model explanatory efficiency.

4.2 IV estimation

Using the OLS model with fixed effects may reduce the impact of endogeneity and represent causal effect of Tmall in live streaming. But it still has endogenous problem. For example, Taobao requires each Tmall seller to sell at least 10 types of products but no requirement for Taobao Marketplace sellers. Therefore, the number of products sold relates to Tmall while it will also affect revenue. So to improve estimation precision and the address the endogeneity, we use deposit as an instrumental variable to deal with such problem. The data section explain the definition of deposit and our collection process. Here we focus on discussing the reasons deposit can meet the two essential conditions as instrumental variables.

First, the deposit need to meet the exclusion restriction. According to the official Taobao seller's rule, the deposit amount only associated with the brand censoring status and does not depend on unobservable variables such as company size and brand influence. Consumers do not know the brand's registration status instead the difference between Tmall sellers and Taobao Marketplace sellers when they watch live streaming and purchase goods. In other words, this rule is formulated by Taobao and is not affected or determined by the model. So deposit cannot affect the revenue through unobservable variables, which satisfies exclusion restriction.

Second, deposit need to associate with the endogenous variables. Sellers who wish to enter Tmall must pay deposit, which is mandatory and prerequisites by Taobao. So deposit correlates with $Tmall$ and meet the condition. Finally, we used the following two stage functions with same controls and fixed effect to make alternative estimations.

$$Tmall_i = \alpha_0 + \alpha_1 * Deposit_i + \alpha * C'_{ijt} + \xi_j + \eta_{ijt} \tag{2}$$

$$y_{ijt} = \beta_0 + \beta_1 * \hat{T}mall_i + \beta * C'_{ijt} + \mu_j + \epsilon_{ijt} \tag{3}$$

Equation (2) is to illustrate our first stage estimation, where $Tmall_i$ is instrumented by the

$Deposit_i$. We then plug the estimation results from the first stage $\hat{Tmall}_i$ into the 2nd stage with same live streaming controls.

Table 3 shows IV regression results, where panel A and panel B shows the 2nd stage and 1st stage results, respectively. Panel B indicates the regression results of the first stage. β_1 in the first stage is highly significant ($p < 0.01$) with a tiny standard error(close to 0). The R^2 is 0.8 in column (4) and the F-statistics of first stage is F(14, 9490)=512 which is bigger than 10 and they both confirm the solid correlations between our IV and endogenous variable. It means that deposit can be used as an instrument variable for Tmall.

Panel A suggests that $Tmall$ has the significant ($p < 0.01$) and positive(+) relationship with the revenue, which is much greater than the OLS estimation. It indicates that results from Table 2 is biased and there would be downward bias without IV strategy (from 7,068 to 5,632). From column (2) to column (4) we can know that Tmall sellers would earn an average of over 5,000 yuan ($769) more than Taobao sellers. Besides, after adding the live streaming control variables, the price becomes no longer significant($p > 0.1$).

5 Discussion & Limitation

5.1 Discussion

The revenue difference between Tmall sellers and Taobao Marketplace sellers identifies the impact of reputation. This may be because the product with reputation can further reduce consumer uncertainty with the help of live streaming. Reputation directly associate with the quality (Allen, 1984; Tirole, 1996) and previous studies has proved its powerful role in decision making (Rice, 2012). Within the live streaming context, interaction can reduce the consumers risk perception and their decision-making costs for these reputation products efficiently. Consumers just need to know the information which reputation does not contain to help them make decision. For instance, consumers may care the delivery date for the Florida oranges. They don't have to know other information like the taste or smell about the it as the reputation has already provide it. So the live streaming provides them with a method to know such information and has the icing on the cake for these products.

However, products without or low reputation mainly rely on live streaming to sell goods would encounter several problems, which further widening the revenue gap. Whether interaction or videos in live streaming show part of product information, which cannot replace the role of reputation. For example, consumers may know the origins of mangoes but not for taste and smell. Even though the streamer show its taste by trying to taste one, consumers may not believe it as such information is not solid as reputation. Besides, sellers may deliberately show some better-quality products for live streaming, which results in consumers cannot know the full profile of products. These factors will increase consumers' the risk perception, weaken the efficient of live streaming. As a result, products with different reputations lead to huge revenue gaps within the same live streaming context .

Our paper is the first research to explore the role of reputation in the context of agri-food products live streaming and results has following implications. First, the positive and significant relationship between $Tmall$ and revenue indicates that the product reputation plays a pivotal role in agri-food live streaming: it can help increase revenue, which means live streaming can be an effective tool for products with reputation. Our results show that the live streaming revenue of Tmall sellers is 7,068 yuan ($1,087) more than that of Taobao sellers on average per day. Therefore, we roughly estimate that the revenue from Tmall sellers may be 2 million yuan ($326,100) more than Taobao sellers per product[7]. This result can provide a decision-making reference for small and medium-sized companies that plan to use live streaming. For example, they can compare the cost of improving the quality of live streaming or inviting celebrity to sell goods with the cost of entering Tmall to select a better investment plan.

[7] $1087*300(days)=$326,100

5.2 Limitation

Even if we try to improve the estimation accuracy with instrumental strategies, there are still limitations. First, our data is limited to live streaming, which means that we cannot compare the effects before and after the adoption of live streaming. This issue relates to the basic strategic choice for a small or medium-sized firms. Therefore, future research can collect and compare sales before and after the live streaming to answer this question.

Second, we cannot distinguish the reputation effect from Tmall or streamer on revenue. Tmall is a gathering platform for various brands(like the department store but it is online). We can regard the reputation from Tmall as collective reputation. Consumers may buy products because of the collective reputation (for example, red wine with French origins label, oranges with Florida origins). In other words, consumers will buy products because of the platform reputation rather than product reputation. Similarly, consumers buy some products because they prefer a certain streamer (e.g. they are the fans of a celebrity). These reputation can affect our estimation results. So future scholars can explore the ways to separate different sources of reputation and make more precise estimation.

Third, using $Tmall$ as reputation indicator may contains the measurement errors. Although Taobao act as third party to measure reputation, some Taobao marketplace sellers also have certain reputation. For example, some Taobao marketplace sellers have millions of fans with high store ratings and they have their own brands (this brand may not be recognized by Tmall). Such sellers choose to sell products on Taobao Marketplace because they do not want to bear the deposit required to enter Tmall. In order to indicate the reputation of the Taobao Marketplace sellers, Taobao design a special dynamic grading scale for such marketplace sellers, which ranges from 1 to 20. Previous research adopt it to measure its impact on online shopping sales (Fan et al., 2016). The reason why we did not include it in our research is because our database does not count the seller's dynamic grading within the selected period. Therefore, future research can take Taobao grading scale into account in live streaming context.

6 Conclusion

Live streaming is an emerging sales channel for agri-food products, but since it is new for many businesses, there are gaps in understanding the main factors that drive live streaming sales. We use the entry barriers pertaining to rules on a prominent live streaming platform (Taobao) that segment sellers into two types to study the role of reputation explaining variation in live streaming sales. Specifically, the unique feature of Taobao deposit rules were used to analyze firms of different types via an instrumental variable in a first stage regression. The results for the second stage regression that accounts for these differences in firm types show that products or companies with higher reputation cause more daily 7,068 yuan ($1,068) live streaming revenue on average than low or no reputation products or companies. These effects are large as they are nearly 6 times the average revenue of low or no reputation products (companies).

These results have a valuable and practical implication information: reputation plays a pivotal role in increasing revenue via live streaming sales. Therefore, for the small and medium-sized companies that hope to increase revenue through live streaming, building reputation will plausibly help generate revenue and enhance live streaming efficiency.

Our contribution to food and consumer science research is providing an empirical evidence of reputation's role in a brand-new context. Admittedly, our analysis was limited to 10 types of fresh fruits, and the live streaming variables just control the duration of live streaming views and consumer satisfaction indicators (i.e., thumbs up). As we claimed, our primary purpose in this paper was to provide insights regarding the role of reputation in this new and emerging marketing channel.

Agri-food products live streaming is still in an initial stage and many other valuable topics can be explored in future research. For example, consumers may need different information for various types of agri-food products. For instance, accounting for consumers concerns regarding whether the product is organic (vegetables, fruits, etc.) and the type of beef (sirloin, steak, etc.) may be even more (or less) important in live streaming than other marketing channels. Therefore, future researchers can collect data from a wider range type of agri-food products to expand on the findings of this study.

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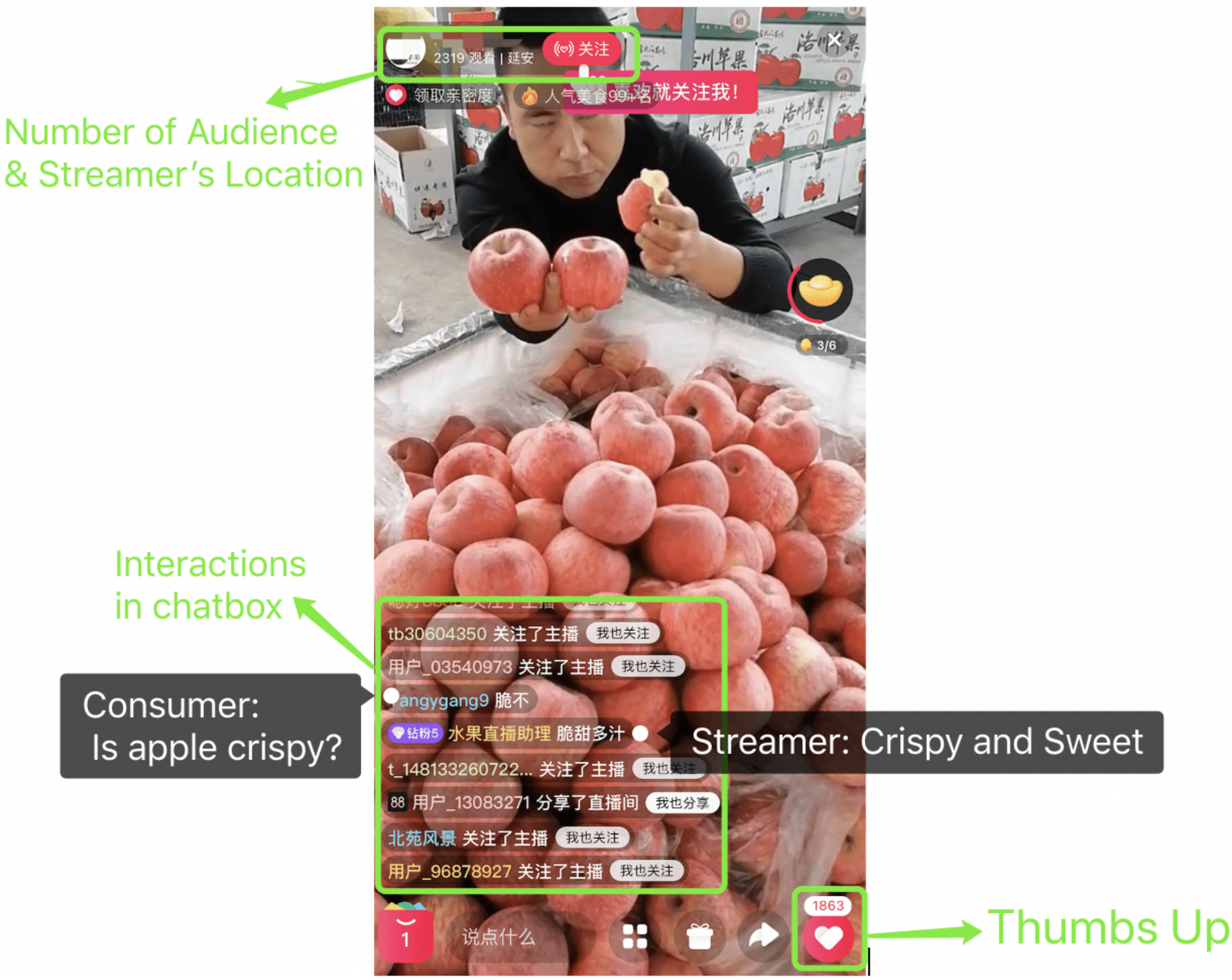
Figure 1: Retailers sell apples in Taobao Live Streaming



Note: the store name is intentionally omitted

Figure 2: Selecting Agri-food Live Streaming rooms in Taobao Live Streaming

Table 1: Summary Statistics

Variables	Taobao Marketplace Sellers (N = 1536)	Tmall Sellers (N = 7969)	Total (N = 9505)
Revenue (yuan)			
Mean (SD)	1279.83 (14390.38)	9185.95 (55851.24)	7908.33 (51547.43)
Min, Max	0.00, 553520.00	0.00, 3980355	0.00, 3980355
Live Streaming Duration (Hours)			
Mean (SD)	11.04 (12.23)	14.58 (17.85)	14.01 (17.12)
Min, Max	0.00, 91.25	0.00, 287.53	0.00, 287.53
Audience (10k viewers)			
Mean (SD)	6.73 (9.16)	6.47 (78.74)	6.51 (72.19)
Min, Max	0.00, 96.01	0.00, 5340.58	0.00, 5340.58
ThumbsUp (10k times)			
Mean (SD)	13.08 (28.42)	6.47 (62.23)	7.54 (58.17)
Min, Max	0.00, 538.55	0.00, 4273.20	0.00, 4273.20
Service Rating			
Mean (SD)	4.69 (0.10)	4.59 (0.12)	4.61 (0.12)
Min, Max	4.60, 4.90	4.50, 4.90	4.50, 4.90
Deposit (yuan)			
Mean (SD)	8373.76 (17101.07)	83491.03 (25089.90)	71352.14 (36600.09)
Min, Max	996.00, 51000.00	50000.00, 150000.00	996.00, 150000.00
Fruit Type			
Apple	395 (25.7%)	1861 (23.4%)	2256 (23.7%)
Coconut	153 (10.0%)	444 (5.6%)	597 (6.3%)
Dragonfruit	212 (13.8%)	961 (12.1%)	1173 (12.3%)
Jujube	64 (4.2%)	271 (3.4%)	335 (3.5%)
Kiwi	80 (5.2%)	766 (9.6%)	846 (8.9%)
Lemon	158 (10.3%)	574 (7.2%)	732 (7.7%)
MandarinOrange	145 (9.4%)	673 (8.4%)	818 (8.6%)
Mango	105 (6.8%)	356 (4.5%)	461 (4.9%)
Passionfruit	44 (2.9%)	936 (11.7%)	980 (10.3%)
Pear	180 (11.7%)	1127 (14.1%)	1307 (13.8%)

Table 2: OLS Fixed Effect Panel Regression

Variables	(1) Revenue	(2) Revenue	(3) Revenue	(4) Revenue
Tmall	4,778**	6,787***	5,013***	5,632***
	(1,969)	(1,821)	(1,811)	(1,862)
Price	154.9***	94.37***	69.33**	59.94*
	(32.66)	(30.23)	(30.03)	(30.74)
ThumbsUp		332.2***	326.6***	326.0***
		(8.284)	(8.223)	(8.235)
Live Duration			393.1***	394.5***
			(30.47)	(30.49)
Service Rating				7,508
				(5,256)
Constant	-3,861	-12,980	-14,443	-48,665
	(29,153)	(26,949)	(26,716)	(35,885)
Observations	9,505	9,505	9,505	9,505
R-squared	0.049	0.187	0.201	0.202
Fruit Type*Origin Dummy	YES	YES	YES	YES

Table 3: IV Regression

Variables	(1) Revenue	(2) Revenue	(3) Revenue	(4) Revenue
Panel A: Two-Stage Least Squares				
Tmall	4,165	7,909***	4,978**	7,068***
	(2,595)	(2,400)	(2,392)	(2,427)
Price	157.2***	90.13***	69.46**	53.78*
	(33.16)	(30.69)	(30.46)	(31.35)
ThumbsUp		332.3***	326.6***	326.1***
		(8.254)	(8.194)	(8.204)
Live Duration			393.1***	392.9***
			(30.42)	(30.42)
Service Rating				8,451
				(5,336)
Constant	-3,935	-12,848	-14,447	-52,797
	(29,044)	(26,847)	(26,613)	(36,027)
Observations	9,505	9,505	9,505	9,505
R^2	0.049	0.187	0.201	0.202
Type*Origin Dummy	YES	YES	YES	YES
Panel B: First Stage for Tmall				
Variables	(1) Tmall	(2) Tmall	(3) Tmall	(4) Tmall
Deposit	6.94e-06***	6.94e-06***	6.94e-06***	8.04e-06***
	(6.19e-08)	(6.19e-08)	(6.22e-08)	(7.00e-08)
Price	0.00319***	0.00319***	0.00318***	0.00249***
	(0.000109)	(0.000109)	(0.000109)	(0.000107)
ThumbsUp		8.11e-06	7.06e-06	-3.12e-05
		(3.07e-05)	(3.07e-05)	(2.94e-05)
Live Duration			7.22e-05	7.17e-05
			(0.000114)	(0.000109)
Service Rating				0.643***
				(0.0215)
Constant	-0.116	-0.117	-0.117	-3.054***
	(0.0998)	(0.0998)	(0.0998)	(0.137)
Observations	9,505	9,505	9,505	9,505
$F-stat$	475	469	462	512
R^2	0.782	0.782	0.782	0.801
Type*Origin Dummy	YES	YES	YES	YES