The Value of Live Chat on Online Purchase

Completed Research Paper

Xue Tan
Michael G. Foster School of Business
University of Washington
#350 Mackenzie Hall, University of Washington, Seattle, WA, 98105
xuetan@uw.edu

Youwei Wang
School of Management, Fudan University
#714 Siyuan Faculty Building, 670 Guoshun Road, Shanghai, China
200433
ywwang@fudan.edu.cn

Yong Tan
Michael G. Foster School of Business
University of Washington
#461 Paccar Hall, University of Washington, Seattle, WA, 98105
ytan@uw.edu

Abstract

In this paper, we empirically investigate the value of live chatting tools on purchase. We use a clickstream data from a leading online marketplace where live chats between e-tailers and customers are documented. We follow the classic two-stage choice model proposed by Moe (2006), and incorporate the choice of chatting as a new stage. In our model, consumers make a three-stage sequence of choices. In the first stage, they choose a product to view; In the second stage, they decide on whether to initiate a live chat; In the third stage, they decide on whether to purchase. This process iterate until consumers decide to stop. We find that consumers choose products with low price and high reputation in the first stage. They request live chat when e-tellers’ reputation is low and the price is low. Finally, live chat has positive impact over purchase, especially for low reputation e-tailers.

Keywords: Live chat, e-commerce, conversion, online marketplace, clickstream
The Value of Live Chat

Introduction

E-commerce has seen a magnificent prosper in the last decade. The U.S. e-commerce sales reached $340 billion in 2015, constituting 7% of the total retail sales. More strikingly, The Chinese e-commerce market has reached $1.6 trillion, become the largest in the world in 2016, and contributed to 40% of the global e-commerce spending. Despite the surging growth of the e-commerce market, e-tailers (those who sell electronically) suffer from fierce competition and low conversion rate.

Unlike brick-and-mortar stores, online stores face the disadvantage of information asymmetry, lack of trust and adaptive assistance to customers. In physical store customers can judge the trustworthiness of the retailer by the appearance and display of the stores. They can touch and feel the products to evaluate their quality. Further, customers are offered adaptive assistance by salespersons. Salespersons can recognize customers’ decision style, and provide tailored service and recommendations (Perrault and Brousseau 1989). In online marketplace, customers interact with a system. They face a different set of information, including the picture and description of products, and the review and ratings of sellers in the marketplace. Online marketplace usually provides search engine service for customers to search products based on keywords, price, and ratings. This search engine intends to help customers in choosing products to view like what salespersons do in a physical store. Based on the limited information available in online stores, customers heavily rely on the reputation score. Therefore, e-tailers with high ratings are able to attract more customers, leading to “the rich get richer.” On the contrary, sellers with low ratings or fewer number of ratings suffer more from the disadvantage of online stores.

Live chatting tools have been used by e-tailers to increase spontaneous engagement and reduce the uncertainty faced by consumers. According to a survey conducted by Forrester Research (Strothkamp et al. 2010), “Around 44% of online consumers say that having questions answered by a live person while in the middle of an online purchase is one of the most important features a Web site can offer.” It seems that by providing adaptive assistance to potential customers, e-tailers can improve customer satisfaction, build business-to-customer relationship, and finally make more profits. According to a study, 25% of live chatters end up making 51% to 75% of their purchases online (Ecommerce 2009), while only 10% of consumers make purchases without live chat. However, these statements cannot rule out the bias that customers who initiate live chat conversations are usually those who are more likely to purchase. This casts doubt on whether live chat actually increases purchase propensity.

The impact of live chat over purchase probability has never been examined empirically. An empirical examination will not only account for the selection issue of live chat, but also provide quantitative estimation of live chat’s monetary value. This will allow sellers to conduct a cost-benefit analysis to make better decision on whether to provide live chat services with human-based web assistance. It is noteworthy that the cost associated with live chat tool can be considerably high relative to the size of a business. It was reported that the average fully-burdened cost per incident for live chat is $15 in 2009 (Bocklund 2010).

This study is designed to estimate the value of live chat. We address the selection issue of live chat, and explore answers to the following research questions: 1) When will customers initiate a live chat conversation? 2) Will live chat increase conversion rate? If so, by how much can it improve the purchase probability? 3) How can sellers leverage live chatting tools to improve their profits?

Our work is conducted using a clickstream data from a leading online marketplace in China. Our data is collected in the submarket of tablets, over a duration of four months. Using 959 users’ searching, chatting, and purchasing trajectory, we uncover the black box of live chat. Our research method follows Moe (2006)’s two-stage choice model for Internet clickstream data (Moe 2006). We extend this model and propose a three-stage choice model to include consumers’ choice of starting a live chat. We present the business process as follows: 1) consumers search products in the first stage to form a consideration set. This is operationalized by the observed clickstream data. Specifically, if a consumer browses the item page of a specific product, we believe that she includes this product into her consideration set; 2) Each time after a consumer browses through a product page, she decides whether to start an online chat. If a consumer starts a live chat, her knowledge about this product will increase, resulting in an enhanced choice set; 3) Consumers face the purchase decision after each product viewing trip. Consumers continue to search until the search cost exceeds the expected utility from an additional product in the consideration set. The sequence of the three stages iterates until a consumer stops searching. By endogenizing the decision process of starting a live chat, we are able to identify the actual contribution of live chats to purchase decision. By
comparing customers’ choice criteria for viewing detailed product page, requesting live chat, and purchasing, we reveal the criteria for consumers’ choice of live chat.

We have several interesting findings. First, we find that at different stages of shopping, consumers have different criteria for choosing products. In the first stage when customers seek for products to view, they prefer products with low price and high ratings. In the second stage when customers make choices of whether to start a live chat after viewing a detailed product page, they will choose sellers with lower ratings and lower prices. Finally, when they make purchase decisions out of their consideration set, they no longer care about the reputation of sellers. Surprisingly, they will choose products with higher price from their consideration sets. Next, we find that consumers usually choose low-price products to view in their early phases of exploration, and will gradually add higher-price products to their consideration sets. Finally, we find positive evidence that live chat boosts purchase probability. In our extended analysis, we find that the effect of live chat over purchase is only significant when e-tailers have low level of reputation. When they have well-established reputation, the effect of live chat is not significant for purchase decision.

We make the following contributions to the existing literature. First, this paper is the first to examine the role of live chat in consumers’ online purchase decision. Second, we extend the classic two-stage consumer choice model to a three-stage model where the choice of live chat is incorporated. By allowing each product to have a latent attribute that cannot be displayed from the product page but can be learnt with live chat, we make contributions to the choice set literature. Third, by allowing consumers to have different criteria of choice at different stages of shopping, we reveal consumers’ cognitive evolvement in forming their purchase decisions. Finally, we understand how live chatting tools can substitute reputation. Given the general availability of clickstream data and under-exploration of live chat, our findings carry significant importance to both researchers and practitioners.

The rest of this manuscript is organized as follows. In section two, we introduce related works. In section three, we provide a description of our research context and the business flow. In section four, we propose a conceptual framework, followed by formal presentation of our three-stage model. In section five, we describe our data. In section six, we present our results. In section seven, we discuss our findings. Finally, we end our paper with conclusions in section eight.

**Literature Review**

Our work is related to the literature of electronic commerce and choice models. In electronic commerce literature, business-to-consumer communication media is studied to improve consumers’ shopping experience. Åberg and Shahmehri (2000) proposed human-based web assistants, and developed a prototype system to evaluate its performance (Åberg and Shahmehri 2000). They found that web assistants can improve the usability of online shops in terms of relevance, efficiency, attitude, and learnability. Basso et al. (2001) used an experiment to compare online store with no audio or real time interpersonal communication, and that with different forms of communication media (Basso et al. 2001). They found that online stores with web-based instant messenger creates more trust than those without such instruments. The trust will in return lead to customers’ higher willingness to share the information to their friends, and repeated purchase.

A two-stage choice process is usually used to model how consumers first select a subset of products to view, and choose one or more from the subset to purchase (Bettman 1979, Gensch 1987). It has been proposed that consumers’ decision rules in determining which products to view (Stage 1) and which products to purchase (Stage 2) are different because of their cost-benefit trade-offs. In general, simpler rules are used in early stages because consumers face a larger set of choices, and more effortful rules are used in later stages to achieve the highest level of benefit (Gensch 1987). Two stage choice models analyzing purchasing data have been proposed to understand the distinction between different phases of purchasing. While most models assume the first stage to be latent, Moe (2006) addressed the limitation with a model that explicitly examine the determinants of choice in both stages. The implementation of such a model requires the observation of stage 1’s choices, which is available from the clickstream data in online shopping. Our work follow the framework proposed by Moe (2006), and extends it to incorporate the consumers’ choice of live chat. Along this line, Olbrich and Holsing (2011) used a logit model to understand consumer’s purchasing behavior in a social shopping community (Olbrich and Holsing 2011). Another stream of marketing literature use structural search model to explicitly model consumers’ search behavior. With the availability
of additional identification source, they can recover the underlying search cost. Hong and Shum (2006) developed a structural approach to recover consumers’ search cost with aggregate data (Hong and Shum 2006). De los Santos et al. (2012) also used a structural approach to recover the search costs for automobile, and they find significant search costs which will result in only a few dealer search attempts (De los Santos et al. 2012). Chen and Yao (2015) advanced the search model to incorporate search refinement with sorting and filtering (Chen and Yao 2015). Our work mainly follows the approach developed by Moe (2006) because we are interested in customers’ preference of choice at each stage.

**Research Context**

We obtained our individual-level clickstream data from a large online marketplace. Our data is from the section of tablet markets. The online tablet market is prosperous in China because of the price difference and release time difference. Apple prices its tablets higher in China than in Hong Kong and many other areas and countries. In addition, Apple used to release its new tablets at different times in different countries. Both the price difference and time gap cultivated the secondary market which largely operates online.

**Platform**

This platform sells enormous varieties of products, and is one of the biggest online marketplace in the world. It is a typical two-sided market where sellers and customers both need to register in order to sell or buy. Each seller owns an online shop with a distinct link. Products are displayed in each online shop for consumers to browse and purchase.

This online marketplace provide several ways to navigate consumers through their shopping experiences. First, the landing page of this online marketplace provides a catalogue of products. Editor’s picks and best sellers are also highlighted in the landing page (Figure 1 (a)). Second, the search bar allows users to customize their search key words. A search result can be further refined by filtering and sorting through prices, reputations, and so on (Figure 1 (b)). The availability of the refinement tools greatly reduced consumers’ search cost, and make it easy for consumers to compare products based on their attributes like prices.

![Figure 1. Screenshots of the Online Marketplace](image)

**Clickstream**

We obtain consumers’ URL requests for each detailed product page like in Figure 2 (b). Consumers have different ways of reaching the detailed product page. For example, they can use the search bar to obtain a catalog of products related to the keyword they key in. In the search results, product price, seller’s name, total sales volume, and sellers’ reputation are all displayed like in Figure 2 (a). Consumers click through the
The Value of Live Chat

link of their interest, and visit the detailed product page. They can also ask their friends, and get the link to the shop directly. In this work, we cannot distinguish the source of a page view on a detailed product page. But we document the full trajectory of consumers’ search path in all detailed product pages. On the detailed product page, human web assistants are displayed like in Figure 2 (c). If consumers click the chatting button, they will be directed to the chatting window like in Figure 2 (d). A human-based web assistant will chat with the customer and provide adaptive assistance. These human-based web assistants are employed by each seller, instead of by the platform.

While the web assistants are managed by sellers, the live chatting tool is provided by the marketplace. The online marketplace developed its own instant messenger for the use of communication between sellers and buyers, and all chatting conversations are documented by the platform. When disputes happen, the platform often use the chatting histories as evidence to arbitrate.

Finally, consumers decide on whether to purchase the products, based on the information in the webpage and their conversation with the web assistants. After making their purchase decisions, they can keep visiting other detailed product page, or stop searching.

Reputation System

Although tablets are highly homogeneous products with low level of information uncertainty, customers face potential loss due to dishonesty of sellers. Specifically, some sellers label refurbished tablets as new, and earn high profit margin from cheating.

The reputation system within this online marketplace provides customers with information about the trustworthiness of sellers. This reputation system consists of measurements like Feedback Scores. Feedback score is one of the most important piece of sellers’ reputation profile. Customers will rate sellers after the completion of each transaction. A positive rating corresponds to +1 point in the feedback score, a neutral rating leads to no point change, and a negative rating translates into -1 point in the feedback score. The feedback score is a cumulative representation of sellers’ reputation and sales volume.
The Value of Live Chat

Figure 2. Web Interface of Searching and Live Chatting

Model

To show why a three-stage model is needed, we illustrate the conceptual framework with an example (Table 1). We then specify the formulation of our model which operationalizes the conceptual model.

Conceptual Model

Our conceptual model extends that of Moe (2006) by adding a stage of live chat choice.

Table 1. Example of Three-Stage Choice Process

<table>
<thead>
<tr>
<th>Decision Point (t)</th>
<th>Product Viewed (Stage 1)</th>
<th>Choice Set</th>
<th>Live Chat (Stage 2)</th>
<th>Enhanced Choice Set</th>
<th>Purchase Decision (Stage 3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Shop I - A</td>
<td>I-A</td>
<td>No chat</td>
<td>I-A</td>
<td>No purchase</td>
</tr>
<tr>
<td>2</td>
<td>Shop II - A</td>
<td>I-A,II-A</td>
<td>No chat</td>
<td>I-A,II-A</td>
<td>No purchase</td>
</tr>
<tr>
<td>3</td>
<td>Shop I - B</td>
<td>I-A, II-A,</td>
<td>Chat with Shop I</td>
<td>I-A’,II-A,I-B’</td>
<td>Purchase I-A</td>
</tr>
<tr>
<td>4</td>
<td>STOP</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 1. Example of Three-Stage Choice Process

In this example, shops (sellers) are denoted by I and II, and product models are denoted by A and B (for example, Apple Ipad4 (16G) WIFI). A consumer viewed three distinct product pages, two of them are of model A and the other is of model B. Shop I and shop II sell both models, which is common in the tablet market.

Each shopping trip is one row in Table 1. In the first trip, the customer viewed product A offered by shop I in stage 1, adding I-A into her choice set. She didn’t choose to chat with web assistant in stage 2, maintaining the same choice set for decision in stage 3. In stage 3, she chose not to purchase anything, and ended this trip. In her second shopping trip, she viewed product II-A, possibly trying to compare model A sold by different sellers. She left the page without chatting or purchasing. Since she has viewed product II-A, it is added to her choice set. In her third trip, she viewed product I-B. We can guess that she went back to shop I possibly due to some information she obtained in her first trip at shop I. In the third trip, she requested a live chat with web assistance. This led to an enhanced choice set. Now I-A has changed to I-A’ and I-B has changed to I-B’. It is important that once a customer chat to a seller, all products sold by the seller are enhanced because: 1) customers’ perception of the seller as a whole has been updated; 2) the seller may introduce multiple items from his shop, and we do not observe which products are discussed about. We are only able to measure an average effect of live chat on the seller. Finally, in stage 3 of this trip, the customer purchased product I-A, which she viewed in her first stage. It is important that a customer can purchase...
any item from her choice set, even those that she browsed long ago. After the purchase, she no longer browsed any more product page, and ended her session.

**Three-Stage Choice Model**

Following the example above, we formally propose our three stage choice model.

**Stage 1 – Product View**

In this stage we model consumer $i$’s search process in terms of whether to keep searching and which product to view if keep searching. Let $j$ be an index of the available choices, where $j = 1, 2, \ldots, J+1$; the first $J$ options are the available products to view, and $J+1$ is the option of stopping searching. The sequence of decision points in time are indexed by $t$, and $t = 1, 2, \ldots, T_i+1$, where $T_i$ is the number of unique product pages viewed by $i$, and $T_i+1$ is the decision point when she decided to stop searching. This follows the framework proposed by Moe (2006).

The probability that consumer $i$ will choose option $j$ at decision point $t$ to view is

$$
p(view)_{it} = \delta \exp \{U_{it}(j)\} + (1-\delta) c_{it},
$$

where $U_{it}(j)$ is the utility of searching option $j$, and $c_{it}$ is a stopping constant measuring the utility of stopping searching. $A_i$ is the set of product choices available for individual $i$ at time $t$. $\delta$ is a dummy variable which takes value of 1 if searching was chosen, and takes value of 0 if stopping was chosen. Following Harlam and Lodish (1995), we let the choice of viewing depend not only on the attributes of the products, but also on how the attributes are different from that of consumer $i$’s existing choice set at time $t$.

$$
U_{it}(j) = \beta_1 reputation_{jt} + \beta_2 (price_{jt} - \overline{price}_{i(t-1)}) + \beta_3 price_{jt} + \beta_4 reputation_{jt} \times (price_{jt} - \overline{price}_{i(t-1)}) + \beta_5 Product_Dummy,
$$

where a vector of product dummy are used to denote each tablet model. In this study we use the log-transformed feedback score as the measurement of reputation ($reputation_{jt}$) for each seller. Sellers’ ratings change dynamically, and we use subscript $t$ to denote the time dimension. We employ the log-transformed price ($price_{jt}$) as well as the price difference between a product to view and the average price in user’s consideration set ($price_{jt} - \overline{price}_{i(t-1)}$) to control for the trend of searching. Note that $\overline{price}_{i(t-1)}$ is the average price of all items consumer $i$ browsed before this current shopping trip. Further, we included the interaction between the price difference ($price_{jt} - \overline{price}_{i(t-1)}$) and the reputation $reputation_{jt}$ to examine the substitution pattern between price and reputation. We don’t include ($reputation_{jt} - \overline{reputation}_{i(t-1)}$) in our model because the dispersion at reputation level is low, and this is highly correlated with $reputation_{jt}$.

The stopping constant $c_{it}$ measures the latent utility of stop searching. When it is high relative to the utility from searching, consumers are more likely to stop searching. When consumers’ goals of searching are met, they are less likely to keep viewing product pages. Therefore, we model $c_{it}$ as a function of number of
products bought \((\text{num\_bought})\), number of live chat conducted \((\text{num\_chat})\), and number of views generated \((\text{num\_view})\). Compared to the classic model, we add the number of live chat conversations and number of products viewed because they are potential indicators of consumers’ purchasing phase.

\[
c_u = \alpha_0 + \alpha_1(\text{num\_bought}_u) + \alpha_2(\text{num\_chat}_u) + \alpha_3(\text{num\_view}_u) \tag{3}
\]

**Stage 2 – Live Chat**

We use a logit model to represent individual’s binary choice of whether to initiate a live chat conversation after viewing each product page.

\[
p(\text{chat})_{ijt} = \frac{\exp\{U_{ijt}\}}{\exp\{U_{ijt}\} + 1}, \tag{4}
\]

The formulation of \(U_{ijt}\) is similar to that of the first stage.

\[
U_{ijt} = \beta_1 \text{reputation}_{jt} + \beta_2 (\text{price}_{jt} - \text{price}_{i(t-1)}) + \beta_4 \text{price}_{jt} + \beta_4 \text{reputation}_{jt} \times (\text{price}_{jt} - \text{price}_{i(t-1)}) \tag{5}
\]

We further calculate the residuals for this stage as \(\eta_{ijt}\) to be used in our estimation of the third stage.

\[
\eta_{ijt} = \text{chat}_{ijt} - p(\text{chat})_{ijt}, \tag{6}
\]

**Stage 3 – Purchase**

In the purchase stage, we include dummy variable of live chat \((\text{chat})\) to indicate whether a live chat has been conducted after each product view. This variable is obviously endogenous because it is correlated with unobservable factors that also drive the purchase decision, like users’ income level and urgency of use. To account for this endogeneity, we use control function estimator to correct such a bias. Specifically, we include the residual from the choice of chatting \((\eta_{ijt})\) as a dependent variable into stage 3 (Petrin and Train 2010). This residual captures the unobserved factors that drive the decision of a live chat conversation. Including it in the third stage estimation will make the dummy variable chat to be uncorrelated with the error term. This resolves the endogeneity issue. Since the \(\eta_{ijt}\) is not the true value, but an asymptotic estimate, we need to take into account its variation in stage 3 with adjusted standard error. To do this, we bootstrap the process 100 times to calculate the standard error.

\[
p(\text{purchase})_{ijt} = \frac{\exp\{U_{ijt}\}}{\exp\{U_{ijt}\} + 1}, \tag{7}
\]

\[
U_{ijt} = \beta_1 \text{reputation}_{jt} + \beta_2 (\text{price}_{jt} - \text{price}_{i(t-1)}) + \beta_4 \text{price}_{jt} + \beta_4 \text{reputation}_{jt} \times (\text{price}_{jt} - \text{price}_{i(t-1)}) + \beta_5 \text{chat}_{ijt} + \beta_6 \eta_{ijt} \tag{8}
\]

**Data**

The data we collected is from 3/10/2013 to 7/10/2013. We sample 959 users who had at least one page view on 4/10/2013, and track down all their page view, live chat, and purchase history all the way to 7/10/2013. We choose 4/10/2013 as the starting point of our sampling because it is more likely to give us a full shopping history rather than a truncated one.
These 959 consumers in total generated 3140 unique page views, over 54 products. After the 3140 page views, 56 live chat conversations were requested from consumers. In total, 45 purchases were made. Out of the 45 purchases, 17 transactions happened after live chatting. These purchases are conducted by 38 distinct customers. 32 of them bought one product, 5 of them bought 2 products, and 1 of the users bought 3 products.

Timestamp of each activity is kept to identify the order in the search and purchase sequence, and customer id is used to uniquely identify each customer. The summary statistics is listed in Table 2. The purchase rate is about 0.00132%, the chat rate is about 0.00133%, and the view rate is 0.0918%. We find that the reputation has a wide range between 0 and 880120. This indicates the co-existence of huge sellers and small sellers. The reputation is highly skewed, and we take the log in our estimation. The price of tablets ranges from ¥ 300 to ¥ 17500. The price can go high because some sellers bundle their products.

To form a basic understanding about the level of reputation and the price, we make a scatter plot to visualize their relationship in Figure 3. We make log transformations before we plot the graph. Clearly, we see a positive relationship between reputation and price. That is to say, sellers with higher reputation level can charge a higher price. This enhances the motivation of our study to understand how e-tailers with low ratings can survive under this competitive market.

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>S.D.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>purchase</td>
<td>0.0000132</td>
<td>0.00363</td>
<td>0.0</td>
<td>1</td>
</tr>
<tr>
<td>chat</td>
<td>0.0000133</td>
<td>0.003641</td>
<td>0.0</td>
<td>1</td>
</tr>
<tr>
<td>chatted</td>
<td>0.0007299</td>
<td>0.027</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>view</td>
<td>0.000918</td>
<td>0.0303</td>
<td>0.0</td>
<td>1</td>
</tr>
<tr>
<td>Reputation</td>
<td>21912.85</td>
<td>66122.11</td>
<td>0.0</td>
<td>880120</td>
</tr>
<tr>
<td>Price difference</td>
<td>534.269</td>
<td>1492.896</td>
<td>-7909</td>
<td>17361.67</td>
</tr>
<tr>
<td>price</td>
<td>2682.884</td>
<td>1198.287</td>
<td>300.0</td>
<td>17500</td>
</tr>
</tbody>
</table>

Table 2. Summary Statistics

![Figure 3. Scatter Plot for Price and Reputation](image-url)
Results

The results for each stage are listed below. The interdependence between stage 1 and the other two stages are operationalized by the hierarchical specification of the utility from stopping searching. Stage 2 and Stage 3 estimation can be regarded as a 2SLS.

<table>
<thead>
<tr>
<th>Table 3. Regression Results</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
</tr>
<tr>
<td>Live Chat</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Reputation</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Price Difference</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Price</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Price Diff×Reputation</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>η</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>c_μ</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Pseudo R2</td>
</tr>
</tbody>
</table>

Note: * for p<.05, ** for p<.01, and *** for p<.001, control variables are not listed.

Table 3. Regression Results

From the above results, we learn that consumers consider different factors at different stages. Even for the same factor, consumers may prefer a low level at one stage, and high level at another stage. We discuss the findings for each stage as follows.

Stage 1

When consumers choose products to view, they would prefer products sold by sellers with high reputation and with low price. This can be seen from the positive coefficient of reputation (.220, with p-value<0.001). While the price difference alone does not have a significant effect, the interaction between price difference and reputation has a significantly negative coefficient (-0.2e-10, with p-value<0.001). This indicates that the positive role of reputation is moderated by the price difference. When the price is higher than the market price for the same model, the positive reputation effect diminishes. This is intuitive because people prefer...
products with low price. It is important to note that price alone does not have a significant impact. Its effect is bundled with reputation. This means that customers value reputation as a more dominant role. We can also see that the coefficient for the interaction term is much less than that for reputation in terms of magnitude. This further show that the moderation effect is limited, and reputation plays the most important role in the first stage.

We visualize the dispersion in terms of price and reputation at the three stages below in Figure 4. The search set contains products available to be browsed. The view set contains the products that are chosen by consumers for visiting. The chat set contains products that consumers choose to initiate live chat. We plotted the boxplot to show the general distribution in the dimensions of reputation and price. A general trend is that at later stages, the dispersion of price shrinks. Consumers become more certain about their preference and the level of reasonable price. We have other interesting findings. It can be seen from the left panel of Figure 4 that there are a lot of products priced very low in order to attract consumers to click. However, after evaluating these choices, consumers didn’t click through to the detailed product pages. Neither did they purchase those low-priced products. This indicates that some e-tailers are manipulating the prices to take advantage of the ranking system. From a platform perspective, these fraudulent e-tailers should be handled to lower consumers’ transaction cost.

It is also interesting to see the fluctuations in the reputation level at different stages (right panel of Figure 4). In the first stage, the reputation level for all products in the search set is lower than the reputation level for products selected by customers to view (the view set). Finally, when we look at the reputation level of sellers in the chat set, the reputation leveled down in terms of the maximum and minimum level. This indicates that consumers choose to talk to sellers with lower reputation scores.

![Figure 4. Boxplot for Reputation and Price over Chat](image)

**Stage 2**

In the stage of live chat, we find that customers are more likely to initiate live chat conversations when the feedback score for the seller is low. At a lower level of price (compared to the market price for the same model), the negative effect of reputation is further strengthened. This is evidenced by the negatively significant coefficient of reputation (-.168, with p-value<0.01) and negatively significant coefficient of the interaction between price difference and reputation (-.0001019, with p-value<0.05). In Figure 4, we plot the boxplots of reputation and price conditional on the chatting decisions to show the distribution difference. From Figure 5, we can see that the reputation and price of products associated with chatting are significantly lower than those without chatting. From the right panel of Figure 5, we can also learn that price is highly dispersed in the viewing stage, with outliers both at the top and the bottom. Consumers have no interest to chat with sellers of products that are outliers with high price, but are willing to chat with sellers of products that are outliers with low price. Overall, our findings imply that low rating and low price signals low quality. By initiating a live chat, consumers hope to gain additional information to verify
whether this offer is of low quality. The effort they make in conducting a live chat brings them higher expected benefit—they may find high quality products sold by sellers with lower ratings. On the other hand, when the rating is high or the price is high, consumers are more certain about the quality, and less likely to request help from web assistant.

![Boxplot for Reputation and Price over Chat](image)

**Figure 5. Boxplot for Reputation and Price over Chat**

### Stage 3

From the control function estimator, we can see that customers actually would purchase more expensive products because the coefficient for price is positive (0.000322, at p-value<0.05). This is a surprising result as customers prefer products with lower price in the first stage when they build up their choice sets. The rationale behind such a phenomenon is that price screening is done in earlier stages, and consumers make a more effortful decision in the last stage. This may result in purchase choices of products with higher quality, which is signaled by a higher price.

It is also important to notice the significant effect of live chat over purchase. After controlling for the endogeneity, the coefficient for chat is positively significant at the level of 6.462. This indicates that conducting a live chat will increase the odds of purchasing by a multiplicative factor of 640. While we should carefully interpret this coefficient because we are facing a sparse data where the purchase rate is very low, we can still conclude qualitatively on the positive effect of live chat in improving conversion rate. The coefficient for the residual term $\eta$ was significant, showing the existence of endogeneity. It is also worth mentioning that the effect of live chat may differ for different product categories. Tablets are considered expensive goods over this marketplace, and consumers will have a higher cost with inferior goods.

Practically, e-tailers can plug in their level of reputation and price to calculate the increased probability of purchasing. They can multiply this increased probability with the traffic of their store to estimate the potential profit gain. This will allow them to make better decisions of their live chatting strategy.

### Robustness Check

**Split-Sample-Analysis**

To further validate our assertion that live chat is more effective for sellers with low reputation, we conduct a split-sample analysis. We separate sellers into two group with the cutoff being the 50% percentile of their reputation score. From our result, we find that the effect of live chat is only significant for the group with low reputation, and insignificant for the group with high reputation. This finding demonstrates the more salient role of live chat for small e-tailers. The cutoff value for reputation is 8.16 (based on log scale). For readability, we only list the estimation result for the variable chat.

<table>
<thead>
<tr>
<th>No chat</th>
<th>Chat</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log(Ren)</td>
<td>Log(Price)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>log_seller_sum</th>
<th>log_bid</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.5</td>
<td>10.1</td>
</tr>
</tbody>
</table>

**Table 4. Split-Sample Analysis**
Table 4. Split-Sample Analysis

<table>
<thead>
<tr>
<th></th>
<th>Low-reputation</th>
<th>High-reputation</th>
</tr>
</thead>
<tbody>
<tr>
<td>chat</td>
<td>7.059**</td>
<td>5.1656</td>
</tr>
<tr>
<td></td>
<td>(2.282)</td>
<td>(4.845)</td>
</tr>
</tbody>
</table>

Note: * for p<.05, ** for p<.01, and *** for p<.001, control variables are not listed.

Discussions

Our findings have great value for the online marketplace and e-tailers who sell in the marketplace. The platform owner can learn that in consumers’ first stage search, they seek for products with high rating and low price. This can be easily achieved with refinement tool (sorting and filtering) in the search engine of the online marketplace. However, a potential danger is that e-tailers can fraudulently mark down their prices to be listed in better rankings. As this will increase the transaction cost for consumers, the platform owner may want to take actions toward these e-tailers. Further, knowing the great effect of live chatting tools, e-tailer can charge e-tailers from using such tools. The design of such tools can be complicated. Other than a simple instant messenger that allow the web assistant to talk to potential buyers, the live chatting tool an integrate customers’ shopping trajectory information. For example, by informing the e-tailer with the products the customer just visited, the page they are currently on, and other user information, the system can equip live chatting web assistants with better capability to convert the potential buyers.

For e-tailers with low reputation level, leveraging live chatting tools is essential for them to survive on this ever-competitive market. From our analysis, customers’ motivation of chatting with them is to evaluate the quality of their products. Therefore, they need to signal the high quality in the live chatting conversation. In the example of tablet market, the e-tailers may want the web assistants to have a good knowledge about the tablet market. If the web assistants can provide professional advice over the choice of tablets, they signal high quality of the online store. This will translate into customers’ trust, leading to higher propensity of purchasing.

For e-tailers with high reputation level, the take-away is that they don’t need to establish trust of high quality products between customers. The quality of their products is already well signaled by their high level of reputation. This is evidenced by our robustness analysis where live chat was found insignificant in improving the conversion rate for sellers with high level of reputation. It is advised that e-tailers with high reputation level focus on conducting cross selling and inducing repeated purchase.

Limitations

Our work has its limitations. First, although we are able to observe users’ visiting trajectories regarding to product pages, we do not know how users are directed to these pages. Users can arrive at product pages after typing the keyword in the search engine. They may have used a combination of the refinement tools so that they easily find products with low price and high reputation. Another source is advertisement. Advertisements can be found both inside and outside this marketplace. Or, users simply choose the product because of word of mouth – their friends shared the link of the product they purchased. The lack of information in refinement tools should not affect our results because refinement tools only reduce search cost and allow users to better compare products at multiple dimensions. However, the lack of ranking information from a search result may potentially bias our results if the recommendation system has a different priority than that of the customers. Since most marketplaces try to build recommendations that best predict consumers’ preference, the ranking can be regarded approximately as a simplification of the combination use of refinement tools. That is to say, if the ranking information is mainly a combination of the observed factors like price and reputation, it is already reflected from our inclusion of these factors. Further, the lack of this information does not seem to affect our estimation on the second and third stages. From the data, we find that almost no users initiate live chat conversations from the search results directly. People choose to initiate live chat conversations from the product pages they visited. It is highly likely that users take little, if any, consideration in how they arrive at the product page while deciding whether to initiate live chat conversations.
Second, while we document the timestamps of when live chat conversations have been conducted, we don’t explicitly know the content of live chat. If such information is available, we can further explore the different impacts from different types of conversations. For example, sellers can leverage the opportunity of live chat conversations to enhance customer relationship, conduct cross-selling, and answer their questions. We believe that such analyses will provide further insights that can benefit e-tailers.

Conclusions

Over the last decade, a giant amount of transactions take place in online marketplaces like Amazon, Ebay, and Taobao. Mature e-tailers have accumulated good reputation, and make stable profits on a daily basis. However, many young sellers are still struggling to survive because of the lack of reputation. Their life and death is important to the whole market because their existence will keep the competitive level of online marketplaces, and guarantee lower prices and higher consumer surplus. This is exactly what the platform owners want to see.

Using a clickstream data from a leading online marketplace, we disentangled the role of live chat in customers’ purchase decisions. We find that consumers will choose sellers with higher reputation when they form their consideration sets by visiting the detailed product page. Interestingly, they will initiate live chat conversations with web assistants when the feedback scores of sellers are low. Such a negative reputation effect in initiating live chat conversations is strengthened when the product prices are low. Eventually, in the purchase stage, consumers end up buying products that are of higher price among all products in their consideration sets. Our finding indicates the substitution effect of live chat to low reputation levels. Consumers face uncertainty of product quality, and would spend effort by chatting with the web assistants to obtain additional information about the quality of the product. This provides small e-tailers opportunities to grab the segment of consumers who have less income and more time. Our findings are the initial exploration on the role of human touch in online shopping, and provides magnificent implications to small e-tailers.

With the findings above, we end our paper by suggesting small e-tailers with low reputation to invest more on live chatting tool. These e-tailers should develop live chatting strategy to signal high quality and establish trust relationship with customers. On the other hand, large e-tailers with high reputation can focus more on cross selling, maintaining customer relationship than in persuading customers to purchase. They should reinforce customers with the great ratings they have instead of spending a large amount of time to build the initial trust.

Reference

Ecommerce 2009Ecommerce, R. (2009), ‘How helpful is live chat?’.