Does Online Credit Scoring Matter: An Empirical Analysis of the Effect of Zhima Credit on Short-Term Rental

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Abstract

In recent decade, the short-term rental market is growing at a rapid rate. But some negative issues have followed. Trust has been regarded as one of the main impediments to the development of the short-term rental industry. In 2016, Xiaozhu.com encouraged hosts to present their Zhima Credit-a most popular third party online credit scoring in China-as a way to earn trust. We collect data of hosts in Shanghai and Beijing before and after they post Zhima Credit and conduct a difference-in-difference analysis to figure out whether reservations would be influenced by this action. According to our study, the entry of Zhima Credit does have a positive impact on the hosts’ reservations on Xiaozhu.com and the effect will last for quite a long time.

Keywords: Short-term rental, credit scoring, Zhima Credit, trust/online trust, difference-in-difference

Introduction

In the recent decade, sharing economy is growing at a rapid rate, especially in travel and tourism services (Pizam 2014). China’s online short-term rental market could reach 1.5 billion dollars in transaction volume by 2017, up from an estimated 98 million dollars in 2016 (Zaleski and Chen 2016). It is a new trend that has a broad development perspective. Lots of people have participated in sharing economy activities. According to Pwc’s research, the revenue of the so-called “sharing economy” is expected to
reach $335 billion in 2025 globally (PwC 2015). As for room-sharing service, it has gained its share in the hospitality market through the short-term rental platform like Airbnb in the U.S. and Xiaozhu.com in China.

Meanwhile, online trust is of vital importance in E-business considering sellers and buyers are not familiar with each other (Shankar 2002). Since trading with strangers in P2P marketplaces involves asymmetric information and economic risks, these businesses have developed reputation mechanisms to encourage trust among traders (Resnick & Zeckhauser 2002). In December 2014, the PwC has conducted a survey to 1000 sample consumers who were familiar with the sharing economy about their opinion on sharing economy. The result reveals that most of the consumer regard trust between providers and users as the premise of sharing economy activities. 69% admit they will not trust sharing economy companies until they are recommended by someone they trust (PwC 2015). To help consumers build up trust in hosts, Xiaozhu.com invites hosts to publish their Zhima Credit – an independent third-party credit score. However, whether the presence of the Zhima Credit works remains unknown. Moreover, little research reveals how and why it would bring changes to the short-term rental reservations, and whether or not this effect would be moderated by other factors. Thus, we take these three questions as our research questions.

To address these questions, we collected purchase data from the leading short-term room rental platform in China-Xiaozhu.com. We use a Difference-in-Differences (DID) model, a popular way to estimate the effect of a certain treatment, to examine the difference in sales performance before and after the introduction of the Zhima Credit.

The analysis indicates that the entry of the Zhima Credit does play a positive role in consumers’ decision making. Implications of this finding are obvious: trust-building is the key to improving sales performance on a short-term rental platform. In order to raise considerable revenue, online credit scorings, like the Zhima Credit, can be used as an effective and efficient way and promoted.

In the next section, we present related literature. Section 3 is the hypotheses. Section 4 is the research context. Section 5 is the research method including data collection and model specification. Results from the data analysis are in section 6. After that, it is the Robustness check. Following is the discussion and implication of our study. The last section summaries, and points out the potential defects and outlooks of this study.

**Related literature**

**Short-term rental platform**

Sharing is not a cutting-edge phenomenon, while collaborative consumption and the sharing economy are phenomena born of the Internet age (Belk 2014). This popular topic has attracted so much attention these days. With information and communications technologies, sharing economy platforms allow anyone in the world with internet access to trade anything in the world at any time of day or night (Karlsson et al. 2016). In the field of the short-term rental platform, individuals share their usable but unused rooms or places with travelers for a fee or other compensation, and travelers can rent the room or place temporarily, which creates opportunities for their connectivity and communications about special experiences (Avital et al. 2015). Peer-to-peer networks, therefore, have features of traditional economies such as profit and utility maximization, as well as introducing new dimensions such as sharing and trust (Botsman and Rogers 2011).

Researches on short-term rental platform spread across various fields, mainly focus on customer behavior, its impact and role in the traditional economy, and legislative regulation.

There is a handful of papers related to purchase behavior. The satisfaction and the likelihood of choosing a sharing option are predominantly explained by determinants serving users’ self-benefit, namely utility, trust, cost savings, and familiarity (Mohlmann 2015). Ert et al. (2016) conducted an empirical analysis of Airbnb’s data and a controlled experiment to test customers’ preference on hosts’ photo profile. They also found review scores of the listing would affect customers’ decisions only when varied experimentally (Ert et al. 2016). Karlsson et al. (2016) study from the other perspective - host’s choice about their customers. According to their study, the key attributes that affect hosts’ decisions to grant or deny permission to buy include not only aspects directly to the trip, such as the number of nights, the
motivation for the trip, and the travel party and the self-reference of guests about their behavior, but also personal characteristics, such as gender, age and the profile picture (Karlsson et al. 2016).

Many studies have been done about the impact of the emergence of short-term rental platforms. Given the growth and success of this new phenomenon, scholars have not agreed on whether it will continue to flourish and become a mainstream in the hospitality and tourism industries. And more importantly, either it is a blessing or blight for the traditional hospitality and tourism establishments and the travel consumers remains unknown (Pizam 2014). Home-sharing visitors who use short-term rental platforms are likely to stay longer, spend more money overall, and bring new income to local neighborhoods (Oskam and Boswijk 2016). On the other hand, they will have negative impacts on local hotel revenue, particularly those at the lower end of the market, hurting established local providers and their employees (Oskam and Boswijk 2016; Guttentag 2015).

There are also some scholars conduct their study out of legal aspect. For instance, Gottlieb (2013) comments on whether governments should put forward regulation to the short-term rental industry. Palombo (2015) states short-term rental platforms, like Airbnb, raised legal and regulatory questions in terms of liability, taxes, and zoning although they had contributed to city economies.

**Online Trust**

The widely accepted definition of trust is a willingness to believe or as beliefs regarding various attributes of the other party, such as ability, predictability, benevolence, and honesty (Mcknight and Chervany 2001; Mayer and Schoorman 1995). Benevolence, like honesty and credible, is prerequisite the of trust (Canon 1982; Sitkin and Ruth 1993). Trust establishes connections between strangers. It is a relevant factor that can affect people’s decision making (Stolle and Hooghe 2004). Consequently, trust facilitates the success of transaction by persuading consumers to make the final decision under information asymmetry.

In the online market full of uncertainty, there is information asymmetry between buyers and sellers, which leads to a disappointing fact that consumers are faced with privacy disclosure and the risk of property loss (Golbeck et al. 2009). In online short-term rental platforms, this issue becomes especially severe. Accounts are registered with no more than an email address or phone number, which can be obtained in minutes and fosters a culture of anonymity. Under this circumstance, consumers have to decide if someone is trustworthy depending merely on faith, which is something not everyone is willing to do (Nunes and Correia, 2013). Especially, trust is of vital importance in peer-to-peer accommodation networks where people open up their homes to complete strangers (Guttentag, 2013). Trust stands at the center of an accommodation host granting a guest permission to stay in their house or room as well as the guest agreeing to book a certain accommodation (Karlsson, 2017). Scholars discover that only if the customer is willing to trust the seller can he make the purchase (Nor et al. 2013; Gefen 2002; Kim et al. 2008).

In a peer-to-peer marketplace, the credibility must be paid attention to (Ring and van de Ven 1992), considering uncertainty and risks talked above. Verifying user identity and building online reputations increase trust (Ufford 2015). To foster trust, many peer-to-peer networks have taken actions to help hosts and renters build trust on each other. For example, Airbnb asks users to create virtual profiles so that others can have access to these virtual profiles, typically containing a picture and personalized messages to learn more about one another and, optimally, learn to trust one another (Guttentag, 2013).

**Third party assurance**

Online purchase intention depends on perceived value and trust (Ponte 2015). Xiaozhu.com implement the Zhima Credit trying to build online trust between customers and hosts. Indeed, the third party assurance, like the Zhima Credit, is not novel to online markets. Scholars have done plenty of studies on its mechanism and effectiveness. Jiang et al. (2008) stated there is a relationship between third-party identifying logos, trust transfer, and trust build-up. Psychologically speaking, the perception of third-party assurance and the level of consumer trust in online shopping are positively related to transfer of trust from certification to online e-marketers (Jiang et al. 2008). There are three focal concerns that keep customers from the online purchase, namely privacy, security, and product and service concerns (Mousavizadeh et al. 2016). According to Enrique Bonsón Ponte’s (2015) experiment on 451 participants, third party certification plays a clear role in the consumers’ perceived security.
Moreover, the effect of third party assurance has been widely recognized. Özpolat et al. (2013) exploited a dataset of 9,098 shopping sessions at an online retailer’s website and measure the value and effectiveness of a third party assurance- assurance seal - on the likelihood of purchase by shoppers. Evidence showed its presence increases the likelihood of purchase conversion. (Özpolat et al. 2013) The buySAFE, a third-party certification system bonding for qualified sellers on eBay, increases customers’ willingness to pay for the goods and services offered as well as the margins and total revenues of the sellers (Clemons 2014).

Hypotheses

Trading with strangers involves asymmetric information and economic risks, these businesses have developed reputation mechanisms to encourage trust among traders (Resnick & Zeckhauser, 2002). The emergence of the Zhima Credit step into the breach and help build trust between consumers and providers. According to Nunes and Correia’s (2013) study, consumers are more willing to trust based on a better trust score and trust profile, which supports that there is, in fact, an improvement of trust when using online credibility sources. Melnik and Alm (2005) conduct study on eBay customer behavior and point out that a seller’s overall reputation based on the individual previous performance often has a positive and statistically impact on a buyer's trust perception and willingness to pay. Lu et al. (2010) propose and empirically test a model of trust based on the trust formation mechanism using data collected from Taobao Virtual Community and find that trust in sellers positively affects the intention to get information and the purchase intention. In addition, numerous studies have also shown that online merchants’ personal attributes are a direct reflection of trust and will affect consumers’ willingness to purchase (Chen 2003; Connolly and Bannister 2011; McKight et al. 2002). Considering the Zhima Credit is a third-party personal credit scoring system that can provide neutral credit suggestions to consumers, we hypothesize,

**H1**: The disclosure of host’s Zhima Credit has a positive impact on orders.

**H2**: The impact of host’s Zhima Credit on orders would persist.

Trust is a really complex concept. There is a lot of studies focused on this. In the trust-building process, many factors would play roles, such as personal character, past experience, broad societal institutions and intermediary mechanisms, and so on (Chang et al. 2013). For instance, gender is an important factor in interpersonal trust. It is quite interesting to know that gender is a burning issue in the trust-building process. Early study has indicated that males are more independent, active and aggressive, while females are more positive, warm-hearted, optimistic and compassionate (Jackson and Sullivan 1993). Males are willing to trust and female are easier to be trusted (Chaudhuri and Gangadharan 2007; Dittrich 2015; Buchan et al 2008). The gender of both the trusted and the trust may influence the establishment of trust. And the difference shows up because different gender information may produce stereotype, which is confirmed as a leading and important motivation element of interactions (Fehr and Gächter 2000). In an empirical analysis of Airbnb's data and a controlled experiment, Ert et al. (2016) conclude the individuals may prefer females to males to be their hosts. Croson and Buchan (1999) examine gender differences in bargaining using the 'trust game'. They report gender differences in proposer (trusting) behavior and responder (reciprocating) behavior. They find there is no significant effect of gender on the amount sent by proposers (trust behavior). However, Women return (reciprocate) significantly more of their wealth than men so that they can earn more trust in the game and more profit in return (Croson and Buchan 1999). Chaudhuri et al. (2013) also conduct an investment game in order to test the differences in behavior between genders. The results found, no matter for trusting or reciprocating, the effect of gender is significant. Women are more likely, compared to men, to believe in other people. At the same time, the proportion of investors to invest in women is significantly higher than males. That is a direct evidence for the women carry more credibility than men (Chaudhuri et al. 2013). Innocenti and Pazienza (2006) discover women showed more altruistic behavior than men, and thus gained more trust. In reality, females are more active than men to maintain trust (Cross 2000). Sometimes, in order to establish and maintain this trust, they are willing to sacrifice their own interests to a certain extent (Amanatullah et al. 2008). Compared with males, females are less likely to act in a way that is detrimental to interpersonal relationships. Therefore, females may be more likely to get the trust of others. Thus, considering that the gender plays an role in the trust-building process. We argue that gender is an inevitable issue that should be taken into consideration when estimating the effect of the Zhima Credit.
H3a: Host’s gender moderates the effect of the Zhima Credit on the total reservation.

Scholars state trust is built based on two main factors: good intention and capability to achieve the intention (Yamagishi and Yamagishi 1994). According to Chang et al. (2013), consumers would refer to host’s history records when choosing a liable host, like reply rate, confirm time, accept time, and comments from former rentals. The reason may lie in the fact that a buyer would believe that the supplier who is able to provide a high-quality product if the supplier shows satisfying performance before (Mayer and Schoorman 1995). On XiaoZhu.com, consumers sometimes chat with hosts they interested in to get more information, such as detailed room condition, special tips, and so on. Although hosts are not obligatory to reply, a high reply rate can show their kindness and leave customers a better impression. As for confirm time, customers may not waste too much time waiting for confirmation from the hosts if the host can respond quickly. It can also be regarded as a way for hosts to show their goodwill and offer renters better service experience. Kindness expressed through these actions can be regarded as the foundation of trust. As Mayer (1995) points out, a trusted person would do good to someone who is willing to trust out of altruism rather egoism. Other researches state trust refers to the trusted person live up to others expectations out of kindness so that they can earn the trust (Gefen 2002; Freitag and Traunmüller 2009). That is to say, when people get the feeling that their own interests are paid attention to, they would be willing to trust and maintain the trust in a long term. If merchants can stand on customers’ toes and safeguard interests at the same time try their best to meet their demands and solve their problems, they can convincingly win the trust of customers and increase the revenue.

Capability, referring to the appropriate skills to do a job and the ability to provide a higher quality product or service to the buyer, is another principal part of the trust-building process (Butler and Cantrell 1984). In the peer-to-peer market, consumers expect businesses to provide goods and services that can meet their needs, and has the ability to create a convenient, fast and intuitive transaction environment. Thus, the buyer is more willing to believe in those who have demonstrated better service in the past and can provide high-quality products or services to the seller (Mayer 1995). The same as before, a host with higher acceptance rate in the past deserves to be trusted since he has the ability and is willing to accept reservations. All these characteristics, such as good intentions and kindness, can be taken as the crux of trust (Cook and Wall 1980). Therefore, we argue that the history records of a host could influence the process for customers building trust the host. We suppose that:

H3b: Host’s history records moderate the effect of the Zhima Credit on total orders.

Research Context

Xiaozhu.com

Xiaozhu.com, founded in 2012, is one of the first online short-term rental platforms which are based on sharing economy. So far, holding more than 100,000 listings in over 310 cities and 10 million active users, Xiaozhu.com has taken the leading position in its field (Xiaozhu.com 2016). It aims to provide a guaranteed platform for online communication and transactions for hosts and guests. Different from the traditional hotel industry, Xiaozhu.com provides guests with more humanized accommodation experience and at the same time maximize the value of hosts’ idle resources through sharing. Meanwhile, it tries to enhance the social relationship and interaction between hosts and guests. Actions have been taken to achieve this goal through mechanisms such as property and personal safety guarantee schemes as well as identification. One of these measures is the introduction of the Zhima Credit. Thus, we take Xiaozhu.com as an example to explore the effect of the Zhima Credit on purchase behavior.

The Zhima Credit

On Jan 2015, the Zhima Credit – the first personal credit scoring in China- was officially launched by Ant Financial Services Group, an affiliate of the Chinese Alibaba Group and associate of the Chinese government. The Zhima Credit is an independent third-party credit agency. It is a measure of credit risk for both individuals and enterprises through techniques like cloud computing and machine learning. To date, the Zhima Credit has expanded its product line to a broad range involving the credit card, hospitality, the car rental industry, the dating service and the public service. The Zhima Credit has provided credit services to its patrons under hundreds of scenarios. More than 10 million patrons have
made use of their credit services. The Zhima Credit has made it easier to build trust between individuals and business (Zhima Credit 2017).

The Zhima Credit generates credit scores based on the online behavior of consumers and small businesses on Alibaba’s Taobao (consumer-to-consumer) and Tmall (business-to-consumer) marketplaces (Xiang 2015). By tapping into Alibaba’s vast online ecosystem, the Zhima Credit collects data including web pages users visit, goods they purchase, and payment histories on Alipay. Data are also obtained from partners, public agencies, financial institutions, and various types of merchants so that the score can effectively assess consumers’ creditworthiness (Christie and Li 2015). Considering there are more than 300 million real-name registered users and 37 million vendors that use Alibaba’s platforms (Shu 2015), and few other Chinese companies are able to collect as much data as Alibaba, the Zhima Credit is taking the leading place in credit scoring systems in China.

As shown in Figure 1 that contains a screen shot of the Zhima Credit page, the Zhima Credit is an indication of the users’ creditworthiness, which ranges from 350 to 950 points with higher the number the better. The scores are calculated using five different factors, each with different weightings that can vary according to individual profiles (Christie and Li 2015):

- **Credit History** reflects a user’s past payment history and indebtedness, for example, credit card repayment and utility bill payments.
- **Behavior and Preference** reveals a user’s online behavior on the websites they visit, the product categories they shop, etc.
- **Fulfillment Capacity** shows a user’s ability to fulfill his/her contract obligations. Indicators include the use of financial products and services and Alipay account balances.
- **Personal Characteristics** examine the extent and accuracy of personal information, for example, home address and length of time of residence, mobile phone numbers, etc.
- **Interpersonal Relationships** reflect the online characteristics of a user’s friends and the interactions between the user and his/her friends.

The Zhima Credit is an individual credit information system. Unlike FICO that collects mainly financial information, the Zhima Credit is based big data model. Although the detail evaluation algorithm of these
two credit scoring systems remain secrecy to public due to security concern, based on what they have officially announced, the evaluation methods and information sources of these two models are totally different. In the traditional model, the credit agency collects mainly financial information which is small data. And then, financial information is analyzed and end up in the form of a credit scoring. However, the coverage is somewhat limited. The traditional credit investigation industry is not well developed in China right now. Data sharing between the various departments of the authority is sometimes not highly effective and smooth. The absence of data may end up in inaccurate prediction. As for the big data model, this gap can be filled. According to the official announcement by Ant Financial Services Group about the information sources of the Zhima Credit, the scope is reasonably broad, including transaction, social network, personal Characteristics, behavior, as well as the credit history. The final scoring is produced based on a careful and thorough analysis of all the information.

Besides, the target marketing of the Zhima Credit and traditional credit investigation systems are also different. Take FICO as an example, it is a financial services institution. One of the main XXX that FICO does is to give lenders a fast, objective measurement of a person’s credit risk. That is to say, people use FICO scores when they want to get a loan from the lender when they purchase a home or apply for a new credit card. On the contrary, the business partners of the Zhima Credit include short-term rental platform, car-rental company, blind dating websites, and so on. It aims to provides not only financial services above, but also activities in our daily life. The Zhima Credit can serve as a trust certification in the era of sharing economy.

**Methods**

**Data collection**

We use a crawler program to collect data directly from Xiaozhu.com—a leading short-term rental platform in China. The Zhima Credit was firstly introduced on January 2015. However, Xiaozhu has not taken any action to cooperate with Zhima Credit until November 2015. On Jan 2016, it is the first time that Xiaozhu actually published hosts’ Zhima Credit scoring on their web pages. Thus, we choose the time range lasting from November 2015 to March 2017. We take hosts from Beijing and Shanghai as our sample because they are the two largest marketplaces. In total, it includes 1200 hosts from Beijing and 437 hosts from Shanghai. Data is collected about their characteristics (gender and Zhima Credit), history records (reply rate, confirm time, and accept rate), and reservations (order total). Table 1 provides the summary statistics.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1)OrderTotal</td>
<td>66.643</td>
<td>122.194</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(2)ZhimaCredit</td>
<td>0.085</td>
<td>0.280</td>
<td>0.230</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(3)Gender</td>
<td>0.416</td>
<td>0.493</td>
<td>-0.044</td>
<td>-0.004</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(4)ReplyRate</td>
<td>0.866</td>
<td>0.211</td>
<td>0.176</td>
<td>0.126</td>
<td>-0.105</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(5)ConfirmTime</td>
<td>12.300</td>
<td>43.392</td>
<td>-0.073</td>
<td>-0.048</td>
<td>0.041</td>
<td>-0.130</td>
<td></td>
</tr>
<tr>
<td>(6)AcceptRate</td>
<td>0.686</td>
<td>0.321</td>
<td>0.2460</td>
<td>0.174</td>
<td>-0.078</td>
<td>0.515</td>
<td>-0.150</td>
</tr>
<tr>
<td>(1)OrderTotal</td>
<td>120.354</td>
<td>200.624</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(2)ZhimaCredit</td>
<td>0.200</td>
<td>0.399</td>
<td>0.231</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(3)Gender</td>
<td>0.407</td>
<td>0.491</td>
<td>-0.077</td>
<td>0.054</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(4)ReplyRate</td>
<td>0.891</td>
<td>0.192</td>
<td>0.151</td>
<td>0.114</td>
<td>-0.028</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(5)ConfirmTime</td>
<td>7.368</td>
<td>24.269</td>
<td>-0.068</td>
<td>0.008</td>
<td>-0.035</td>
<td>-0.131</td>
<td></td>
</tr>
<tr>
<td>(6)AcceptRate</td>
<td>0.770</td>
<td>0.264</td>
<td>0.211</td>
<td>0.129</td>
<td>-0.011</td>
<td>0.567</td>
<td>0.112</td>
</tr>
</tbody>
</table>
Model specification

Since 2016, Xiaozhu.com asked all hosts to make the decision on whether they agree to publish their Zhima Credit or not. For those who agree to present their Zhima Credit, we set them as treatment group. Other whose Zhima Credit remain unknown to customers are set as control group. In Figure 2, we calculate the total order number in each time period divided by months and get the average order number per month in each period. As it shows, the average order number per month of treatment group is always larger than that of the control group. With the development of the short rental platform and the implementation of various promotion measures, this industry develops prosperously. At the same time, other factors may also play roles in this process, such as Matthew effect also known as "the rich get richer and the poor get poorer". If we merely calculate the difference before and after the entry of the Zhima Credit, chances are that the difference would be misunderstood as a result of the treat. The reason for this misunderstanding is that the fact that the trend of control group also changed in the sample period is ignored.

![Figure 2. Total Order Number for Shanghai and Beijing](image)

To observe the discrepancy of changing trend between two groups, we then calculate the difference in the mean and median of order total between treatment group and control group (see Figure 3). As it shows, the difference in order totals between two groups is obviously increased, either the median or the mean. For example, in Shanghai, the difference in mean of order totals between treatment group and control group rises from 41.149 at the first time period to 105.719 at the sixth time period. In Beijing, the difference is even more considerable, rising from 63.647 to 149.464. But the growth rate varies over time. It reveals that, although there is a common trend of improvement, there are still differences in the changing trends for two groups. The difference may be caused by both the introduction of the Zhima Credit and other unobserved factors, like the development of the platforms and costumers' preference on sellers with high sales volume. To exclude the effect of factors other than the presence of the Zhima Credit, the DID method is employed. We separate all samples into treatment group and control group according to whether they public their Zhima Credit and simulate the situation where both groups follow the same trend so that we can lead to effective removal of unobserved factors.
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To measure the reservation of host short-term rental listings, we use OrderTotal as the dependent variable which is $Y_{it}$ standing for the total order number of host $i$ in time $t$. It measures the total numbers of times that the host’s listings have been booked. We set a dummy variable as $treat$ to indicate whether the host agrees to public his/her Zhima Credit. If the host belongs to the treatment group, $treat=1$; otherwise, $treat=0$. At the same time, we use another dummy variable – $time$. The time Zhima Credit was published and after are set as 1. Others are set as 0. The treatment effect is measured as the difference of OrderTotal before and after one’s Zhima Credit is posted. Accordingly, we generate an equation as follows:

$$ Y_{it} = \beta_0 + \beta_1 time_t + \beta_2 treat_i + \beta_3 time_t* treat_i + \mu_{it} $$ (1)

When $treat=0$, which means only control group is contained in the equation, $Y_{it}= \beta_0 + \beta_1 time_t + \mu_{it}$. The original equation can be transferred as follows:

$$ Y_{it} = \begin{cases} 
\beta_0 + \mu_{it}, & \text{time } = 0 \\
\beta_0 + \beta_1 + \mu_{it}, & \text{time } = 1 
\end{cases} $$ (2)

The difference before and after the introduction of the Zhima Credit for control group is $diff_1=(\beta_0+\mu_{it})- (\beta_0+\mu_{it})= \beta_1$, which is all the effect to the reservation except for the Zhima Credit.

When $treat=1$, which means only treatment group is contained in the equation, $Y_{it}= \beta_0 + \beta_1 time_t + \beta_2 + \beta_3 time_t + \mu_{it}$. The equation can be transferred as follows:

$$ Y_{it} = \begin{cases} 
\beta_0 + \beta_2 + \mu_{it}, & \text{time } = 0 \\
\beta_0 + \beta_1 + \beta_2 + \beta_3 + \mu_{it}, & \text{time } = 1 
\end{cases} $$ (3)

The difference before and after the introduction of the Zhima Credit for treatment group is $diff_1=(\beta_0+\beta_2+\mu_{it})- (\beta_0+\beta_2+\mu_{it})= \beta_1 + \beta_3$, which is effect of both the Zhima Credit and other factors. Therefore, the effect of the Zhima Credit is:

$$ diff = diff_2-diff_1 = (\beta_1 + \beta_3)- \beta_1 = \beta_3 $$ (4)

Then, to study how the Zhima Credit influences the reservation in a long time period, we use the relative time model and equation as follows:

$$ Y_{it} = \beta_0 + \beta_1 time_t + \beta_2 treat_i + \beta_3 time_t*treat_i + \sum \beta_j time_j*treat_i*reltime_j + \mu_{it} $$ (5)

As before, $Y_{it}$ stands for the total order number of host $i$ in time $t$. The $time_t$ is the time fixed effects. The $treat_i$ represents the treatment effects of the Zhima Credit for host $i$. The $reltime_j$ is the vector of relative time dummies. The $\mu_{it}$ is the error term.

Figure 3. The Difference between Treatment Group and Control Group

To measure the reservation of host short-term rental listings, we use OrderTotal as the dependent variable which is $Y_{it}$ standing for the total order number of host $i$ in time $t$. It measures the total numbers of times that the host’s listings have been booked. We set a dummy variable as $treat$ to indicate whether the host agrees to public his/her Zhima Credit. If the host belongs to the treatment group, $treat=1$; otherwise, $treat=0$. At the same time, we use another dummy variable – $time$. The time Zhima Credit was published and after are set as 1. Others are set as 0. The treatment effect is measured as the difference of OrderTotal before and after one’s Zhima Credit is posted. Accordingly, we generate an equation as follows:

$$ Y_{it} = \beta_0 + \beta_1 time_t + \beta_2 treat_i + \beta_3 time_t* treat_i + \mu_{it} $$ (1)

When $treat=0$, which means only control group is contained in the equation, $Y_{it}= \beta_0 + \beta_1 time_t + \mu_{it}$. The original equation can be transferred as follows:

$$ Y_{it} = \begin{cases} 
\beta_0 + \mu_{it}, & \text{time } = 0 \\
\beta_0 + \beta_1 + \mu_{it}, & \text{time } = 1 
\end{cases} $$ (2)

The difference before and after the introduction of the Zhima Credit for control group is $diff_1=(\beta_0+\mu_{it})- (\beta_0+\mu_{it})= \beta_1$, which is all the effect to the reservation except for the Zhima Credit.

When $treat=1$, which means only treatment group is contained in the equation, $Y_{it}= \beta_0 + \beta_1 time_t + \beta_2 + \beta_3 time_t + \mu_{it}$. The equation can be transferred as follows:

$$ Y_{it} = \begin{cases} 
\beta_0 + \beta_2 + \mu_{it}, & \text{time } = 0 \\
\beta_0 + \beta_1 + \beta_2 + \beta_3 + \mu_{it}, & \text{time } = 1 
\end{cases} $$ (3)

The difference before and after the introduction of the Zhima Credit for treatment group is $diff_1=(\beta_0+\beta_2+\mu_{it})- (\beta_0+\beta_2+\mu_{it})= \beta_1 + \beta_3$, which is effect of both the Zhima Credit and other factors. Therefore, the effect of the Zhima Credit is:

$$ diff = diff_2-diff_1 = (\beta_1 + \beta_3)- \beta_1 = \beta_3 $$ (4)

Then, to study how the Zhima Credit influences the reservation in a long time period, we use the relative time model and equation as follows:

$$ Y_{it} = \beta_0 + \beta_1 time_t + \beta_2 treat_i + \beta_3 time_t*treat_i + \sum \beta_j time_j*treat_i*reltime_j + \mu_{it} $$ (5)

As before, $Y_{it}$ stands for the total order number of host $i$ in time $t$. The $time_t$ is the time fixed effects. The $treat_i$ represents the treatment effects of the Zhima Credit for host $i$. The $reltime_j$ is the vector of relative time dummies. The $\mu_{it}$ is the error term.
To achieve a solid model, we take into consideration the characteristic control (gender) and history records control (ReplyRate, ConfirmTime, and AcceptRate) as independent variables that may also play roles in reservation. $X_i$ is the effect of other controls, namely gender, reply rate, confirm time, and accept rate. To test the effect of each factor above, we use the following equation:

$$Y_{it} = \beta_0 + \beta_1 \text{time}_t + \beta_2 \text{treat}_i + \beta_3 \text{time}_t \text{treat}_i + \beta_4 X_i + \mu_{it} \quad (6)$$

$X_i$ stands for the effect of other controls, namely gender, reply rate, confirm time, and accept rate. Results are in Table 5.

**Results**

It depends solely on a host’s choice whether he or she is willing to publish the Zhima Credit on the platform. And hosts may demonstrate their preference for presenting higher Zhima Credit scores. To verify that the change in reservation number is a result of presence of the Zhima Credit, more tests on treatment group selection has been conducted. The Zhima Credit scoring updates every month according to a user’s behavior in the last month. Table 2 is the statistics summary of the Zhima Credit scoring of treatment group. It clearly shows that, both in Beijing and Shanghai, the Zhima Credit scoring of the treatment group in all time period is slightly different. At the same time, the credit scorings are distributed. According to the official Zhima Credit gradation, hosts’ credit rating ranging from fair to excellent. Only the poor session is left out. Due to some security and privacy issues, the Ant Financial Services Group will not release Zhima Credit scoring without users’ authorization. Neither does it publish the average level or distribution of all users’ scoring in general. The Zhima Credit scoring of the control group is inaccessible. Without necessary explanation, customers are hardly possible to assess hosts’ credit level based on the scoring as a single number. Besides, considering Xiaozhu.com has also set a series of criteria for being an individual host and re-verify qualifications occasionally, verified hosts on Xiaozhu.com are of reliability of host (Xiaozhu.com 2017). Under this circumstance, the presence of the Zhima Credit to customers is more likely to be seen as a way to express hosts’ kindness. The scoring itself is less explanatory.

Thus, although the credit scorings of the treatment group vary, it can still be regarded as randomly selected among all hosts. And the change in reservation number before and after is a result of presence of the Zhima Credit.

<table>
<thead>
<tr>
<th>DV</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>T3</td>
<td>732.6071</td>
<td>43.01191</td>
<td>633</td>
<td>832</td>
</tr>
<tr>
<td>T4</td>
<td>735.75</td>
<td>43.02737</td>
<td>633</td>
<td>839</td>
</tr>
<tr>
<td>T5</td>
<td>738.0179</td>
<td>42.97546</td>
<td>633</td>
<td>843</td>
</tr>
<tr>
<td>T6</td>
<td>743.0536</td>
<td>42.13158</td>
<td>638</td>
<td>845</td>
</tr>
</tbody>
</table>

According to equation (1) and equation (4), we estimate the effect of the Zhima Credit. Table 3 and 4 reveal the treatment effect on reservations. The post of the Zhima Credit has an obviously positive effect on host’s total order number. Both in Shanghai and Beijing, the coefficient of DID treatment is positive.
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(12.898 and 20.002). And these two models both pass the significance test (p<0.01). According to these two tables, Hypothesis H1 is well supported.

<table>
<thead>
<tr>
<th>Table 3. DID Estimation Zhima Credit on Order Number in Shanghai</th>
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</thead>
<tbody>
<tr>
<td>Outcome Var.</td>
</tr>
<tr>
<td>----------------</td>
</tr>
<tr>
<td>Before Control Group</td>
</tr>
<tr>
<td>Treatment Group</td>
</tr>
<tr>
<td>Diff (T-C)</td>
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<tr>
<td>After Control Group</td>
</tr>
<tr>
<td>Treatment Group</td>
</tr>
<tr>
<td>Diff (T-C)</td>
</tr>
<tr>
<td>Difference-in-Difference</td>
</tr>
</tbody>
</table>

R-square: 0.07

*** p<0.01; ** p<0.05; *p<0.1
Means and Standard Errors are estimated by linear regression

<table>
<thead>
<tr>
<th>Table 4. DID Estimation Zhima Credit on Order Number in Beijing</th>
</tr>
</thead>
<tbody>
<tr>
<td>Outcome Var.</td>
</tr>
<tr>
<td>----------------</td>
</tr>
<tr>
<td>Before Control Group</td>
</tr>
<tr>
<td>Treatment Group</td>
</tr>
<tr>
<td>Diff (T-C)</td>
</tr>
<tr>
<td>After Control Group</td>
</tr>
<tr>
<td>Treatment Group</td>
</tr>
<tr>
<td>Diff (T-C)</td>
</tr>
<tr>
<td>Difference-in-Difference</td>
</tr>
</tbody>
</table>

R-square: 0.06

*** p<0.01; ** p<0.05; *p<0.1
Means and Standard Errors are estimated by linear regression

In order to estimate the effect of the Zhima Credit in a long run after its introduction, we conduct another DID estimate with equation (5). All hosts need to make the decision whether they agree to publish their Zhima Credit. However, all the host do not make the agreement at the same day. That is why we use a relative time model and set the time a certain host actually disclose the Zhima Credit as T₀. Table 5 is the result of the DID estimate using relative time model. As a whole, it keeps the same with the former conclusion which is about the effect of the Zhima Credit. When we try to keep tracking the changes of treatment effect in each period (see Figure 4), there is an obvious pattern showing up. One month after the entry of the Zhima Credit, the effect reaches its peak. After that, the positive effect wears off and
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gradually reaches stable. Nonetheless, the effect remains to be positive, which means the presence of the Zhima Credit can constantly promote reservation. Consequently, Hypothesis H2 is confirmed.

| Table 5. Relative Time Model of the Effect of Zhima Credit on Total Order Number |
|---------------------------------|-------------------------------------------------------------|
| DV                | OrderTotal in Shanghai | OrderTotal in Beijing |
| T_{-1}            | 12.875 (15.634)        | 5.895 (20.944)       |
| T_{0}             | 25.538 (21.364)        | 43.333 (26.344)      |
| T_{1}             | 4.538 (25.193)         | 18.058 (32.207)      |
| T_{2}             | 11.270 (26.845)        |                   |
| T_{3}             | 10.367 (28.917)        |                   |
| R-Squared         | 0.07                   | 0.08                |

Figure 4. Effect of Zhima Credit on Total Order Number in Shanghai and Beijing

To test H3a and H3b, we add various control variables into the equation. According to the previous study, both of the hosts’ characteristics and history records performance have impacts on renters’ decision making. Thus, we take gender as host characteristic and as host history records performance into consideration. Results in Table 6 resembles former finding which confirms that the Zhima Credit has a positive impact on reservations.

The coefficient of ReplyRate is positive (33.207) in Shanghai which means the higher the reply rate is, the more reservations the host would receive. But with Beijing data, it does not pass the significance test with \( p > 0.1 \). We make further analysis of this variable and find that the mean, median, and upper quartile of ReplyRate are respectively 0.89, 0.96, 0.99, which means that most of the values are so close to that we suppose that ReplyRate is not significantly different among hosts, and it may make no considerable difference on guests’ decision-making. As for confirm time, the coefficients are -0.079 in Shanghai and -
0.540 in Beijing. The result suggests consumers in Beijing prefer hosts to confirm the reservation as soon as possible. Yet, in Shanghai, confirm time fails the significance test with \( P>0.1 \), which means confirm time is not a relevant factor. Accept rate would have a dramatic impact on customers decision-making because the coefficient is much larger than other factors. In Shanghai, it is 64.013; while in Beijing, it is 118.273. It implies a history of denying orders may prevent customers from booking the room.

The result about hosts’ gender indicates consumers do have a preference on host’s gender. We use 1 to represent male host and 0 to represent females. Considering effect of gender in Shanghai (-9.059) and Beijing (-35.707) are both negative. It refers that female hosts enjoy advantages over males in the effect of posting their Zhima Credit scoring.

To sum up, Hypothesis H3a is well supported. On the contrary, Hypothesis H3b is partially supported. Host’s history records can influence customers’ decisions. But the effect of hosts’ reply time and confirm time remains uncertain. Renters in both Shanghai and Beijing care about the accept rate. Customers from Shanghai are sensitive to low reply rate, while customers from Beijing may be fine with it. They worry more about confirm time.

<table>
<thead>
<tr>
<th>Table 6. DID Estimation of Zhima Credit on Order Number with Control in Shanghai and Beijing</th>
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<tr>
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<tr>
<td>Before</td>
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<tr>
<td>Control Group</td>
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<tr>
<td>Treatment Group</td>
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<tr>
<td>Diff (T-C)</td>
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<tr>
<td>Diff (T-C)</td>
</tr>
<tr>
<td>Difference-in-Difference</td>
</tr>
<tr>
<td>ReplyRate</td>
</tr>
<tr>
<td>ConfirmTime</td>
</tr>
<tr>
<td>AcceptRate</td>
</tr>
<tr>
<td>Gender</td>
</tr>
<tr>
<td>R-square</td>
</tr>
</tbody>
</table>

*** \( p<0.01 \); ** \( p<0.05 \); * \( p<0.1 \)

Means and Standard Errors are estimated by linear regression.
Robustness check

We also conducted a set of comparison analyses in order to check the rationality and robustness of our models. We perform regressions using two estimators, namely OLS and Poisson.

The absence of a pre-treatment in our previous estimations argues against a perfect Gaussian distribution of our dependent variable. Take the skewness of data distribution into consideration, we use the nature log(+1) of the OrderTotal of host i in time t as the dependent variable in the first Robust check. Logging the variable allows us to interpret the effect as a percentage change and resolves a normality concern (Greenwood and Wattal 2017). We do an OLS regression using the same equation as before. Results are in Table 7. Comparing these results with the original model shown in Table 3 and 4, there is no marked change in the coefficients of main research variables and estimate significance.

For our case, the data we use is count variable containing many zeros. Unlike traditional OLS or negative binomial, Poisson permits us to obtain consistent, robust standard errors, even under conditions of over-dispersion (Wooldridge 1997). No true fixed effect estimator has yet been proposed in the NB case, whereas a conditional fixed effect Poisson estimator is available (Allison and Warerman 2002). Additionally, the Poisson estimator has also been shown to significantly outperform a log-OLS specification when data contains many zeroes (Silva and Tenreyro 2011) because it can avoid biased estimates (O’Hara and Kotze 2010), particularly under conditions of heteroscedasticity, as a result of Jensen’s inequality (Santos Silva and Tenreyro 2006). To further confirm the robustness of our conclusion, we then perform a Poisson regression using the non-transformed OrderTotal as the dependent variable. The results (see Table 7) clearly show that the effect of the Zhima Credit remains significant. The result is robust rather than a random result of the sample estimate.

To sum up, results of robustness checks well support the consistency of our estimated effects.

| Table 7. Robustness Check of Zhima Credit on Total Order Number |
|-----------------|-----------------|-----------------|-----------------|-----------------|
| DV.             | (1)             | (2)             | (3)             | (4)             |
|                 | In(OrderTotal+1) | In(OrderTotal+1) | OrderTotal      | OrderTotal      |
| Estimator       | OLS             | OLS             | Poisson         | Poisson         |
| Zhima Credit    |                 |                 |                 |                 |
| Shanghai        | 0.559***        |                 | 0.037***        |                 |
|                 | (0.189)         |                 | (0.013)         |                 |
| Beijing         |                 | 0.275***        |                 | 0.129***        |
|                 |                 | (0.128)         |                 | (0.008)         |
| N               | 2622            | 2400            | 2622            | 2400            |
| P               | 0.000           | 0.000           | 0.000           | 0.000           |
| R-squared       | 0.12            | 0.12            |                 |                 |
| Pseudo R-Squared |                 |                 | 0.10            | 0.09            |
| Log Likelihood  |                 |                 | -152170.74      | -223763.4       |

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

Discussions and implications

Theoretical implications

In this work, we investigate the effect of the presence of hosts’ Zhima Credit on reservations on the short-term rental platform. Based on the DID estimate, we confirm that the Zhima Credit does have a positive influence to the promotion of reservations on Xiaozhu.com and the effect will last for quite a long time.
Meanwhile, Hosts’ characteristics, like their gender, can moderate the positive effect produced by the presence of the Zhima Credit.

Firstly, this study focus on the first and most prevailing credit scoring in China - the Zhima Credit. The Zhima Credit is a new and developing third-party credit scoring system. The fact that it has been widely used in Chain make it deserve to be attached assiduous attention to. Currently, there are a bunch of papers focusing on online trust or online credit (Kim and Peterson 2017; Ghoreishi and Mohannade 2015; Nunes and Correia 2013; Guttentag, 2013). Melnik and Alm (2005) study costumers' performance sellers' rating on eBay. Ert et al. (2016) assess the effect of Airbnb host profile and review scores of the listing on purchase behavior. However, none of them take this emerging and promising concept as the research object. Our study fills this gap. Although the Zhima Credit reaches success in widespread adoption, its practical effect remains unknown. Our research confirms that the Zhima Credit can significantly increase customers' trust in the online vendor and then lead to an enormous improvement in reservations.

Besides, it is true that there are a few scholars taking other credit rating mechanisms, similar to the Zhima Credit, as their research objects. But, most of them carry out theoretical researches. They mainly study its operation mode, legislative regulation, risk assessment, and so on (Nunes and Correia 2013; Shankar et al. 2002). Different from them, we use a quantitative analysis method, DID, to test the economic change produced by the Zhima Credit. It reveals the Zhima Credit’s contribution in a more direct way.

Moreover, we keep tracking the Zhima Credit’s effect for more than 1 year. Melnik and Alm (2005) examine the effects of reputation in online auctions, using U.S. silver Morgan dollar coins in "Almost Uncirculated” condition that are sold on eBay and find that a seller's overall reputation has a positive impact on a buyer's willingness to pay while negative comments about a seller often have a negative impact. Karlsson et al. (2016) discover specific attributes of the booking inquiry that may affect the likelihood of getting permission to book on short-rental platforms. Chang et al. (2013) conduct a questionnaire survey to find out what characteristics have an effect on the trust of the online vendor. All of the studies above are based on one single set of cross-sectional data. As for our study, we conduct DID estimate using both the traditional model and a relative mode. Aside from the immediate economic effect brought by the Zhima Credit, it indicates how this third-party credit certificate influences trust-building in a long run. The effect obviously peaks immediately after the introduction of the Zhima Credit. After that, the effect becomes weaker with time elapsing. Still, the fact that the presence of the Zhima Credit can promote the reservation remains the same.

Practical implications

According to the all the analysis above, the introduction of the Zhima Credit does lead to a strong promotion on the reservation quantity. Based on these findings, our research also carries fundamental some practical implications and has several suggestions to the host as well as the short-term rental platform.

For hosts, those who are able to gain more trustworthiness have a better chance to get their house or room reserved (Belanger et al. 2002). Thus, for the sake of revenue increase, they can take the presence of the Zhima Credit as a way to improve reservation amount. Also, a good history record would also encourage customers to make the purchase. Hosts can try to improve their history record by responding promptly and avoiding order denial so that they can provide customers with a better impression that they are trustworthy.

As for the short-rental platforms, many of them have realized that lack of trust has been identified as a major impediment to the adoption of online shopping (Chang et al. 2013). For example, Airbnb provides identity verification service and virtual profiles of hosts (Gutten tag 2013) to its potential customers in the interest of helping them build trust in hosts as well as the platform itself. Under this circumstance, Xiaozhu.com performs an action by presenting hosts’ Zhima Credit. Our study has confirmed that the Xiaozhu’s measure to open host’s Zhima Credit is an effective approach. Considering the effect is gradually mitigated after its first peak, in order to maintain trust at a relatively high level, actions should be done to improve the Zhima Credit scoring system either by Xiaozhu.com from the way it is been used or by the Zhima Credit from the way it is been calculated.
Conclusions

In this paper, we conduct a study based on the real data from Xiaozhu.com to examine whether the introduction of hosts’ Zhima Credit would have an impact on hosts’ reservation and how it is influenced. According to estimates above, we conclude that the introduction of the Zhima Credit does promote the reservation quantity.

However, in this research, there still exist some limitations. One of them is that the sampling is relatively small. We merely take hosts in Shanghai and Beijing as study objects. Although these are the two largest marketplaces in short-term rental activities, compared to the large group of all 10 million active users, the sample representative has obvious geographical limitation. In the future, we will test using data from other cities to see if this conclusion can be applied to the whole user groups. Besides, in this study, we merely take into consideration whether or not the host publishes his/her Zhima Credit instead of the exact scoring. In the following study, we take it as a potential direction.

Moreover, we simply use four-period data for Beijing and six-period data for Shanghai to stimulate the changing pattern. We will keep tracking the data in the long term and form a more solid estimate.

References


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