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Investigating the impact of home-sharing on the traditional rental market

Xiuzhi Zhang
Renmin University of China, Beijing, China
Zhijie Lin
Tsinghua University, Beijing, China, and
Junghyun Maeng
National University of Singapore, Singapore, Singapore

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Abstract

Purpose – The sharing economy has enjoyed rapid growth in recent years, and entered many traditional industries such as accommodation, transportation and lending. Although researchers in information systems and marketing have attempted to examine the impacts of the sharing economy on traditional businesses, they have not yet studied the rental housing market. Thus, this research aims to investigate the impact of the sharing economy (i.e. home-sharing) on traditional businesses (i.e. rental housing market).

Design/methodology/approach – The authors assemble rich data from multiple sources about the entry of a leading Chinese home-sharing platform (i.e. Xiaozhu.com) and local housing rental price index. Then, econometric models (i.e. linear panel-level data models) are employed for empirical investigation. Instrumental variables are used to account for potential endogeneity issues. Various robustness checks are adopted to establish the consistency of the findings.

Findings – Overall, the estimation results show that the entry of a home-sharing platform will decrease the local housing rental price. Moreover, this impact would be strengthened in a more developed city. Additionally, this impact would be strengthened with higher prices of new houses or second-hand houses.

Originality/value – First, this research is one of the first to study the impact of the sharing economy (i.e. home-sharing) on traditional markets (i.e. housing rentals). Second, it contributes to the relevant literature by documenting that the impact of a platform's entry is not uniform but contingent on city and housing market characteristics. Third, practically, the findings also offer important implications for platform operators and policy makers.

Keywords Home-sharing, Sharing economy, Platform entry, Rental price, Housing market

Paper type Research paper

1. Introduction

The sharing economy (also known as collaborative economy or gig economy) has been growing rapidly in recent years. It is a peer-to-peer two-sided business that relies on a third-party digital platform to facilitate the exchanges or transactions between sellers (providers) and buyers (consumers) (Sundararajan, 2016). This business is becoming popular because it has transformed users' consumption pattern from "owning" a brand new resource to simply "renting" an under-utilized one (Filippas *et al.*, 2020). The sharing economy has emerged in many different industries, such as home-sharing (e.g. Airbnb), ride-sharing (e.g. Uber),

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workspace-sharing (e.g. WeWork), and peer-to-peer lending (e.g. Lending Club). According to Statista (2020c), the total value of the global sharing economy was predicted to increase to some 335 billion US dollars by 2025, from only 15 billion US dollars in 2014. Particularly, China has become the largest market for the sharing economy in the world (Statista, 2020a).

With the popular advent of the sharing economy, academic researchers have become interested in understanding the sharing economy (Trabucchi *et al.*, 2019; Trenz *et al.*, 2018; Lee *et al.*, 2018; Shao and Yin, 2019; Akhmedova *et al.*, 2021; Park *et al.*, 2019; Abhari *et al.*, 2019). It has also been widely reported that the entry of sharing economy platforms may influence various businesses and societal outcomes (Greenwood and Wattal, 2017; Burtch *et al.*, 2018; Zervas *et al.*, 2017; Santi *et al.*, 2014; Huang *et al.*, 2020; Li *et al.*, 2021). For instance, Li *et al.* (2021) focus on the impact of Uber entry into the labor market. They analyze this issue from the perspectives of the supply and demand sides of the labor market. Their findings reveal that the entry of Uber has an empowering effect on workers (the supply side), meaning that Uber entry has created and offered job opportunities for workers to work as drivers. Also, they suggest that Uber entry has a competition effect on traditional jobs (demand side), indicating that the entry of Uber has attracted more low-wage workers (who were not very interested in becoming taxi drivers) to the ride-sharing business.

Similarly, the entry of home-sharing platforms (i.e. Airbnb) has also attracted many researchers' attention. For instance, Zervas *et al.* (2017) examine how the entry of a home-sharing platform (i.e. Airbnb) transforms traditional businesses in terms of the hotel industry. However, it has been overlooked in the past literature that the rental housing market, as a traditional business, could also be affected by the sharing economy. As a type of large consumer goods, houses are much more expensive and more difficult to be owned by consumers than other small consumer goods. Hence, rental housing has become more and more popular these days, especially for young people who do not have enough savings to afford a house. According to Statista (2020b), in 2019, over 30% of people did not own a house and 49% of tenants were under 30 years old in the USA. Thus, a fluctuation in rental prices will bring a huge impact to both tenants and house owners, in terms of their activities in the rental housing market. Therefore, it is of great importance to investigate housing rental prices. Housing rental prices could depend both on the demand and supply of rental housing, and both of them could be affected by various economic factors of local cities, including income, land prices, financing costs and other city characteristics (De Leeuw and Ekanem, 1971). Moreover, a related event or a new business (e.g. the sharing economy) could also bring changes to the demand and the supply of rental housing. However, these have not been investigated.

A few studies have attempted to analyze this question from the perspective of the rental housing supply. Specifically, on the one hand, some studies argue that the traditional rental housing market is typically targeted at local residents whereas the home-sharing market on digital platforms is mainly for visitors. As home-sharing platforms make rentals easier, some house owners may switch from offline to online. Thus the reduction in local housing supply may drive up rental prices for local residents (Horn and Merante, 2017; Garcia-López *et al.*, 2020). However, on the other hand, some other thoughts argue that the arrival of digital platforms and technologies has simplified the housing rental process, and attracted more house owners (who previously were not very interested in renting out their houses) to start participating in this business. Thus, rental housing supply may increase. Moreover, house owners typically rent out the entire unit/house to a single tenant in the traditional rental market, whereas the unit/house can be shared by multiple tenants via digital home-sharing platforms. This may further increase the housing supply. Lastly, the simplified rental process may also lower the transaction cost, compared to the high commission fee charged by brokers in the traditional rental housing market. All these arguments instead suggest that the entry of home-sharing platforms may decrease rental prices. As a result, these two potentially conflicting arguments make the effect of a platform's entry on rental prices complicated. Unfortunately, this still remains an important unanswered question. Moreover, it is equally important, but unknown, what would be the contingent factors (e.g. city and other housing market characteristics) that alter the above entry impact. Specifically, a more developed city (a higher city tier) needs a higher demand for rental housing due to a larger immigrant population. Thus, a more developed city may attract more hosts to participate on those platforms, altering the entry effect on the rental housing market. Also, a higher level of price for purchasing houses means that potential buyers have to pay more, which may prevent them from purchasing a house (Rudel, 1987). This would also result in a higher rental housing demand and more hosts joining the market. Therefore, the analysis on how these contingent factors moderate the platform's entry effect not only helps us derive a deeper understanding of the boundaries and conditions of the effect but also offers important practical implications for platform operators and policy makers.

To address these gaps, our research questions are

RQ1. How does the entry of a home-sharing platform affect traditional housing rental prices?

RQ2. How do the contingent factors of city tiers and housing prices moderate the impact?

To examine these questions, we collected data from multiple sources about the entry of a Chinese home-sharing platform (i.e. Xiaozhu.com) and the local rental housing market. Based on rigorous identification strategies and estimation methods, we find evidence that the entry of a platform reduces the local rental price. Furthermore, we discover that this relationship is strengthened in a city with higher tier and higher housing prices.

Our research has a few notable contributions. First, our study extends the prior literature on the impact of the sharing economy on the rental housing market, by addressing the possibly opposing views of the impact of a platform's entry on rental prices. Second, we further validate some contingent factors, the results would help us derive a further understanding of the boundaries or conditions of the entry effect of home-sharing platforms on the rental housing market, or the relevant important factors that could enhance or weaken the impact. Lastly, the notable findings from this research also offer important practical implications to practitioners and policy makers.

2. Related works

The development of information technology has enabled the creation of a new business model (i.e. the sharing economy). The sharing economy is a form of two-sided markets and consists of three components: consumers, lenders or owners of goods, and the platform (Weber, 2014). Through the platform, lenders are connected with consumers and are able to share their idle resources with consumers, including tangible resources (e.g. houses, cars) and intangible resources (e.g. skills).

As home-sharing becomes increasingly popular, more researchers have become interested in the topic and motivated to discover the mechanisms of how home-sharing affects traditional businesses. The relevant research on this topic is mainly about the effect of home-sharing platforms on the hotel industry. The home-sharing market is highly overlapped with the hotel business since the main users on home-sharing platforms are visitors from other cities and often rent a room only for a short period. Therefore, with the entry of home-sharing platforms, some visitors may switch from hotels to home-sharing. Zervas *et al.* (2017) analyze Airbnb's entry and demonstrate that the entry of Airbnb has a causal effect of 8–10% on hotel revenue. The advent of home-sharing platforms may also transform the business model of hotels. Gutiérrez *et al.* (2017) reveal a close spatial relationship between Airbnb and hotels, with a marked center-periphery pattern, and Airbnb capitalizes more on the advantages of proximity to the city's main tourist attractions than does the hotel sector. Li and Srinivasan (2019) also study the impact of home-sharing platforms on hotel sales and the hotels' transformation in business models. They find that market conditions, including seasonal pricing pattern, quality and the supply elasticity of home-sharing platforms, play a crucial role in determining the effect of home-sharing on the hotel industry. Fu *et al.* (2021) conduct a discrete choice experiment to understand users' choice of hotels and peer-to-peer (P2P) accommodation sharing, and find that the positive valence rate of reviews has a higher impact on the selection of traditional hotels than P2P accommodations, while the number of online reviews has a higher impact on the selection of P2P accommodations than traditional hotels.

More closely related to our research, there is some increasing research attention on the effect of home-sharing on the local housing market. For instance, Filippas *et al.'s* (2020) model how home-sharing platforms affect a player's equilibria both in the short run and the long run, finding that home-sharing platforms would expand consumption and increase surplus. However, this does not directly shed light on the impact of home-sharing on rental prices. Unfortunately, there has been a lack of relevant studies into the potential impact of home-sharing platforms on the housing market in terms of rental prices. More importantly, what contingent factors could moderate such an impact and can be leveraged for better practices remains unclear. These thus constitute critical research gaps in the literature which our research attempts to address.

Table 1 presents a summary of the above representative studies.

3. Data

3.1 The platform: Xiaozhu.com

Xiaozhu [1] is a Chinese home-sharing platform launched in 2012. Analogous to Airbnb, Xiaozhu maintains and hosts a marketplace that allows house owners to list their homes on the platform for rental. Users can select and reserve a home via the platform for a planned stay. As of May 2019, Xiaozhu has entered more than 400 cities in mainland China and attracted more than 50 million active users (Xiaozhu, 2021). Apparently, Xiaozhu is one of China's leading platforms in the sharing economy, and has become the largest home-sharing platform in China (PR Newswire, 2019).

As we seek to examine the relationship between home-sharing and the traditional rental market, we focus on the impact of Xiaozhu's entry into a city on local housing rental prices. Thus, we need to obtain Xiaozhu's entry dates in different cities. However, we did not have direct access to this information. Fortunately, we were able to observe some proxy information. Specifically, Weibo [2], analogous to Twitter, is one of the leading social media platforms in China. Users can share contents such as texts, photos and videos to interact with their friends. Typically, users prefer to share their travel experience on Weibo with information such as which city they went to and where they found their homestay (e.g. via Xiaozhu) (Market Me China, 2018). Therefore, this provides a convenient context for us to extract necessary information, that is, we searched all the postings on Weibo using a combination of "Xiaozhu" (in Chinese) and city name (e.g. Beijing, in Chinese) as the keywords, and identified the date of the earliest posting in the search results. We also manually checked the posting content to avoid irrelevant information. Through this approach, we are confident that Xiaozhu had already entered a certain city by that date. We repeated this process to extract the proxy dates of the platform's entry into many cities in China.

Table 1. Summary of representative studies

Study	Platform	Methodology	Outcome	Factor	Moderator	Key findings
Zervas *et al.* (2017)	Airbnb	Econometrics	Hotel room revenue	Airbnb listings	Hotel type	Airbnb's entry has a causal effect of 8–10% on hotel revenue
Gutiérrez *et al.* (2017)	Airbnb	Econometrics	Location distribution	Distance, activity, land use	–	There is a close spatial relationship between Airbnb and hotels, with a marked center-periphery pattern, and Airbnb capitalizes more on the advantages of proximity to the city's main tourist attractions than does the hotel sector
Li and Srinivasan (2019)	Airbnb	Econometrics	Competitive landscape	Airbnb entry	Market conditions	Airbnb has an impact on hotel sales and hotels' transformation in business models. The market conditions, including seasonal pricing pattern, hotel prices, and quality, the supply elasticity of home-sharing platforms, play a crucial role in determining the effect of home-sharing on the hotel industry
Filippas *et al.* (2020)	Airbnb	Analytical survey	Ownership decision	Estimated usage, income, unpredictability, chunkiness	–	Sharing-economy markets always expand consumption and increase surplus, but may increase or decrease ownership
Fu *et al.* (2021)	P2P accommodation sharing platform	Experiment	Accommodation choice	Review volume, review valence, discount strategy	Price acceptance ranges	Positive valence rate of reviews has a higher impact on the selection of traditional hotels than P2P accommodations, while the number of online reviews has a higher impact on the selection of P2P accommodations than traditional hotels
This study	Xiaozhu	Econometrics	Housing rental price	Platform entry	City tier, prices of new houses, prices of second-hand houses	The entry of home-sharing platforms will decrease local housing rental prices. Moreover, this impact would be strengthened in a more developed city. Additionally, this impact would be strengthened with a higher price of new houses or second-hand houses

3.2 The database: CREIS

After we collected information about Xiaozhu's entry, we also need information on the housing market. Relevant information can be found from the China real estate index system (CREIS) database [3]. This database is managed by the China Index Academy [4]. It covers rich information about the housing market (e.g. prices, sales), macroeconomic factors [e.g. gross domestic product (GDP), consumer price index (CPI), resident income] and demographic factors of many cities in China.

We thus worked with the China Index Academy to collect and assemble a rich data set that includes the price index of the rental housing market. Furthermore, in order to construct a rich set of control variables, we also collected data on the housing market, macroeconomics and demographics.

Overall, by assembling the entry data and the CREIS data, we are able to conduct empirical investigations of the impact of a platform's entry on housing rental prices.

4. Model and analysis

4.1 Empirical model

Based on the above discussion on our motivations, our first question is to examine how Xiaozhu's entry into a city affects the local housing rental price. We conduct our analysis at the city–month level to construct all our model variables. Let subscript i denote each city, and subscript t denote each month. To examine the impact of a platform's entry on rental prices, our *dependent variable*, house rental price index RPI_{it}, indicates the price index of the rental housing market of city i in month t. This index was obtained directly from the CREIS database, which was computed based on the most straightforward Laspeyres Index. This index has been widely adopted by industries, governments and academia (Braithwait, 1980; Fisher and Griliches, 1995; Mansfield, 1987). Our *independent variable*, a platform's entry ENT_{it}, equals to one if Xiaozhu has already entered city i in month t, otherwise zero. Lastly, we assemble a comprehensive set of factors as our *control variables*, including (1) average transaction price (Chinese Yuan per square meter) of new houses of city i in month t (NP_{it}), (2) average transaction price (Chinese Yuan per square meter) of second-hand houses of city i in month t (SP_{it}), (3) gross domestic product of city i in month t (GDP_{it}), (4) per capita disposable income (Chinese Yuan) of residents of city i in month t (INC_{it}), (5) consumer price index of city i in month t (CPI_{it}), (6) net population migration rate (the difference between the number of immigrants and the number of emigrants over the total population) of city i in month t (POP_{it}), (7) a linear time trend variable (TND_t), indicating the time indicator (starting from one) of each month t and (8) a set of time dummies at the monthly level (T_t). Control variables (1) and (2) are included because rental, new and second-hand housing markets could be correlated (Jiang *et al.*, 2020; Zhai *et al.*, 2018). Control variables (3) to (6) are macroeconomic and demographic factors, which are typical drivers of housing prices (Leung, 2004; Mulder, 2006). Control variable (7) is included to control for the natural growth of the housing market and changes in rental prices over time. Lastly, (8) is incorporated to account for other unobserved time-variant factors that are correlated with rental prices.

In sum, the panel-level model is specified in Equation (1):

$$\begin{aligned} RPI_{it} = {} & \beta_1 ENT_{it} + \beta_2 \ln(NP_{it}) + \beta_3 \ln(SP_{it}) \\ & + \beta_4 \ln(GDP_{it}) + \beta_5 \ln(INC_{it}) + \beta_6 CPI_{it} \\ & + \beta_7 POP_{it} + \beta_8 TND_t + T_t\theta + \alpha_i + \varepsilon_{it} \end{aligned} \tag{1}$$

where βs and θ are the model coefficients, α_i captures unobserved city-specific and platform-specific effects in a city, and ε_{it} indicates the residual random error term. The coefficient β_1 is the difference-in-differences estimate of the effect of a platform's entry on the rental price index. This approach has been widely adopted in prior research (e.g. Chan and Ghose, 2012; Dranove *et al.*, 2003).

After assembling and cleaning various data, and eliminating incomplete records for all the above variables, we construct a final unbalanced panel data set with 508 observations. Table 2 presents a summary of our model variables.

4.2 Main results

We first estimate a fixed effects (FEs) model of the housing rental price index (*RPI*) on all the control variables. As reported in Table 3, Column (1), various control variables have significant relationships with *RPI*. These significant relationships imply that our control variables have good explanatory power and can control for many factors that confound our investigation of the impact of *ENT* on *RPI*. Beyond these control variables, we then estimate a full FEs model by further including the independent variable of a platform's entry (*ENT*). We summarize the results in Table 3, Column (2). As indicated, the estimated coefficient of *ENT*, −85.856 (±42.747), is negative and statistically significant, showing that *ENT* has a negative relationship with *RPI*. This interesting estimate implies that after Xiaozhu's entry into a city, the city's housing rental price will decrease. We consider the results of this full FEs model as our baseline results, as this model can derive consistent estimates even when the city-specific effects are correlated with our regressors. We also employ the FEs model estimation for subsequent analyses.

4.3 Identification

The baseline result in Table 3, Column (2), shows that a platform's entry has a negative relationship with the housing rental price index. However, the above analysis might be subject to potential endogeneity issues as a platform's entry could be endogenous due to the omission of relevant factors. For instance, some cities may have more job opportunities or are

Variable	Definition and measurement	Mean	Std. Dev	Min	Max
RPI_{it}	House rental price index, the price index (Laspeyres index) of rental housing market of city i in month t	1638.858	401.507	699.000	2367.000
ENT_{it}	Platform entry, equals to one if Xiaozhu has already entered city i in month t, otherwise zero	0.531	0.499	0.000	1.000
NP_{it}	New house price, average transaction price (Chinese Yuan per square meter) of new houses of city i in month t	16031.240	8159.994	4529.000	54096.610
SP_{it}	Second-hand house price, average transaction price (Chinese Yuan per square meter) of second-hand houses of city i in month t	22800.320	14738.870	5192.000	63581.000
GDP_{it}	GDP, gross domestic product of city i in month t	9417.165	6574.745	762.010	33106.000
INC_{it}	Income, per capita disposable income (Chinese Yuan) of residents of city i in month t	24426.720	14068.090	1881.000	67990.000
CPI_{it}	CPI, consumer price index of city i in month t	102.601	1.879	96.960	107.540
POP_{it}	Net population migration rate of city i in month t, (number of immigrants − number of emigrants)/total population	85.848	41.422	29.978	247.069
TND_t	Linear time trend, the time ID (starting from one) of each month t	85.484	40.463	1.000	167.000

Note(s): Number of observations = 508. All variables are at the city–month level

Table 2. Summary of model variables

Table 3.
Baseline results

Variable	(1) Fixed effects control	(2) Fixed effects full
ENT (Platform entry)		-85.856^{**} (42.747)
NP (New house price)	-60.519^{**} (25.342)	-59.565^{**} (25.232)
SP (Second-hand house price)	383.161^{***} (25.388)	381.616^{***} (25.285)
GDP (GDP)	324.022^{***} (54.717)	323.706^{***} (54.469)
INC (Income)	-137.857^{***} (33.956)	-136.179^{***} (33.813)
CPI (Consumer price index)	1.874 (5.169)	1.831 (5.146)
POP (Net migration rate)	0.844^{***} (0.129)	0.844^{***} (0.129)
Constant	-3008.112^{***} (740.574)	-3016.463^{***} (737.235)
Time trend	Included	Included
Time dummies	Included	Included
R^2	0.8933	0.8945

Note(s): Standard errors in parentheses; $^{**}p < 0.05$, $^{***}p < 0.01$

more livable and attractive, Xiaozhu may observe these merits and is more likely to launch its platform in this city. At the same time, these merits could be correlated with housing rental prices as well, and consequently might lead to endogeneity issues. Nevertheless, we have attempted to include a large set of control variables to avoid omitting important variables. Furthermore, we next employ some identification strategies to address the potential endogeneity concern. For ease of reference, Table 4, Column (1), presents the baseline results from Table 3, Column (2).

Specifically, we make use of an instrumental variable (IV). An ideal IV should be correlated to the endogenous variable (*ENT*) but uncorrelated to the error term (or dependent variable). Based on this criterion, we first construct an IV, TA_{it}, to indicate the number of AAAAA (5A) tourist attractions in city i in month t. In the rating categories used by the Ministry of Culture and Tourism of China, 5A is the highest level. We posit that more 5A tourist attractions are likely to attract more tourists and the entry of Xiaozhu. However, the number of tourist attractions should have no direct correlation to the rental price. Likewise, we construct a second IV, AP_{it}, to indicate the number of airports in city i in month t. We believe that more airports, thus more convenient transportation, are more likely to attract the entry of Xiaozhu, but should have no direct correlation to the rental price. Based on these two IVs, we employ a two-stage least squares (2SLS) estimation and summarize the results in Table 4, Columns (2) and (3), respectively. As indicated, the estimates of *ENT* remain qualitatively consistent with the baseline estimate in Column (1). It is worth noting that the increase in the magnitude of 2SLS estimate, relative to the baseline estimate, suggests that the impact of a platform's entry on the housing rental price was significantly underestimated. After addressing the endogeneity using IVs, the impact of a platform's entry becomes much more salient. Similar cases of the increase in the magnitude using the 2SLS approach have been observed in the past literature (e.g. Currie and Cole, 1993). Further, we estimate using both IVs jointly and report the results in Table 4, Column (4). Again, the results are consistent. Importantly, based on Column (4), the results of the Sargan test ($\chi^2 = 0.225$, $p = 0.6354$) and the Basmann test ($\chi^2 = 0.148$, $p = 0.7002$) for over-identifying restrictions test further confirms the validity of the two IVs.

In sum, the above identification strategies and results suggest that a platform's entry has a negative impact on the housing rental price index, after accounting for potential endogeneity issues.

4.4 Robustness

We further corroborate our findings by checking the robustness and consistency in multiple ways. For ease of reference, Table 5, Column (1), and Table 6, Column (1), present the baseline results from Table 3, Column (2).

Table 4. Identification

Variable	(1) Baseline	(2) IV: # Tourist attractions	(3) IV: # Airports	(4) IV: Both
ENT (Platform entry)	−85.856** (42.747)	−14038.051* (7836.096)	−9934.688** (4137.713)	−11487.073*** (3484.835)
Constant	−3016.463*** (737.235)	4.380 (7442.592)	97.095 (5267.881)	62.019 (6087.419)
Control variables	Included	Included	Included	Included
R^2	0.8945			
Wald χ^2		102.18	203.27	158.75

Note(s): Standard errors in parentheses; $^{**}p < 0.05$, $^{***}p < 0.01$

Table 5.
Robustness (1)

Variable	(1) Baseline	(2) RE	(3) PA	(4) MLE	(5) RC
ENT (Platform entry)	−85.856** (42.747)	−297.472*** (101.744)	−86.210** (36.797)	−86.163** (34.728)	−88.473** (39.213)
Constant	−3016.463*** (737.235)	314.847 (1230.480)	−3053.430*** (619.242)	−3054.477*** (586.578)	−2425.033*** (610.921)
Control variables	Included	Included	Included	Included	Included
R^2	0.8945	0.9152			

Note(s): Standard errors in parentheses; $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

First, we check the robustness of our finding across different model specifications and estimation methods. Our main analysis employs a fixed effects model for estimation. Now, we estimate a random effects (REs) model, a population-averaged (PA) model that allows for an exchangeable correlation structure of a generalized linear model, and a random effects model estimated via maximum likelihood (MLE). The corresponding results for the RE, PA and MLE models are shown in Table 5, Columns (2), (3) and (4), respectively. The model parameter estimates remain consistent with that in Column (1).

Second, some might be concerned about the unobserved heterogeneities of cities. To dismiss this concern, we exploit a random coefficient (RC) model (Boudreau and Jeppesen, 2015). RC can capture the possibility that the rental price index varies due to any latent, unobserved city-specific heterogeneities. Our estimation results in Table 5, Column (5), show that the impact of *ENT* remains negative and significant.

Third, another possible concern would be that the entry of a platform may take some time to generate an impact on the housing rental price, and thus may not affect the price index in the same month. To address this, we use the lagged, instead of the current, term of *ENT* at the various levels (lagged for 1, 2, 3 months) as the new independent variable. All the results in Table 6 remain consistent. More importantly, the significant lagged effects of *ENT* also dismiss the potential concern of the simultaneity bias.

Overall, we believe that all the various tests above indicate the robustness and consistency of our findings regarding the negative impact of a platform's entry on the housing rental price.

5. Moderating effects

The above various results have documented robust evidence that a platform's entry has a negative impact on the housing rental price. In order to answer the second research question to offer more insights, we next conduct more analysis to explore three important and relevant factors as potential moderators for this entry impact. Table 7 presents the results.

Variable	(1) Baseline	(2) Lag: 1-month	(3) Lag: 2-month	(4) Lag: 3-month
ENT (Platform entry)	-85.856^{**} (42.747)	-69.345^{*} (41.332)	-74.953^{*} (39.970)	-83.754^{**} (42.052)
Constant	-3016.463^{***} (737.235)	-2262.593^{***} (739.535)	-1698.255^{**} (763.304)	-1183.517 (761.960)
Control variables	Included	Included	Included	Included
R^2	0.8945	0.8876	0.8723	0.8470

Note(s): Standard errors in parentheses; $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 6. Robustness (2)

Variable	(1) Moderator: city tier	(2) Moderator: new house price	(3) Moderator: second-hand house price
ENT × TIER	59.484^{**} (24.035)		
ENT × NP		-116.127^{***} (35.109)	
ENT × SP			-126.111^{***} (21.361)
Constant	-2750.259^{***} (739.475)	-3636.509^{***} (750.239)	-3594.055^{***} (709.078)
Main effects	Included	Included	Included
Control variables	Included	Included	Included
R^2	0.8780	0.8943	0.8757

Note(s): Standard errors in parentheses; $^{**}p < 0.05$, $^{***}p < 0.01$

Table 7. Moderating effects

First, more-developed cities (i.e. cities with higher tiers) are typically more attractive for their better resources for jobs and the environment for living. Thus, there could be more immigrants, and the local housing market could be more active. Thus, we posit that the impact of a platform's entry could vary across cities. To check this moderating effect, we construct the moderator of city tiers (*TIER*, with a lower value indicating a higher tier). Information on city tiers was adopted from the above CREIS database. The city tier system was widely used in China by the public to indicate the level of development of a city. $TIER = 1$ indicates the four top-tier cities (i.e. Beijing, Shanghai, Guangzhou and Shenzhen), $TIER = 2$ indicates the second-tier cities (e.g. Hangzhou, Nanjing, Wuhan, etc.), $TIER = 3$ indicates the third-tier cities (e.g. Guilin, Shantou, Yangzhou, etc.). Sometimes, the public further lists some least-developed cities as the fourth- or fifth-tier cities. We also construct an interaction term of a platform's entry and the city tier ($ENT \times TIER$). We incorporate and estimate this interaction term in Equation (1) and summarize the results in Table 7, Column (1). As indicated, the estimated result of $ENT \times TIER$, 59.484 (±24.035), is positive and significant. This suggests that the negative impact of a platform's entry on rental prices would be stronger in higher-tier cities (lower value of *TIER*).

Second, the rental, new and second-hand housing markets are typically correlated (Zhai *et al.*, 2018; Jiang *et al.*, 2020). For instance, when housing prices increase, more potential buyers may give up buying but switch to renting. This may consequently generate an increased demand for rental housing, which may allow the impact of a platform's entry to be more salient. To check, we analyze the moderating effect of the new house price (*NP*) and the second-hand house price (*SP*). *NP* and *SP* were also collected from the above CREIS database, and measured as the average transaction prices (Chinese Yuan per square meter) of new houses and second-hand houses in a city. We construct an interaction term between a platform's entry and the new house price (i.e. $ENT \times NP$) and an interaction term between a platform's entry and the second-hand house price (i.e. $ENT \times SP$). We include the interaction terms in Equation (1) for estimation. As shown in Table 7, Columns (2) and (3), the estimated impacts of $ENT \times NP$, −116.127 (±35.109), and $ENT \times SP$, −126.111 (±21.361), are both negative and significant. These results suggest that the negative impact of a platform's entry on rental prices would be strengthened with higher new or second-hand housing prices in the city, which confirms our expectation.

6. Discussion and contribution

Assembling and analyzing data from multiple sources regarding a representative online home-sharing platform (i.e. Xiaozhu) and housing markets in different cities in China, we identify notable findings. First, a platform's entry may decrease housing rental prices. We have conjectured earlier about the two conflicting effects of the entry of a platform. But our results suggest that, overall, the entry of home-sharing platforms is more about stimulating extra housing supply and lowering transaction costs, which results in a decrease in rental prices. Second, we further discover that the impact of a platform's entry on the rental price would be strengthened in more developed cities. Moreover, this impact would also be strengthened with higher prices of new or second-hand houses. Generally, our results are consistent with prior findings that traditional businesses will be shaped by the sharing economy (Zervas *et al.*, 2017; Burtch *et al.*, 2018; Greenwood and Wattal, 2017). However, we further document this evidence in the context of the housing market, and validate the new moderators of city and housing market characteristics that are different from those in the existing literature (Fu *et al.*, 2021; Li and Srinivasan, 2019; Zervas *et al.*, 2017).

Our research findings provide the following contributions. First, our research is one of the first to study the impact of the sharing economy (i.e. home-sharing) on traditional markets (i.e. rental housing). Although prior studies in information systems or marketing have reported some evidence of the impact of the sharing economy on some businesses (Zervas *et al.*, 2017; Burtch *et al.*, 2018) or societal outcomes (Greenwood and Wattal, 2017), they did not focus on large consumer goods in general or housing rental prices in particular. We thus address the possibly opposing views about the impact of a platform's entry on housing rental prices, and hint on the possible mechanism that a platform's entry is more about stimulating extra housing supply which leads to lower rental prices. These insights have extended prior studies about the impact of the sharing economy on housing markets (e.g. Filippas *et al.*, 2020). In fact, although our research context focuses on the rental housing market, we believe the rationale of a platform's entry affecting supply and prices could be similar in traditional marketplaces. Thus, this research may also offer some insights to other contexts.

Second, we provide the first attempt to explore and uncover how the impact of a platform's entry on rental prices varies across relevant moderators. By validating these moderators, we contribute to the relevant literature (e.g. Filippas *et al.*, 2020) by documenting that the impact of a platform's entry is not uniform but contingent on city and housing market characteristics. Through these findings, the research offers a more complete and holistic understanding of the impact of the entry of home-sharing platforms on rental prices.

Practically, these notable findings also offer critical implications to practitioners and policy makers. For instance, home-sharing platforms should realize that their rental price reduction effect would be more salient if they enter cities that are more developed or have higher prices for new and second-hand houses. In this case, home-sharing platforms may lose more users as users could be attracted by the lower rental price of the traditional housing supply. Thus, platforms should be more cautious when choosing cities to enter. Furthermore, policy makers (e.g. government) are not advised to simply label the home-sharing and traditional rental housing markets as competing markets. In fact, they should properly reconsider and better leverage the role of home-sharing platforms in their housing market regulation or housing rental price control. More importantly, policy makers should have heterogeneous reactions (e.g. encouraging or discouraging, and the policy intensity) for different cities with different levels of development and housing prices.

7. Conclusion

Although we have reported some notable findings and important contributions, we still acknowledge some limitations. First, our analysis was not based on a randomized control experiment, but on a secondary data set, and thus we might not have fully addressed all potential sources of endogeneity biases to claim a strong causal relationship. Nevertheless, our extensive control variables, rigorous identification strategies and rich robustness checks all help to derive reliable research conclusions. Second, due to data limitation, we were not able to observe the actual entry dates of the platform into different cities. The proxy entry dates could slightly deviate from the actual dates. However, we believe the time lag between these two dates (i.e. the platform operation starting date and the first Weibo-posting date) should be similar across cities. Our consistent estimates of the lagged effects of a platform's entry could also alleviate this concern. Lastly, we only analyzed a single platform (i.e. Xiaozhu) in our study. Although Xiaozhu is the largest platform in its industry, we were not able to rule out the possible influence from other less-popular platforms in China. Overall, these limitations also provide possible avenues for future extensions.

Notes

1. www.xiaozhu.com/
2. www.weibo.com/
3. https://creis.fang.com/
4. https://industry.fang.com/

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About the authors

Xiuzhi Zhang is an Associate Professor in the School of Public Administration and Policy, Renmin University of China. She received her PhD degree from the Renmin University of China. Her current research focuses on the relationship between information technologies and the housing market.

Zhijie Lin is an Associate Professor in the School of Economics and Management, Tsinghua University. He received his Ph.D. in information systems from the National University of Singapore. His research interests focus on economics of information systems, sharing economy, electronic commerce, and social media. He has published his works in journals such as *MIS Quarterly*, *Information Systems Research*, *Journal of Marketing*, among others. He is an Associate Editor for the *Journal of the Association for Information Systems*. Zhijie Lin is the corresponding author and can be contacted at: dr.zhijie.lin@gmail.com

Junghyun Maeng is currently a doctoral student in information systems at National University of Singapore. He received his Master’s degree from Tsinghua University, and Bachelor’s degree from Peking University. His current research focuses on economics of information systems and online platforms.