

Are Online-Only Real Estate Marketplaces Viable? Evidence from China

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Abstract

Online businesses have been surging worldwide during the past decade, especially during the recent COVID-19 epidemic. However, the market share of online real estate transactions is still limited, mainly due to the information-asymmetry problem. In this study, we manually collect data on online judicial housing auctions in China, which is currently the largest online real estate market globally, and investigate how information disclosure facilitates real estate transactions. The empirical results suggest that disclosing better quality information online can attract more potential buyers. In particular, providing more comprehensive information such as professional appraisal reports or videos of the property can help to convert buyers' initial interests into completed transactions and higher sales proceeds. The positive effects of information are particularly strong when combined with offline services, in a more mature online market, and for low-value properties. We also provide preliminary analysis of factors affecting online-information-disclosure quality from both the macro and micro perspectives. We also provide preliminary analysis of factors affecting online-information-disclosure quality from both the macro and micro

Keywords Online business \cdot Information \cdot Real estate transactions \cdot Judicial housing auction

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Introduction

The past decade has witnessed the surge of online business worldwide, especially in the online retail sector.¹ The literature highlights several major advantages of online business, such as lower transaction costs (Alba et al., 1997; Childers et al., 2001; Gallino & Moreno, 2014), lower price-adjustment costs, and lower price dispersions on the seller side (Brynjolfsson & Smith, 2000), and higher quality and efficiency of decision-making on the buyer side (Häubl & Trifts, 2000). The real estate market is well known for high search and transaction costs for both buyers and sellers (Wheaton, 1990; Genesove & Han, 2012), which, in theory, implies a great potential for online real estate market platforms. In practice, the online real estate market's development still lags behind most other major markets. To our knowledge, no purely online-based property marketplace exists in China or other major economies besides the online judicial housing auction market analyzed in this paper.

Despite the proliferation of online property portals, most real estate transactions are still conducted with a combination of an online listing, offline visits, and bargaining. In this paper, we provide insights on the feasibility of an online-only real estate market, using the empirical evidence from China's online judicial housing sector as an example. We focus on whether and to what extent the information disclosure on the online platform can help mitigate the information-asymmetry problem in the real estate market and facilitate online transactions.

The real estate asset market is one of the few sectors where the share of online transactions is still tiny. An increasing number of online real estate platforms have developed in major economies, such as Zillow and Redfin in the US and Lianjia and Anjuke in China. However, these online platforms only serve to circulate listing units' information and attract potential buyers with initial interests. In most cases, an interested buyer still needs to contact the agent or seller to arrange onsite inspections of the property and have intense face-to-face negotiations with the agent/seller, instead of completing the whole transaction process online. One essential challenge in the development of a direct online real estate transaction platform comes from the substantial information-asymmetry problem in the real estate market (Cramton, 1984; Garmaise & Moskowitz, 2003; Wit & Klaauw, 2013; Kurlat & Stroebel, 2015). Due to the high heterogeneity of real estate properties, relying solely on online information to get an adequate understanding of the property and judging how the property meets her preferences is difficult for a buyer. The combination of the high value of a real estate property and the complexity of property-rights issues further exaggerates the informationasymmetry problem, making the online transaction of real estate properties less feasible.

¹ According to the statistics by eMarketer, a leading analysis company on global online business, the GMV (gross merchandise value) of Taobao and Tmall in China, the world's top two online retail platforms, reached 515 billion and 432 billion US dollars, respectively, in 2018, followed by Amazon with 344 billion US dollars. As an extreme case, on November 11, 2019, the so-called Online Shopping Festival in China, the aggregated GMV of Taobao and Tmall exceeded 268 billion yuan RMB (about 38 billion US dollars) within one day setting a new world record.

The leading online real estate platforms worldwide have made considerable efforts to overcome the information-asymmetry problem and promote the feasibility of online real estate transactions. Several new technologies have been adopted to provide more comprehensive property-related information on online platforms, such as 3D scanning, virtual and augmented realities (VR and AR), and drones (Ullah et al., 2018). The recent COVID-19 epidemic led to a new round of attempts to promote online real estate transactions in the industry. Due to the public health requirements of home isolation and social distancing during the epidemic, arranging onsite inspections or face-to-face discussions has been less feasible for buyers, which makes online real estate transactions more attractive. For instance, Zillow introduced pre-recorded video tours, 3D home tours, and live video walkthrough services. Redfin also launched video-chat tours in which a local agent visits the house in person and tours live with the client. One can expect that these efforts would also exist after the epidemic or even trigger the emergence of the online real estate market. However, from an academic perspective, few studies have been conducted to identify the challenges and/or directions of future efforts in developing online real estate transactions, mainly due to the lack of related data.

This study uses online judicial housing auctions in China to investigate how online information disclosure can help facilitate online real estate transactions. The online judicial auction sector started to develop in China in 2012. Since January 2017, all the judicial auctions in mainland China must be implemented on the designated online platforms, with over 40% of the execution properties as dwelling units. Due to the constraints associated with execution properties, in most cases, potential buyers cannot make an onsite inspection of the unit. Additionally, an interested buyer will not directly negotiate or bargain with the seller (i.e., the court); by contrast, all interest buyers compete via an online English auction. Thus, such online judicial housing auctions can be perceived as a representative type of online real estate transaction. During the sample period of 2017–2019, 215,559 dwelling units were listed on the "Taobao online judicial auction" platform, the largest designated online judicial auction platform in China. Over 65% of the listed units were sold, making it the world's largest online real estate platform.

We manually collect information on the first auctions of the 215,559 dwelling units listed on the Taobao platform. Most importantly, for each auction, we identify whether the court provides each of the 14 information items on the webpage: one video, one package of photos, three attached files, and nine text information items on physical attributes and property rights. Meanwhile, we collect the number of buyers setting reminders, which serves as the proxy for buyers attracted with initial interests, and the number of registered bidders, which serves as the proxy of actual participants. We can also observe whether the auction resulted in a successful transaction and, if so, the transaction prices. Thus, we can empirically investigate whether and how online information disclosure helps attract buyers to participate in online real estate auctions and the final impacts on auction outcomes. One potential endogeneity concern is that information may be released selectively: the court officers may intentionally release more information associated with attractive attributes and, by contrast, hide some less attractive attributes. To rule out this effect, we only use the units handled by officers who always release exactly the same information for each case they handle. In our sample, the information disclosure pattern is therefore exogenously determined by the court officers' (consistent) personal styles and independent of property characteristics. We also construct an index to quantitatively measure each unit's information-disclosure quality and provide a preliminary analysis of the major factors affecting the online-information-disclosure quality during the sample period.

The paper offers three major findings: First, disclosing more and higher-quality information online can significantly help attract more potential buyers. In particular, the effect of online information disclosure is substantially larger in attracting actual participants of the online transactions (i.e., registered bidders) than in attracting initial interest (i.e., potential buyers setting reminders). The results also reveal that buyers focus on different information items in various stages: the eye-catching and less time-consuming information items such as photos can help attract initial interest; but when buyers need to make a more serious purchase decision, they will rely more on more comprehensive information sources such as videos or professional appraisal reports. We also provide evidence that the positive effect in attracting buyers can be finally converted to a higher success probability and a lower discount rate of the auction. Second, we discover a higher probability of online real estate transactions in some specific situations. The online platform could be more effective when combined with offline services, in a more mature online market, or for lower-value properties. Finally, we find evidence that the sellers (i.e., court officers) have realized the importance of online information disclosure. The information quality tends to increase when the court officer has more experience in handling online judicial housing auctions, consistent with the pattern of "learning by doing."

This study speaks directly to the growing literature on the efficiency of online markets (Alba et al., 1997; Degeratu et al., 2000; Ansari & Mela, 2003; Zhang & Krishnamurthi, 2004; Robinson et al., 2007; Zhang & Wedel, 2009; Wang et al., 2014; Aguirre et al., 2015; Li & Lo, 2015; Lin et al., 2016). Most of the existing literature focuses on the well-developed online retail sector. To the best of our knowledge, we provide the first empirical analysis in the context of the online real estate market. Our empirical results reveal the effect of online information disclosure on attracting potential buyers in the housing sector. We also highlight some guidelines for the future development of the online real estate sector.

We also contribute to the rich literature on the impact of information on transaction participants (Tellis & Weiss, 1995; Chandy et al., 2001; Terui et al., 2010; Bertrand et al., 2010; Bertrand & Morse, 2011). The following three contributions are especially noteworthy. First, whereas most studies on this topic mainly rely on lab or field experiments, we provide empirical evidence based on field data. Second, we provide some of the first empirical evidence in the real estate market. Finally, we highlight that information's role changes with the stage of market participants' decision-making.

The paper proceeds as follows. Section 2 describes the institutional background of China's online judicial housing auction sector. Section 3 introduces the data and the empirical strategy. Section 4 presents the main empirical results on the effect of information disclosure on judicial auction outcomes. Section 5 provides

a preliminary analysis of the macro-level pattern and micro-level factors affecting information disclosure quality. Section 6 concludes the paper.

Online Judicial Auctions in China

Similar to most other countries, the judicial auction in China is the work that the court publicly deal with the debtor's property according to the compulsory execution procedure in civil cases, so as to pay off the creditor's debts. The foreclosed collateral of bank loans contributes to a large portion of the execution properties,² with the remainder from condemned properties of criminal cases. Table 9 in the Appendix provides a breakdown of the execution properties by asset type, using the online judicial auctions on the Taobao platform as an example. The real estate properties account for 84.2% of all execution properties, with over half from the housing sector. By law, all individuals and institutes, both in China and abroad, are qualified to bid for the execution properties. Similar to the foreclosure housing market in the US (Clauretie & Daneshvary, 2009; Mian et al., 2015), we can reasonably expect that both homebuyers for living purposes and investors are active in the market. Nevertheless, no official information is available on the buyer side of the judicial housing sector in China.

One unique feature of the judicial auctions in China, including the judicial housing sector, is the prevalence of online auctions. As a critical measure to improve judicial auctions' transparency and efficiency, the Chinese government has implemented a series of policies to promote online judicial auctions during the past decade. In February 2012, the Supreme People's Court, China's highest court, established the official website of judicial auction information disclosure,³ which provides the first signal of introducing the online service to the judicial auction sector. All local courts are required to release the announcement of each judicial auction (either online or offline) on this website, including the information about the execution property. Then, two local courts in Zhejiang province jointly implemented the first online judicial auction on Taobao, the leading e-commercial platform in China, in July 2012. On August 31, 2012, the Amendment of the Civil Procedure Law became effective, which legally permits courts to implement online judicial auctions, and triggered the emergence of this new sector around the country. As a milestone in the development of the online judicial auction sector, the Supreme People's Court issued the "Provisions on Several Issues Concerning the Online Judicial Auction by People's Courts" (Judicial Interpretation No. 2016-18; "Provisions on Online Auction" for short hereafter) on August 2, 2016.⁴ As an essential part of the document, since January 2017, all the judicial auctions in mainland China should be conducted

 $^{^2}$ No official statistics are available on the breakdown of execution properties in China. For the housing sector, we can take the data from the Taobao platform as an example. Among the 87,661 housing units with mortgage information disclosed, 79,127 are foreclosed collateral of mortgage loans, accounting for 90.26%.

³ https://www.rmfysszc.gov.cn.

⁴ http://www.court.gov.cn/fabu-xiangqing-24391.html.

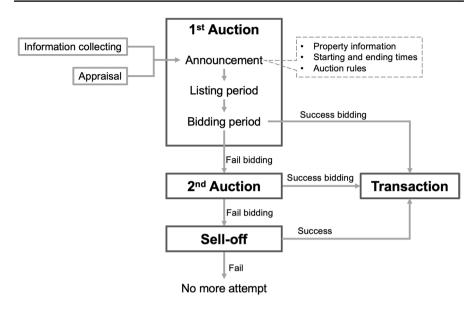


Fig. 1 The typical online judicial auction process. This figure visualizes a typical process of online judicial auctions in China during the sample period

online only based on the officially authorized online platforms. The document also includes detailed requirements on the online platforms and the procedures of online auctions. Since then, the online judicial auction market has been rapidly developing around China. We thus adopt January 2017 as the starting point of the sample period in the empirical analysis.

Figure 1 depicts the standard procedures of an online judicial auction. At most three attempts are made to auction off a property (or a pack of multiple properties). The first auction of the property follows the procedures of a conventional English auction. As the auctioneer, the court will first set a starting price open to all the bidders. If more than one bidder accepts the starting price, they will compete by bidding higher prices online within a designated period (24 h in most cases). A delaying mechanism is embedded in the bidding process. When a new bid is placed within five minutes before the designated ending time, the ending time will be automatically extended by five minutes after the last bid. In other words, the bidding process will only stop if no new bids are made within five minutes before the ending time. Such a delaying mechanism can help avoid the potential impacts of so-called snipers (a bidder who submits a bid in the closing moment of an auction hoping to win at the minimal cost added). The highest bidder wins the competition and has to purchase the property at the final bidding price. If no bidder accepts the starting price, the first auction fails, and the court will implement a second auction for the same property within 30 days. The second auction follows the same procedure as the first auction, the only difference being that the starting price is typically 20% lower

than in the first. If the second auction fails as well, a last sell-off attempt is made.⁵ The court will re-list the property on the online platform for 60 days, using the starting price of the second auction again. The first buyer accepting this price will get the property. If the sell-off attempt also fails, no further attempts are made.

This study mainly focuses on the information-disclosure arrangements associated with the above procedures and their outcomes. Here, we adopt the first auction as an example, whereas the arrangements are similar for the second auction and the sell-off attempt. For a specific execution property, the court will randomly appoint one of its officers to handle this online judicial auction⁶. The officer will collect the information on the property herself via, for example, onsite visits and due diligence⁷. As required by the Supreme People's Court, she also needs to appoint a professional third-party appraiser to provide an appraisal price for the property. The appraisal price is expected to reflect the property's market value and serve as the benchmark for the starting price. After all the preparations, the court will issue an official announcement for the auction on both the online auction platform and the Supreme People's Court's official judicial auction information-disclosure website. The auction announcement includes the name and a brief description of the execution property, the designated online platform for the auction, the starting (which is typically about 30 days after the announcement) and ending times of the auction, the starting price and appraisal price, and a series of auction rules. More detailed information on the execution property will also be simultaneously listed on the online auction platform.

Figure 2 provides an example of a representative listing webpage for an online judicial auction of a dwelling unit, including almost all the information that a potential buyer can access on the execution property and the online auction. Besides the brief description in the announcement, buyers can visually observe the house through a video and a few photos. Moreover, the related files, the detailed physical attributes, and property-rights information are also provided in the property description. The online information is all free and open to the public; in other words, no one can access more online information from the webpage by paying extra money or owning the purchasing priority.

 $^{^5}$ Before January 2017, a third auction occurred between the second auction and the sell-off stage. The procedures of the third auction are consistent with the first and second auctions, with the starting price about 20% lower than in the second auction. This arrangement was abolished in the "Provisions on Online Auction."

⁶ The judicial system in China has long promoted random assignment of cases to ensure the impartiality and objectivity of justice. Quite a lot of courts have designed their own procedures to randomly assign cases to officers like Tianjin in 2012 (http://www.chinapeace.gov.cn/chinapeace/c25056/2012-08/ 24/content_11892031.shtml), Beijing in 2013 (https://news.sina.com.cn/c/2013-08-28/020528063574. shtml?sinatracker=tao123_index), Chongqing in 2017 (https://cqfy.chinacourt.gov.cn/article/detail/2017/ 08/id/2986103.shtml), and so on.

⁷ According to the "Provisions on Several Issues Concerning the Online Judicial Auction by People's Courts" (http://www.court.gov.cn/fabu-xiangqing-24391.html), the court should be responsible for the collection and listing of the execution property's information. We randomly selected an officer from each province and phone-interviewed them about the information collection process. According to our interview, in practice, the specific information-related work is undertaken by the appointed officer herself.

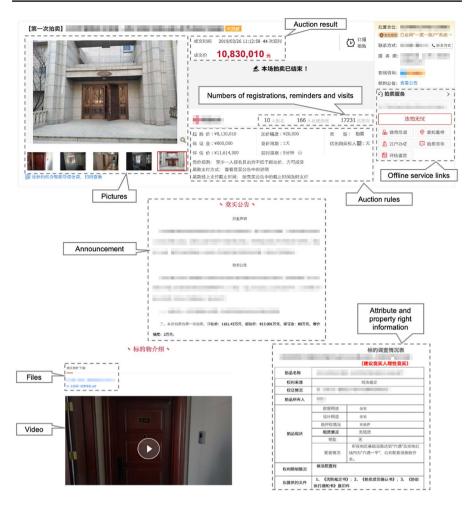


Fig. 2 An example of the listing webpage for an online judicial auction. This figure shows a representative example of a dwelling unit's online judicial auction listing webpage (sf-item.taobao.com/sf_item/ 587646539573.htm). The core information parts that we focus on are all displayed and marked

Three arrangements are noteworthy here. First, the Supreme People's Court only puts forward some online-information-disclosure principles in the "Provisions on Online Auction", instead of detailed stipulations of information contents or formats. Thus, the information provided on the website is largely determined by the officer, which provides considerable variations for us to investigate the effect of information disclosure on auction outcomes. Second, the courts will not arrange onsite inspections for potential buyers. For each unit, its detailed address, including both the community's name and the room number, is released publicly on the website. However, interested buyers typically will find it difficult to inspect the dwelling units themselves due to the potential seal-up conditions or tenants still occupying the units. Moreover, if the unit is part of a gated community (which is prevalent in China), the buyers cannot enter the community either. The buyers could turn to professional agents for offline services, but the agents face the same difficulties when attempting onsite inspections. In sum, it is typically infeasible for potential buyers to collect valuable offline information. In other words, the online platform is the dominant, if not only, channel for interested buyers to collect property-related information. Third, with emerging online judicial auctions, in some cities, professional agents provide related offline services, which mainly help solve the post-transaction property transfer problems⁸. The online auction platform (instead of the court) will automatically match available local offline services with the online judicial auction and provide the service links on the webpage. We also collect information on the availability of such offline services for each online judicial auction and investigate their effects in the empirical analysis.

During the listing period (i.e., the period between the announcement and the start of the auction, usually more than 30 days), all individual and institutional buyers can visit the webpage and contact the officer for inquiries. The information provided by officers in response to inquiries is, in most cases, identical to data already offered on the webpage⁹. The listing webpage also records and publicly reports a few indicators of the potential buyers' behaviors, and we mainly focus on two indicators in the following analysis. First, if a potential buyer is interested in the property, she can sign up for an automatic reminder when the auction is ready to start. No cost is involved in setting this reminder, so we expect that most potential buyers with an initial interest in the property will use it. Therefore, in the following empirical analysis, we adopt the number of potential buyers setting reminders as the proxy for the outcome in attracting initial interest. Second, a buyer needs to register if she plans to bid in the auction formally. For the registration, she needs to complete a detailed form and, more importantly, transfer a substantial deposit to the court, which typically amounts to 5–20% of the starting price.¹⁰ Accordingly, we can reasonably expect that a potential buyer would only register when she has a real intention to participate in the bidding process. We thus adopt the number of registered buyers to reflect the achievement in attracting actual participation.

Data and Empirical Strategy

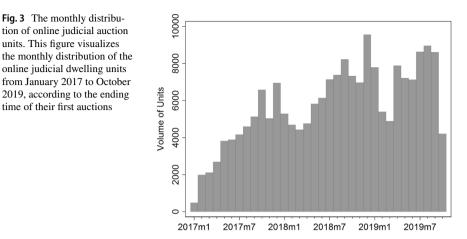
Data

We manually collect the data from the housing sector of the website of "Taobao online judicial auction" (sf.taobao.com), which is the first and currently largest

⁸ Theoretically, the offline services include onsite inspections and post-transaction property transfers. However, according to our survey by reaching out for offline services, the agents can hardly take interested buyers to enter the units or provide additional information. In other words, the role of offline services actually focuses on property transfer.

⁹ We randomly select a property from each province and make telephone inquiries. We find that the inquiry just provides the same information as the online webpage.

¹⁰ The winner of the auction can use the earnest money as part of her payment. For other failed bidders, their registration will be cancelled, and the earnest money will be refunded immediately after the auction. If the failed bidders want to join other new auctions, they need to re-register and pay the earnest money again.



online judicial auction platform in China.¹¹ Between January 2017 and October 2019, the platform had 215,599 dwelling units listed from all the 293 cities across the country. We then cleaned the raw data via the following procedures. First, we excluded properties with priority buyers.¹² Second, we also excluded dwelling units included in multiple-property packs. These procedures resulted in the exclusion of 15,196 units. The full sample includes 200,403 dwelling units for our analysis.

Figure 3 shows the units' monthly distribution according to the ending time of their first auctions. The market witnessed a continuous and rapid development during the sample period, from an average monthly volume of 3,958 units in 2017 to an average monthly volume of 7,074 units in the first ten months of 2019. A significant seasonality also exists. The courts would typically list more units in the last months of a year. One possible explanation is that courts need to meet some specific annual targets in dealing with the execution properties, and thus have a higher incentive at the end of a year to reduce the number of unsold or unlisted execution properties. Figure 4 depicts the province-level distribution of the aggregated number of units during the sample period. Zhejiang province has 23,323 units, which account for the largest fraction of 11.9%, followed by Jiangsu and Henan provinces. Generally, provinces with more auction units are concentrated in the eastern region.

As shown in Table 1, because all the dwelling units in the sample were listed in a first auction, the data include information on 200,403 first auctions, with 88,133 successful transactions. Most of the properties that were not sold in the first auctions entered the subsequent stages¹³: 92,842 properties were listed in their second

units. This figure visualizes

time of their first auctions

¹¹ So far there, China has five officially authorized online judicial auction platforms. No official statistics are available on the market share of these five platforms. We provide a preliminary analysis in Table 10 in the Appendix. The 90% market share occupied by Taobao may indicate the potential monopoly, which does not affect our research analysis.

¹² Priority buyers refer to people who enjoy the priority right over others to purchase. When a priority buyer offers the same price as another buyer during the bidding process, the priority buyer wins. For dwelling-unit auctions, priority buyers typically refer to the tenants or co-owners of the property.

¹³ In most cases, the properties that did not enter the subsequent stages were disposed of in ways other than auctions.

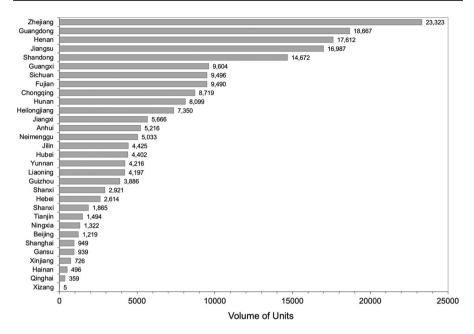


Fig. 4 The province distribution of online judicial auction units. This figure visualizes the provincial distribution of online judicial dwelling units from January 2017 to October 2019

	Total	Success		Failure	Failure		
		Number	Proportion	Number	Proportion		
First auction	200,403	88,133	43.98%	112,270	56.02%		
Second auction	92,842	39,255	42.28%	53,587	57.72%		
Sell-off	21,285	8,150	38.29%	13,135	61.71%		

 Table 1
 Breakdown of the execution properties by stages

This table shows the auction numbers and the distribution of auction results in each stage

auctions, with 42.3% (39,255 properties) being successfully sold; 21,285 properties were listed in the sell-off stage, with 38.3% (8,150 properties) being successfully sold. In this study, we mainly focus on information disclosure and its effects on the first auctions for two reasons. First, there could be quality bias with the samples in the following two stages. Second, in 99.7% of all the cases, the court will duplicate the information of the first auction for the second auction and sell-off attempt. In the remaining 0.3% cases, only minor information changes are made. In other words, the latter two stages provide very little additional information.

For each dwelling unit and its first auction, we collect information on its basic auction characteristics, information disclosure, and outcomes from the webpage (Fig. 2 as an example). The auction-related characteristics include the listing time, starting time, and ending time of the first auction. We then calculate the length of

the listing-period variable, *exposure time*, as the number of days between the listing time and the starting time of the auction. We also collect the appraisal value (*appraisal price*) as the proxy for the market price. Additionally, we identify the name of the court and the officer who handles the auction.

The information-disclosure condition is our primary interest in the empirical analysis. The information variables can be classified into visual information, file information, and text information. The visual information consists of the video and photo. The platform requires a minimum number of one photo and a maximum number of five. Video is not compulsory, and one video at most can be included. We record whether a video is available as the video dummy variable *video* and whether the number of photos reaches five as the photo dummy variable *5photo* (i.e., the counterfactual of the photo dummy is that the website only provides one to four photos).

The file information refers to the official documents attached to the webpage. We measure the degree of file-information disclosure by the variable *file num*, which indicates the number of file types. The file types include the appraisal report, legal document, and property-rights certificate. We identify the existence of each type according to the file title.

The text version of the property description on the webpage contains physical attributes and property-rights information. These two categories' disclosure degrees are measured by the information item numbers, *phy num* and *right num*, respectively. Physical attributes refer to the physical characteristics, including the area, age, floor, type, and decoration of the house. Property-rights information reflects the unit's property-rights conditions, which consist of the right-limit condition (mortgage, seal up, and co-owner condition), with or without a key, the right source of the house, and the kind of certificate. We develop a text-analysis method for each category to determine whether the description contains a designated item.¹⁴

The outcome of the listing process is measured from two perspectives. The first perspective reflects the direct effect of online information disclosure in attracting potential buyers, including the number of reminders and of registered bidders, which are explicitly presented on the webpage as Fig. 2 shows. We adopt the natural log of the number of reminders (ln(reminder)) as the proxy of potential buyers' initial interest in the unit, and the natural log of the number of registered bidders (ln(registration)) as the indicator of actual transaction participation¹⁵. The information disclosure can be perceived as achieving a better outcome if it attracts more potential buyers, especially more actual participants. As for the second perspective, we have two variables on the auction outcomes. The dummy *if success* indicates whether the auction is a success or a failure. The variable *discount rate* quantitatively measures the ratio of the transaction price to the appraisal price (i.e., *discount*)

¹⁴ For each information item, we list a series of related keywords and use them to determine the existence of the item.

¹⁵ We use the natural logs of the number of reminders and the number of registered bidders instead of their original levels, because the original levels of these two variables are both severely right-skewed. The histogram distributions of the number of reminders and the number of registered bidders in the full sample are shown in Fig. 7 in the Appendix.

rate = 1 - transaction price / appraisal price) for successful auctions. The information disclosure can be perceived as achieving a better outcome if the auction is successful, especially with a lower discount rate (i.e., a higher transaction price).

The definition and summary statistics of the major variables are listed in Table 11 in the Appendix. In the full sample, nearly 20% of properties provide a video, and nearly 80% of properties have five uploaded photos. The average file-type number is 0.56. On average, the property description provides information on 2.19 items on physical attributes and 2.20 items on property rights. On average, the number of reminders is 2.95 in the natural log (19.14 in the absolute number), and the number of registrations is 0.78 in the natural log (2.17 in the absolute number). The probability of success in the first auctions is 44.0%, and the successfully transacted properties have an average discount rate of 0.9%.

Empirical Strategy

In this study, we mainly focus on how information disclosure on the online platform helps attract potential buyers and its effect on the auction outcomes. For this purpose, we introduce the micro-level data of the first auctions of the dwelling units, and the main specifications are as follows:

$$y_i = \beta \times information_i + \gamma \times control_i + \alpha_{i,t} + \varepsilon_i$$
(1)

$$P(if \ success_i = 1 | information_i, control_i) = \Phi(\beta \times information_i + \gamma \times control_i)$$
(2)

where Eq. (1) adopts the OLS model and Eq. (2) adopts the binary probit model; $\Phi(\cdot)$ is the cumulative distribution function of standard normal distribution. y_i refers to the outcome variable for dwelling unit *i*, which is located in district *j* and transacted in period *t*. The outcome variables include the number of reminders, the number of registered buyers, and the discount rate for successful auctions. *ifsuccess*_i refers to the dummy indicating whether the auction is a success or a failure. *information*_i refers to the vector of information disclosure variables. *control*_i refers to a series of control variables¹⁶ that depict other transaction features of the property. The county-year-month fixed effects, $\alpha_{j,t}$, control for the district-specific time trend at year-month *t* of district *j*. ϵ_i is the error term that is two-way clustered at the district and year-month levels (Cameron & Miller, 2015).

One potential problem in Eqs. (1) and (2) is that the information disclosure might be endogenously determined. For instance, the officer may be willing to release more information on the listing webpage for a more desirable dwelling unit. By contrast, she may intentionally hide some less attractive attributes of a unit. Such

¹⁶ The control variables include the number of days from announcement to the end of auction (*exposure time*) and its square, the dummy if the right-limit information is listed and the house has a right limit (*with right limit*), the dummy if the locations of the house and the court are not in the same city (*diff city*), the dummy if the court has allocated a single bank account for this case (*account*), and the dummy if there a "Loan available" tag is on the webpage (*loan tag*).

behaviors, if they exist, will lead to an overestimate of the effect of the information disclosure on the number of buyers attracted or the auction outcome. We use the officers' personal styles of information releasing to mitigate such a potential endogenous problem. More specifically, we first select the officers who provide information in a consistent format within all the online judicial auctions she handled during the sample period. Therefore, the information disclosure is purely determined by the officer's own custom instead of any property-level characteristics; in other words, the officer will stick to the same list of information items when collecting and releasing information, no matter how valuable or desirable the property is. Following this strategy, we only include first auctions which are: (1) it is handled by an officer with such a time-invariant personal information-providing style; and (2) the county-yearmonth has more than one such officer in the working sample of the empirical analysis. The summary statistics of the working sample are reported in Table 11 in the Appendix. Not surprisingly, the sample volume shrinks dramatically due to such a strict criterion - the working sample only accounts for about 8% of the full sample. Nevertheless, we still have 15.723 observations in the working sample¹⁷. We also use the full sample to replicate the main results in the robustness checks.

Next, we provide suggestive evidence of the effectiveness of the "consistent personal style" strategy. As discussed in Section 3.2, the major concern is that the court officers intentionally release more desirable information but less undesirable information. Therefore, if our "consistent personal style" strategy can at least partially mitigate this endogeneity, we would observe less desirable information and more undesirable information in our working sample, compared with the sample excluded from the analysis due to the "consistent personal style" criterion. It is difficult to distinguish whether the content is desirable for most information items because potential buyers may have different preferences. Here we adopt the information item of key availability (in the category of "property right") as the example, which is easy for us to evaluate the content: for part of the execution properties, the courts already have the door keys, which would facilitate the post-transaction delivery process; but for the other properties, the courts do not have the door keys (typically due to the existence of tenants). As listed in Table 12 in the Appendix, in the working sample with 15,723 observations, 27.8% of the units release information on key availability, with 13.8% reporting "with keys" (i.e., desirable information) and the other 14.0% reporting "without keys" (i.e., undesirable information). Meanwhile, in the 184,680 observations which are excluded due to the "consistent personal style" criterion, there are 16.7% reporting "with keys" and the other 11.9% reporting "without keys." This pattern is consistent with our expectation, which can serve as a piece of indirect evidence of the effectiveness of the "consistent personal style" in mitigating the potential endogeneity.

In the working sample, the released information is only determined by officers' (consistent) personal styles, which may result from officers' personal working habits or working templates. To show the differences in such personal styles across officers, we calculate the sum of information variables (including *video*, *5photo*, *file*

¹⁷ The histogram distributions of the number of reminders and the number of registered bidders in the working sample are shown in Fig. 8 in the Appendix. The distributions remain right-skewed as in the full sample.

num, *phy num*, and *right num* as shown in Table 11 in the Appendix) for each officer in the working sample. The histogram distribution of the sum is displayed in Fig. 9 in the Appendix with a mean of 5.8 and a standard deviation of 2.6 showing that the differences are significant between officers.

Empirical Results

Main Results

We start with the effect of information disclosure on attracting potential buyers. As discussed before, we mainly focus on the number of potential buyers who have set reminders, which serves as the proxy for initial interests in the property, and the number of registered buyers, which serves as the actual participation indicator. Following Eq. (1), for each specification, besides the information-disclosure variables, we also include the control variables and the county-year-month fixed effects. The results are listed in Table 2. Besides the estimated coefficients of each information variable, we also calculate the relative effect of information disclosure for each information category, which measures the change in the outcome variable by standard deviations when the corresponding information variable increases by one standard deviation. Therefore, the results not only reflect whether and to what extent information disclosure helps attract potential buyers but also help identify the key information categories.

Regarding the number of reminders (column 1), the effect of information disclosure is relatively limited in attracting buyers' initial interests. In all five information categories, only two categories, photo and physical attributes, are statistically significant. After controlling for other variables, the relative effect is 0.049 standard deviations for photos and 0.039 standard deviations for the number of physical-attribute items. The overall relative effect of all five information categories is about 0.082 standard deviations in attracting buyers' initial interests. In other words, the number of reminder settings can increase from 9.2 (the average level of the working sample) to 10.6 if all five information variables simultaneously increase by one standard deviation.

Then, we turn to the number of registered buyers (column 2), for whom the information effect becomes relatively larger. The video and attached files show statistically significant positive effects, for which the relative effects are 0.064 and 0.043 standard deviations, respectively. The variables of *5photo* and *right num* are also positive and marginally significant. The overall relative effect reaches 0.216 standard deviations. That is, whereas an online judicial action in the sample period attracts 1.7 registered bidders on average, the number can increase to 2 if all five information variables increase by one standard deviation simultaneously.

In Table 3, we further decompose the variables of *file num*, *phy num*, and *right num* to the dummies of specific information items to reflect the potential difference in their relative importance. The effects of video and photos are similar to the effects shown in Table 2. For the effects on reminders, we only witness a significant effect associated with the variables of certificate file (an item in the attached file

	(1)	(2)
Variables	ln(reminder)	ln(registration)
Information variables		
video (if a video is uploaded)	-0.004	0.144*
	(0.083)	(0.083)
5photo (if the number of photos reaches 5)	0.215***	0.074
	(0.069)	(0.057)
file num (number of types of files uploaded)	0.006	0.048**
	(0.028)	(0.021)
phy num (number of physical attributes listed)	0.041***	0.010
	(0.011)	(0.011)
right num (number of property-rights items listed)	-0.009	0.031
	(0.036)	(0.026)
Control variables		
exposure time	0.011**	0.003
	(0.004)	(0.004)
square of exposure time	-0.000***	-0.000
	(0.000)	(0.000)
with right limit	0.029	-0.071
	(0.073)	(0.062)
diff city	-0.167**	-0.163***
	(0.062)	(0.058)
account	0.098	-0.002
	(0.099)	(0.098)
loan tag	0.110**	0.027
	(0.051)	(0.052)
Relative Effect		
Overall	0.082	0.216
Video	-0.001	0.064
Photo	0.049	0.034
File information	0.003	0.043
Physical attribute	0.039	0.019
Property-rights information	-0.008	0.056
Observations	15,723	15,723
R-squared	0.887	0.671
County-Year-Month FE	YES	YES

Table 2 Baseline results: The effects on category level

This table explores the impact of information disclosure on attracting potential buyers. The outcomes are the number of reminders (in the natural log) in column (1), and the number of registered bidders (in the natural log) in column (2). For each specification, we control for the county-year-month fixed effects. Robust standard errors are two-way clustered at the county and year-month level. * indicates significance at the 0.1 level; ** indicates significance at the 0.05 level; *** indicates significance at the 0.01 level. The relative effects reflect the increase in standard deviations of the outcome variable when the corresponding information variable increases by one standard deviation

Are Online-Only Real Estate Marketplaces Viable? Evidence...

 Table 3
 The effects on item

level

	(1)	(2)
Variables	ln(reminder)	ln(registration)
video (if a video is uploaded)	-0.003	0.167*
	(0.083)	(0.083)
<i>5photo</i> (if the number of photos reaches 5)	0.228***	0.084
	(0.072)	(0.058)
File information		
appraisal repo	0.016	0.121***
	(0.038)	(0.029)
legal doc	-0.044	-0.113**
	(0.055)	(0.052)
certificate	0.520**	0.468***
	(0.195)	(0.138)
Physical attribute		
area	0.109***	0.039
	(0.040)	(0.047)
age	0.030	-0.006
	(0.040)	(0.036)
floor	-0.013	-0.010
	(0.047)	(0.036)
house type	0.063	0.088***
	(0.045)	(0.026)
decoration	-0.003	-0.044
	(0.045)	(0.038)
Property-rights information		
right limit	0.043	-0.013
	(0.103)	(0.108)
key	-0.058	0.019
	(0.055)	(0.051)
right source	-0.088	0.046
	(0.071)	(0.044)
certificate kind	0.070	0.080*
	(0.061)	(0.046)
Observations	15,723	15,723
R-squared	0.887	0.673
Control Variables	YES	YES
County-Year-Month FE	YES	YES

This table explores the impact of specific information items on attracting potential buyers. The outcomes are the number of reminders (in the natural log) in column (1) and the number of registered bidders (in the natural log) in column (2). For each specification, we control for the county-year-month fixed effects. Robust standard errors are two-way clustered at the county and year-month level. * indicates significance at the 0.1 level; ** indicates significance at the 0.01 level

category) and area (an item in the physical attribute category). For the effects on registration, more information items become significant. If the court can provide the appraisal report (in the attached-file category), certificate file, house type (in the physical-attribute category), or name of the property-rights certificate (in the property-rights category) on the webpage, it can attract significantly more registered bidders. Only one information item has a significantly negative effect—the impact of a legal document on the number of registered buyers. In most cases, the legal document refers to the court verdict that explains why the property should be executed in a judicial auction. Thus, one possible reason for the negative effect is that the legal document's existence may implicitly enhance the so-called stigma effect associated with the execution properties, which has been proven to negatively affect the demand for foreclosure properties in the US (Clauretie and Daneshvary, 2009).

The above results reveal important differences in information's role in various stages of online real estate transactions. A potential buyer's initial interest mainly comes from her preliminary cognition of the dwelling unit, which can be expected to be less rational. Thus, it is not surprising to see that the role of information is limited at this stage, and the eye-catching and less time-consuming information is more likely to be effective, such as photos and verbal descriptions of physical attributes. By contrast, when a buyer needs to make a more serious decision on whether she will bid for the unit (and her reservation price), she would prefer a more comprehensive and more complete source of information, even if it will take her more time to absorb. For instance, compared with just a few photos, she would prefer a video. Similarly, compared with a brief verbal description on the webpage, she will rely more on the completed version of a professional appraisal report.

In Table 13 in the Appendix, we replicate Table 2 for the second auctions and the sell-off attempts, respectively. Compared with the results associated with the first auctions, the contribution of information disclosure is much smaller in these two alternative groups. This finding is consistent with the fact that, in most cases, no additional information is provided during these two stages.

We conduct a series of robustness checks. In Table 14 in the Appendix, we further control for the natural log of starting price and the ratio of starting price to appraisal price in the baseline model. The results generally remain consistent. In Table 15 in the Appendix, we replicate the baseline model with the full sample of first auctions. The pattern remains qualitatively unchanged, whereas the magnitudes of the effects associated with the information variables are generally larger than in Table 2. This finding is consistent with the concern that the potential endogeneity of courts' information-disclosure behaviors might lead to an overestimate of the information effect. In Table 16 in the Appendix, we further differentiate the effect of photos among different numbers from one to five¹⁸ by adding the variables 2*photo*, *3photo*, and *4photo* (similar to the definition of variable *5photo*) into the baseline model and the results remain consistent.

 $[\]frac{18}{18}$ In the working sample (15,723 units), there are 669 units with one photo, 800 units with two photos, 580 units with three photos, 712 units with four photos, and 12,962 units with five photos.

Note that the strategy of using officers' consistent personal styles to construct the working sample may arouse another potential endogenous problem - the information disclosure style may result from the court officers' capability, which might affect the auction performance via other channels. For example, a more capable officer may process all the cases more carefully and patiently, and release more information simultaneously. The buyers may be more willing to focus on or buy the property due to the officer's patient attitude instead of the more information she released. To rule out this endogeneity, here we test the effect of each information disclosure variable one by one while controlling for the fixed effects of all the other information disclosure variables. Taking the test of the video dummy variable as an example, the model writes as follows:

$$y_i = \beta \times video_i + \gamma \times control_i + \alpha_{j,t} + 5photo_i \times filenum_i \times phynum_i \times right num_i + \varepsilon_i$$
(3)

In this analysis, we mainly focus on the coefficient of $video_i$ while controlling for the photo-file-physical-right fixed effects (by multiplying $5photo_i$, file num_i, phy num_i, and right num_i together). Officers who provide the same numbers of photos, files, physical information, and property right information may be very close in capability. Thus, the coefficient of the video dummy variable compares the outcomes with and without a video conditional on officers with very similar capabilities. Similar tests are also done for the photo dummy variable, file number variable, physical attributes number variable, and property rights number variable. The results are listed in Table 17 in the Appendix, consistent with the main results in Table 2. Therefore, it is reasonable to argue that our key findings are not driven by the new potential endogeneity of officers' capability.

Heterogeneity Analysis

First, we focus on the interaction between online information disclosure and the availability of offline services. As introduced in Section 2, potential buyers can access offline services from local professionals in some cities, which can assist in the post-transaction property transfer process. Once a buyer succeeds in bidding for a dwelling unit, she needs to contact the court and the local housing authority to complete the property transfer process, which can only be implemented offline in current China. The transfer process is typically complicated for an execution property due to the potential property-rights problems. We expect that when the difficulty in post-transaction property transfer, which is another bottleneck of online real estate transactions, can be better solved via offline services, the online transactions could become more feasible, and the online information's role could be enhanced. Note that there is no variation for offline services within a city during our sample period. Therefore, we provide a preliminary analysis of the offline service by distinguishing cities with offline services and cities without available offline services. The results are listed in Table 4. The overall effect of information disclosure is substantially larger in cities with offline services. For attracting initial interests, the overall effect is about 0.097 standard deviations in cities with offline service, but only 0.029

Table 4	Heterogeneous	effect:	Bv	offline	service
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	With offline s	ervice	Without offlin	ne service
	(1)	(2)	(3)	(4)
Variables	ln(reminder)	ln(registration)	ln(reminder)	ln(registration)
video (if a video is uploaded)	0.003	0.194**	-0.016	-0.126
	(0.098)	(0.094)	(0.131)	(0.170)
<i>5photo</i> (if the number of photos reaches 5)	0.200***	0.053	0.240*	0.094
	(0.063)	(0.069)	(0.128)	(0.077)
<i>file num</i> (number of types of files uploaded)	0.007	0.042	-0.011	0.067*
	(0.034)	(0.025)	(0.054)	(0.036)
<i>phy num</i> (number of physical attributes listed)	0.039***	0.009	0.053**	0.018
	(0.013)	(0.013)	(0.023)	(0.017)
<i>right num</i> (number of property-rights items listed)	0.012	0.036	-0.076	0.018
	(0.037)	(0.028)	(0.059)	(0.041)
Relative Effect				
Overall	0.097	0.231	0.029	0.114
Video	0.001	0.087	-0.004	-0.056
Photo	0.045	0.024	0.055	0.043
File information	0.003	0.037	-0.005	0.060
Physical attribute	0.037	0.017	0.051	0.035
Property-rights information	0.011	0.065	-0.068	0.033
Observations	10,141	10,141	5,382	5,382
R-squared	0.865	0.659	0.862	0.599
Control Variables	YES	YES	YES	YES
County-Year-Month FE	YES	YES	YES	YES

This table explores the heterogeneous impact of information disclosure on attracting potential buyers from the existence of offline service. The outcomes are the number of reminders (in the natural log) in column (1) and column (3), and the number of registered bidders (in the natural log) in column (2) and column (4). The sample for column (1) and column (2) comprises dwelling units with offline service, and for column (3) and column (4), the sample comprises dwelling units without offline service. For each specification, we control for the county-year-month fixed effects. Robust standard errors are two-way clustered at the county and year-month level. * indicates significance at the 0.1 level; ** indicates significance at the 0.05 level; *** indicates significance at the 0.01 level. The relative effects reflect the increase in standard deviations of the outcome variable when the corresponding information variable increases by one standard deviation

standard deviations in cities without offline service. Similarly, the overall effect in attracting registered bidders reaches 0.231 standard deviations in cities with offline service, whereas the corresponding number is 0.114 in cities without offline service. The results provide evidence of the importance of the "offline-online combination" in the online real estate sector's future development. When the bottleneck of property transfer is solved, the effect of online information gets strengthened.

	Large scale		Small scale	
	(1)	(2)	(3)	(4)
Variables	ln(reminder)	ln(registration)	ln(reminder)	ln(registration)
video (if a video is uploaded)	0.130	0.183*	-0.112	0.116
	(0.078)	(0.095)	(0.123)	(0.113)
<i>5photo</i> (if the number of photos reaches 5)	0.279***	0.086	0.177*	0.067
	(0.079)	(0.110)	(0.102)	(0.065)
<i>file num</i> (number of types of files uploaded)	0.010	0.070**	0.007	0.030
	(0.030)	(0.027)	(0.036)	(0.032)
<i>phy num</i> (number of physical attributes listed)	0.034**	0.006	0.045***	0.015
	(0.017)	(0.018)	(0.012)	(0.013)
<i>right num</i> (number of property-rights items listed)	0.001	0.047	-0.012	0.017
	(0.043)	(0.033)	(0.048)	(0.035)
Relative Effect				
Overall	0.130	0.280	0.051	0.169
Video	0.029	0.082	-0.025	0.052
Photo	0.063	0.039	0.040	0.031
File information	0.004	0.062	0.003	0.027
Physical attribute	0.033	0.012	0.043	0.029
Property-rights information	0.001	0.085	-0.011	0.031
Observations	6,153	6,153	9,570	9,570
R-squared	0.895	0.637	0.858	0.675
Control Variables	YES	YES	YES	YES
County-Year-Month FE	YES	YES	YES	YES

Table 5	Heterogeneous e	effect: By marke	t scale of online	judicial housing auction	n
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This table explores the heterogeneous impact of information disclosure on attracting potential buyers from the market scale of online judicial housing auction. The outcomes are the number of reminders (in the natural log) in column (1) and column (3), and the number of registered bidders (in the natural log) in column (2) and column (4). For each city, we calculated the annual average amount of first-stage dwelling units during the years that the city has online auction records. We use the annual average amount as the proxy for market scale of online judicial housing auction. Employing the median of annual average amounts as the cut-off point, the sample for column (1) and column (2) comprises dwelling units in cities with larger market scales. For each specification, we control for the county-year-month fixed effects. Robust standard errors are two-way clustered at the 0.05 level; *** indicates significance at the 0.01 level. The relative effects reflect the increase in standard deviations of the outcome variable when the corresponding information variable increases by one standard deviation

Second, we focus on the heterogeneity associated with the market scale or market maturity. In cities with a more active or mature online judicial housing auction sector, potential buyers are more likely to get used to this innovative transaction platform and trust the information released. For this purpose, in Table 5, we divide the

cities into two groups according to the annual amount of online judicial housing auctions. As expected, the overall effect of information disclosure is higher in cities with a larger (above median) market scale of online judicial housing auctions. For the number of reminders, the overall effect is 0.13 standard deviations in cities with a larger market scale, compared with 0.051 standard deviations in the other group.

	High value		Low value	
	(1)	(2)	(3)	(4)
Variables	ln(reminder)	ln(registration)	ln(reminder)	ln(registration)
video (if a video is uploaded)	-0.003	0.116	-0.069	0.109
	(0.096)	(0.086)	(0.267)	(0.222)
<i>5photo</i> (if the number of photos reaches 5)	0.150	0.116	0.249*	0.063
	(0.098)	(0.077)	(0.136)	(0.119)
<i>file num</i> (number of types of files uploaded)	0.002	0.028	-0.020	-0.015
	(0.037)	(0.038)	(0.035)	(0.043)
<i>phy num</i> (number of physical attributes listed)	0.022	0.001	0.097***	0.043
	(0.019)	(0.014)	(0.033)	(0.030)
<i>right num</i> (number of property-rights items listed)	-0.016	0.030	0.028	0.044
	(0.039)	(0.026)	(0.062)	(0.039)
Relative Effect				
Overall	0.041	0.186	0.150	0.227
Video	-0.001	0.052	-0.015	0.049
Photo	0.034	0.053	0.057	0.029
File information	0.001	0.025	-0.009	-0.013
Physical attribute	0.021	0.002	0.093	0.083
Property-rights information	-0.014	0.054	0.025	0.080
Observations	6,413	6,413	7,469	7,469
R-squared	0.882	0.661	0.898	0.762
Control Variables	YES	YES	YES	YES
County-Year-Month FE	YES	YES	YES	YES

 Table 6
 Heterogeneous effect: By property value

This table explores the heterogeneous impact of information disclosure on attracting potential buyers from the value of property. The outcomes are the number of reminders (in the natural log) in column (1) and column (3), and the number of registered bidders (in the natural log) in column (2) and column (4). We use the appraisal price as the indicator for property value. By comparing the appraisal price of each dwelling unit with the median appraisal price of the city it locates in, we divide the sample into two groups. The sample for column (1) and column (2) comprises dwelling units with higher values than the median, and for column (3) and column (4), the sample comprises dwelling units with lower values than the median. For each specification, we control for the county-year-month fixed effects. Robust standard errors are two-way clustered at the county and year-month level. * indicates significance at the 0.1 level; *** indicates significance at the 0.01 level. The relative effects reflect the increase in standard deviations of the outcome variable when the corresponding information variable increases by one standard deviation

For the number of registered bidders, the overall effects are 0.28 and 0.169 standard deviations, respectively.

Finally, the role of online information may vary with the property value. A higher property value to pay means higher risk exposure for the buyer, especially in the judicial housing market. Under the risk aversion assumption in decision-making with uncertainty (Deck & Schlesinger, 2010), we can reasonably expect that a potential buyer would show more prudence in purchasing a higher-value dwelling unit. In this case, she may take the due diligence before the transaction more seriously and would be less satisfied with the online information but seek to collect offline information (even with a very high cost). In other words, we could expect that online information disclosure plays a less critical role for more valuable properties. The results in Table 6 echo such an expectation. Within each city, we divide the properties into the higher- or lower-value group, with the city's median appraisal price as the threshold. The results show a larger effect of information disclosure in the lower-value group. For the number of reminders, the overall effect is only 0.041 standard deviations in the higher-value group but reaches 0.15 standard deviations in the lower-value group. Similarly, the overall effect for the number of registered bidders is 0.186 standard deviations in the higher-value group and 0.227 standard deviations in the lower-value group. Therefore, the online housing market is more likely to develop first in the lower-end market but would face more challenges in the luxury end.

Effects on Auction Results

The above analysis indicates better online information disclosure can help attract more buyers to participate in the auction. The question that follows is whether such an effect can be finally converted to a higher success probability and/or a higher transaction price of the auction.

We first explore the impacts of information disclosure on the auction's success probability based on Eq. (2). The results are listed in Table 7, column (1). All five information variables are positive and statistically significant. We then calculate the relative effects based on the marginal effects at the means. The overall relative effect is 0.367 standard deviations. On average, the success probability of a first auction in the working sample is 29.1% points. If all five information variables simultaneously increase by one standard deviation at their means, the success probability would be 16.7% points higher. This result indicates that better online information disclosure can promote the success of real estate transactions.

We then examine the impact on the discount rates of successful auctions based on Eq. (1).¹⁹ As shown in column (2), only two types of visual-related information can help significantly decrease the discount rate of transaction price from appraisal

¹⁹ For the outcome of price discount, Eq. (1) might be biased due to the sample-selection problem, because only the successful first auctions are included in the regression. We also conduct the conventional Heckman two-stage model to check the potential sample-selection problem. The estimated inverse Mills ratio is not statistically significant in the second-stage model. Thus, we directly adopt the OLS method in Table 7, column 2.

	(1)	(2)
Variables	if success	discount rate
video (if a video is uploaded)	0.102***	-0.090**
	(0.031)	(0.036)
5photo (if the number of photos reaches 5)	0.157***	-0.091*
	(0.031)	(0.051)
file num (number of types of files uploaded)	0.158***	0.030
	(0.015)	(0.019)
phy num (number of physical attributes listed)	0.059***	0.003
	(0.007)	(0.008)
right num (number of property-rights items listed)	0.129***	0.003
	(0.013)	(0.015)
Marginal effect at the means		
video	0.034	
5photo	0.052	
file num	0.053	
phy num	0.020	
right num	0.043	
Relative Effect		
Overall	0.367	-0.162
Video	0.028	-0.167
Photo	0.044	-0.130
File information	0.085	0.096
Physical attribute	0.070	0.021
Property-rights information	0.141	0.018
Observations	15,723	3,492
R-squared		0.646
Control Variables	YES	YES
County-Year-Month FE	NO	YES

Table 7	The effects	of information	on the auction result
lable /	The effects	of information	on the auction resu

This table explores the impact of information disclosure on the auction results. We adopt the probit method in column (1) and the OLS method in column (2). The outcomes are the success of auction in column (1), and the discount rate in column (2). In column (2), we control for the county-year-month fixed effects and two-way cluster the robust standard errors at the county and year-month level. * indicates significance at the 0.1 level; ** indicates significance at the 0.05 level; *** indicates significance at the 0.01 level. The relative effects reflect the increase in standard deviations of the outcome variable when the corresponding information variable increases by one standard deviation. In particular, the relative effects in column (1) are calculated based on the marginal effect at the means

price. If a video is uploaded, the discount rate will drop by 9% points. For properties with five photos, its discount rate will be 9.1% points lower than the counterfactual cases (properties with 1 to 4 photos) on average. Considering that the current average discount rate is 2.5% points in the sample as shown in Table 11 in the Appendix, such an alleviation effect of information is economically important. For example, if the property does not have a video, the discount rate will increase from 2.5% points

to 11.5% points. As for the overall effect, a simultaneous increase of all five information variables by one standard deviation can reduce the discount rate by 0.162 standard deviations, or 3.8% points. These results suggest that better online information disclosure can help alleviate the price discount and thus reduce the distortion degree of the property price.

Improvement of Online Information Disclosure

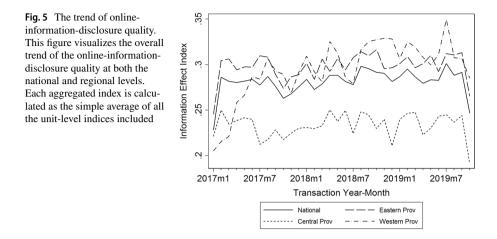
The empirical results above suggest that better information disclosure can help attract more interested buyers and actual participants for an online judicial housing auction, which can be finally converted to a higher success probability or/and a higher transaction price. The next question is whether the courts have realized the importance of online information disclosure and improved its quality. Did the overall information-disclosure quality improve over time? Did some types of courts tend to perform better? And, most importantly, were the courts or officers becoming more and more experienced?

To answer these questions, we first construct an index of information-disclosure quality. As described in Section 3, for an online judicial housing auction, we have considered the effect of 14 information items provided on the webpage: one video, one package of photos, three attached files, five information items on physical attributes, and four information items on property rights. The information-disclosure-quality index is constructed based on these 14 information items as follows:

$$index_{i} = \frac{\sum_{h=1}^{14} \beta_{h} \times info \ item_{i,h}}{\sum_{h=1}^{14} \beta_{h}}$$
(4)

where *index_i* refers to the information-disclosure-quality index for dwelling unit *i*; *info item_{i,h}* refers to the dummy which equals 1 if the court provides information item *h* for dwelling unit *i* and 0 otherwise, the same as the independent variables in Table 3; β_h refers to the corresponding coefficients of the dummies in Table 3, column (2), which reflect each item's relative importance in attracting registered bidders. In other words, for dwelling unit *i*, the information-disclosure-quality index *index_i* is calculated as the average of *info item_{i,h}* weighted by β_h . A higher value of the index implies a higher quality of online information disclosure, especially in attracting actual participants.

We apply Eq. (4) to the first auctions in our sample. As discussed in Section 3.2, for the 15,723 units in the working sample, we believe their information-disclosure quality is purely determined by officers' time-invariant personal styles. We thus do not include them in the following analysis. In other words, the following analysis covers 184,680 units (200,403 - 15,723) from 293 cities between January 2017 and October 2019, for which the handling officers have time-variant information-disclosure sure behaviors.



We start with the overall trend of the information-disclosure-quality index. Figure 5 depicts the national- and regional-level aggregated indices, which are calculated as the simple average of the unit-level indices on a monthly basis. During our

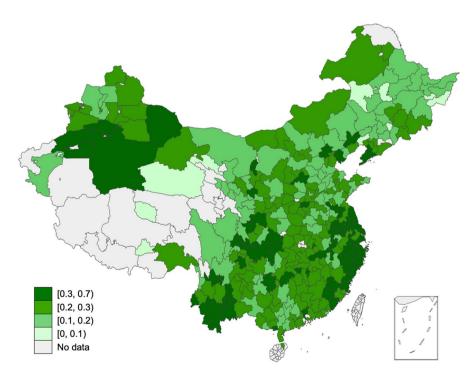


Fig. 6 Spatial distribution of information-quality index. This figure visualizes the distribution of onlineinformation-disclosure quality by prefecture-level cities. For each city, we calculate the average of the information index of all the dwelling units from this city in 2019

sample period, the overall quality of online information disclosure remained relatively stable at the national level, with the monthly average index fluctuating around 0.28. The average indices of the east and central regions share similar patterns, although the average index of the east region was always above the national-level average, whereas the average index of the central region was well below the average. A noteworthy change is a considerable improvement in the information quality of the western cities in the first half of 2017, increasing from about 0.2 to about 0.3, a level comparable to the east region.

Figure 6 provides a snapshot of the spatial distribution of the quality index, with the average index in the first ten months of 2019 as an example. Not surprisingly, the information quality was high in almost all the cities in Zhejiang province, where the online business is most developed. As described in Section 2, online judicial auctions also started from this province. Several other coastal provinces, such as Fujian, Jiangsu, and Liaoning, also had relatively high information quality. Meanwhile, the information quality was also high in a few western provinces, including Chongqing, Sichuan, and Yunnan, which is consistent with the pattern revealed in Fig. 5.

We then turn to the effect of the micro-level factors from three aspects: court levels, if the unit locates in a different city than the courts, and the previous experience. We investigate their effects based on the following specification:

$$index_i = \eta \times micro \ factor_i + \lambda_i + \nu_t + \varepsilon_i \tag{5}$$

where *index_i* refers to the information-disclosure-quality index for dwelling unit *i*; *micro factor_i* refers to the micro-level factor variables for dwelling unit *i*; λ_i refers to the specific micro-level fixed effects for each *micro factor_i* variable, including city fixed effects, court fixed effects, and officer fixed effects; v_t refers to the year-month fixed effects; ϵ_i is the error term.

The results are listed in Table 8. First, we investigate the effect of court levels in column (1). The variable *high level* equals 1 if the court is a High People's Court or an Intermediate People's Court, and 0 if it is a Primary People's Court.²⁰ The result shows the Primary People's Courts perform better than the higher-level courts. Controlling for the city fixed effects (according to the courts' location) and year-month fixed effects, the information index of an online judicial auction implemented by a primary court is 1.9% points higher. One possible explanation is that the primary courts take over many more judicial auctions (about 90.4% in the sample) than the higher-level courts (about 9.6%), and thus have more information-disclosure experience.

Second, for 10.8% of online auctions in the sample, the execution dwelling units were located in different cities than the courts. Collecting and releasing the information would be more difficult and costly for these courts. The result in column

²⁰ Our sample contains three levels of courts: (1) the High People's Courts of provinces, autonomous regions, and municipalities; (2) the Intermediate People's Courts of prefectures, cities, leagues, and autonomous prefectures; and (3) the Primary People's Courts of counties, cities, banners, and autonomous counties.

	(1)	(2)	(3)	(4)
Variables	index	index	index	index
high level (if High / Intermediate People's Court)	-0.019***			·
	(0.001)			
<i>diff city</i> (if house and court not in the same city)		-0.015***		
		(0.001)		
officer exp (number of units officer handled)			0.047***	
			(0.005)	
court exp (number of units court handled)				0.021***
				(0.002)
Observations	168,498	168,633	162,416	162,416
R-squared	0.451	0.635	0.754	0.754
City of Court FE	YES	NO	NO	NO
Court FE	NO	YES	NO	YES
Officer FE	NO	NO	YES	NO
Year-Month FE	YES	YES	YES	YES

Table 8 The performance of information-disclosure work

This table explores the performance of information-disclosure work. The outcome variable in each column is the information-disclosure-quality index. Year-month fixed effects are controlled for in each column. The city-of-court fixed effects are controlled in column (1). Court fixed effects are controlled for in column (2) and column (4). Officer fixed effects are controlled for in column (3). * indicates significance at the 0.1 level; ** indicates significance at the 0.05 level; *** indicates significance at the 0.01 level

(2) confirms the existence of such an information barrier. Controlling for the court fixed effects and year-month fixed effects, the information-quality index is about 1.5% points lower if the unit locates in another city. The courts should exert more effort to overcome such an information barrier to improve information-disclosure quality.

Another important question is whether the pattern of learning by doing applies to courts and officers, that is, whether the information quality can improve when a court or an officer has more previous experience in implementing online judicial housing auctions. In column (3), after controlling for the officer fixed effects and time fixed effects, we introduce the cumulative number of dwelling units that the officer had previously handled on the Taobao platform. As expected, the variable of *officer exp* is statistically significant and positive in the model, which suggests officers can accumulate experience from previous cases and convert the experience into a significant improvement in the following online information disclosure. A similar pattern also applies at the court level. In column (4), we introduce the variable of *court exp*, which measures the cumulative number of dwelling units that the court had handled on the Taobao platform before. It is also significantly positive in the model after controlling for the court fixed effects and time fixed effects. These results provide an encouraging signal that we could expect a continuous

improvement in information disclosure around the country, with the further development of the online judicial housing auctions.

Based on the above results, there are two main factors that determine court officers' information-releasing behaviors. The first factor is court officers' knowledge/ ability on information releasing. If the officers have more experience in online judicial housing auctions, they will know more about which information is important and can release more valuable information. The second factor is information cost. If the cost of obtaining the information is higher (for example, the unit locates in a different city), the information is less likely to be disclosed.

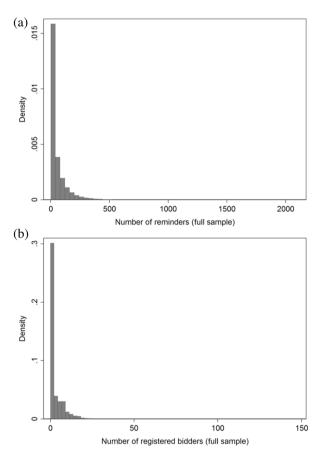
Conclusion

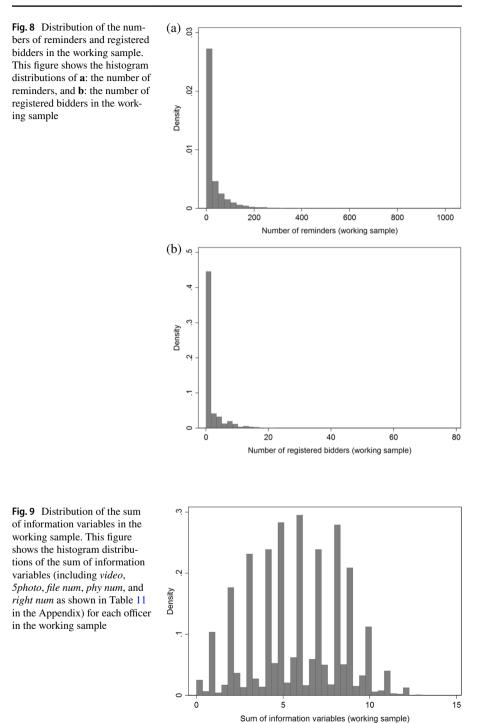
In this study, we use the online judicial housing auction platform in China as an example to investigate how information disclosure helps facilitate online real estate transactions. The empirical results show that a higher quality of online information disclosure can help attract more buyers to participate in the bidding process, which can finally be converted to a higher success probability and a higher transaction price. In particular, although intuitive information sources such as photos can effectively attract buyers' initial interests, the buyers will mainly rely on more comprehensive information sources such as videos or professional appraisal reports when they decide whether to participate in the bidding. We also show rich heterogeneity associated with the above results. Based on the above results, we calculate the information-quality index for the online judicial dwelling units. The empirical results suggest the information quality tends to increase when the officer or the court has more experience in handling online housing auctions.

Admittedly, compared with the conventional offline real estate market, the judicial housing auction is a special and small sector. However, the empirical results of this study can help figure out what information is important in online real estate transactions, thus helping us explore the possible effective forms of future online real estate transactions and providing valuable enlightenment to the future development of online real estate market. Most importantly, the results provide preliminary evidence of the feasibility of online real estate transactions, though the challenges associated with transactions of execution properties might not be totally consistent with conventional real estate properties. Moreover, this study also provides some specific guidelines. Online platforms can consider adopting different information-disclosure strategies at various stages. Especially, if the online platforms aim at converting buyers' initial interests to actual online real estate transactions, they need to provide more comprehensive information such as videos, 3D scanning, VRs, and ARs, and more professional information such as appraisal reports.

Appendix

Fig. 7 Distribution of the numbers of reminders and registered bidders in the full sample. This figure shows the histogram distributions of **a**: the number of reminders, and **b**: the number of registered bidders in the full sample





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Table 9 Breakdown of theexecution properties by asset	Asset type	Number of properties	% of total
type	Real estate property	873,349	84.19%
	Dwelling unit	587,618	56.65%
	Commercial property	179,828	17.34%
	Industrial property	15,018	1.45%
	Garage and parking space	66,143	6.38%
	Land-use right	24,742	2.39%
	Vehicle	106,795	10.29%
	Equipment	21,851	2.11%
	Jewelry	14,567	1.40%
	Equity share ownership	11,616	1.12%
	Antique	3,377	0.33%
	Intangible asset	2,836	0.27%
	Forest ownership	2,083	0.20%
	Creditor's right	456	0.04%
	Mining right	419	0.04%
	All types	1,037,349	100.00%

This table shows the breakdown of the execution properties by asset type, using the online judicial auctions on the Taobao platform from January 2012 to December 2019 as the example

 Table 10
 The market share of 5 online judicial platforms

Platform	Website link	Number of dwelling units	Market share
Taobao	sf.taobao.com	587,618	90.32%
Jingdong	auction.jd.com/sifa.html	52,910	8.13%
Litigation assets web of People's court	rmfysszc.gov.cn	5,355	0.82%
Gongpai	gpai.net/sf/	3,838	0.59%
China association of auctioneers	sf.caa123.org.cn	884	0.14%

This table shows the market share of the five officially authorized online judicial auction platforms in China. The numbers of dwelling units are until December 2019

Table 11 Summary Statistics of the full sample and working sample	s of the full sample	and working sample						
Variables		Explanation	Full sample	e		Working sample	sample	
			Obs 1	Mean	Std. Dev. Obs		Mean	Std. Dev.
Outcome variables								
On buyers	ln(reminder)	Natural log of the number of reminders	200,396 2.952	2.952	1.611	15,723 2.221		1.673
	ln(registration)	Natural log of the number of registered bidders	200,403 (0.775	0.956	15,723 0	0.501	0.829
On auction result	if success	If the auction succeeded, yes $= 1$, no $= 0$	200,403 (0.440	0.496	15,723 0	0.291	0.454
	discount rate	1 - transaction price/appraisal price	81,743 -	-0.009	0.294	3,492 0	0.025	0.233
Information variables								
Visual information	video	If a video is uploaded, yes $= 1$, no $= 0$	200,403 0.198	0.198	0.398	15,723 0	0.164	0.370
	5photo	If the number of photos reaches the maximum of five, five photos = 1, one to four photos = 0	200,403 0.787	0.787	0.410	15,723 0	0.824	0.380
File information	file num	Number of types of files uploaded	200,403 0.564	0.564	0.694	15,723 0	0.688	0.737
	appraisal repo	If an appraisal report is uploaded, yes $= 1$, no $= 0$	200,403 (0.421	0.494	15,723 0	0.496	0.500
	legal doc	If a legal document is uploaded, yes $= 1$, no $= 0$	200,403 (0.136	0.343	15,723 0	0.188	0.391
	certificate	If a property right certificate is uploaded, yes $= 1$, no $= 0$	200,403 (0.007	0.083	15,723 0	0.004	0.065
Attribute information	mnn yhq	Number of physical attributes listed	200,403 2	2.189	1.333	15,723 1	1.864	1.498
	area	If the floor area of the dwelling unit is listed, yes $= 1$, no $= 0$	200,403 (0.792	0.406	15,723 0	0.685	0.465
	age	If the age of the dwelling unit is listed, yes $= 1$, no $= 0$	200,403 (0.491	0.500	15,723 0	0.350	0.477
	floor	If the floor level of the dwelling unit is listed, yes $= 1$, no $= 0$	200,403 (0.403	0.490	15,723 0	0.304	0.460
	house type	If the dwelling unit type is listed, yes $= 1$, no $= 0$	200,403 0.207	0.207	0.405	15,723 0	0.171	0.376
	decoration	If the decoration of the dwelling unit is listed, $yes = 1$, $no = 0$	200,403 0.411	0.411	0.492	15,723 0	0.319	0.466

Variables		Explanation	Full sample	ple		Working	Working sample	
			Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.
Property right information	right num	Number of property-rights information items listed	200,403 2.202	2.202	1.345	15,723	15,723 1.866	1.502
	right limit	If the right-limit information (mortgage, seal up, or co-owner) is listed, yes = 1, no = 0	200,403 0.689	0.689	0.463	15,723 0.583	0.583	0.493
	key	If the information of with or without key is listed, yes = 1, no = 0	200,403 0.285	0.285	0.452	15,723	0.278	0.448
	right source	If the right source information is listed, yes $= 1$, no $= 0$	200,403 0.424	0.424	0.494	15,723	15,723 0.334	0.472
	certificate kind	<i>certificate kind</i> If the kind of certificate is listed, yes $= 1$, no $= 0$	200,403 0.790	0.790	0.407	15,723 0.669	0.669	0.471
Control variables								
exposure time		The number of days from announcement to the end of auction	170,658 33.490 26.783	33.490	26.783	15,723	15,723 34.956 10.011	10.011
with right limit		If the dwelling unit has right limit, yes $= 1$, no $= 0$	200,403 0.647	0.647	0.478	15,723	0.540	0.498
diff city		If the locations of the house and the court are not in the same city, yes $= 1$, no $= 0$	198,734	0.113	0.317	15,723	0.198	0.398
account		If the court has allocated a single bank account for this case, yes = 1, no=0	200,403 0.153	0.153	0.360	15,723	0.139	0.346
loan tag		If there is a "Loan available" tag on the webpage, yes $= 1$, no $= 0$	200,403 0.064	0.064	0.244	15,723 0.044	0.044	0.205

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	Working sample		The rest of the fu	ll sample
Observations	15,723		184,680	
Information item: key availability	Number of units	% in sample	Number of units	% in sample
Disclosing the information	4,368	27.8%	52,825	28.6%
Disclosing good information: with key	2,167	13.8%	30,797	16.7%
Disclosing bad information: without key	2,201	14.0%	22,028	11.9%

This table compares the releasing of the information item "key availability" between the working sample and the rest of the full sample. This table shows the number of observations for each sample and the numbers and percentages of units that disclose the information item "key availability", units that disclose "with key", and units that disclose "without key"

	2nd auction		Sell-off	
	(1)	(2)	(3)	(4)
Variables	ln(reminder)	ln(registration)	ln(reminder)	ln(registration)
video (if a video is uploaded)	0.047	0.056	0.045	-0.509***
	(0.128)	(0.075)	(0.214)	(0.113)
<i>5photo</i> (if the number of photos reaches 5)	0.100	0.050	0.163	-0.086
	(0.127)	(0.070)	(0.189)	(0.173)
<i>file num</i> (number of types of files uploaded)	-0.059*	-0.059**	0.011	0.031
	(0.034)	(0.028)	(0.082)	(0.042)
<i>phy num</i> (number of physical attributes listed)	0.045***	0.025**	0.012	0.027
	(0.015)	(0.010)	(0.053)	(0.017)
<i>right num</i> (number of property-rights items listed)	0.005	0.081**	-0.030	0.035
	(0.052)	(0.034)	(0.109)	(0.049)
Observations	8,403	8,403	1,323	1,323
R-squared	0.873	0.672	0.871	0.778
Control Variables	YES	YES	YES	YES
County-Year-Month FE	YES	YES	YES	YES

 Table 13
 Baseline results for second auctions and sell-off stage

This table replicates the basic specifications for the second auctions in column (1) and column (2), and for the sell-off attempts in column (3) and column (4), respectively. The outcomes are the number of reminders (in the natural log) in column (1) and column (3), and the number of registered bidders (in the natural log) in column (2) and column (4). For each specification, we control for the county-year-month fixed effects. Robust standard errors are two-way clustered at the county and year-month level. * indicates significance at the 0.1 level; ** indicates significance at the 0.05 level; *** indicates significance at the 0.01 level

	(1)	(2)	(3)	(4)
Variables	ln(reminder)	ln(registration)	ln(reminder)	ln(registration)
In(starting price)	-0.145***	-0.165***		
	(0.026)	(0.019)		
starting price/appraisal price			-2.311***	-2.415***
			(0.161)	(0.156)
video (if a video is uploaded)	-0.017	0.128	-0.065	0.084
	(0.082)	(0.078)	(0.071)	(0.072)
<i>5photo</i> (if the number of photos reaches 5)	0.228***	0.090	0.202***	0.088*
	(0.068)	(0.054)	(0.063)	(0.049)
<i>file num</i> (number of types of files uploaded)	0.004	0.046**	-0.034	-0.000
	(0.027)	(0.020)	(0.028)	(0.021)
<i>phy num</i> (number of physical attributes listed)	0.038***	0.007	0.038***	0.002
	(0.012)	(0.011)	(0.012)	(0.011)
<i>right num</i> (number of property-rights items listed)	-0.015	0.024	-0.010	0.033
	(0.036)	(0.026)	(0.040)	(0.031)
Observations	15,723	15,723	14,702	14,702
R-squared	0.888	0.679	0.894	0.704
Control Variables	YES	YES	YES	YES
County-Year-Month FE	YES	YES	YES	YES

Table 14 Robustness check: Add in starting price factors

Compared with the baseline model, this table further controls for the starting price (in the natural log) in column (1) and column (2), and the ratio of starting price to appraisal price in column (3) and column (4). The outcomes are the number of reminders (in the natural log) in column (1) and column (3), and the number of registered bidders (in the natural log) in column (2) and column (4). For each specification, we control for the county-year-month fixed effects. Robust standard errors are two way clustered at the county and year-month level. * indicates significance at the 0.1 level; ** indicates significance at the 0.01 level

	(1)	(2)
Variables	ln(reminder)	ln(registration)
video (if a video is uploaded)	0.082***	0.070***
	(0.020)	(0.015)
5photo (if the number of photos reaches 5)	0.132***	0.044***
	(0.014)	(0.010)
file num (number of types of files uploaded)	0.055***	0.079***
	(0.011)	(0.010)
phy num (number of physical attributes listed)	0.032***	0.012**
	(0.005)	(0.005)
right num (number of property-rights items listed)	0.032***	0.035***
	(0.010)	(0.008)
Observations	156,226	156,226
R-squared	0.814	0.541
Control Variables	YES	YES
County-Year-Month FE	YES	YES

Table 15 Robustness check: Full sample

This table replicates the baseline model with the full sample of first auctions. The outcomes are the number of reminders (in the natural log) in column (1) and the number of registered bidders (in the natural log) in column (2). For each specification, we control for the county-year-month fixed effects. Robust standard errors are two-way clustered at county and year-month level. * indicates significance at the 0.1 level; ** indicates significance at the 0.05 level; *** indicates significance at the 0.01 level

	(1)	(2)
Variables	ln(reminder)	ln(registration)
video (if a video is uploaded)	-0.005	0.147*
	(0.082)	(0.083)
Photo number		
2photo	-0.019	-0.114*
	(0.074)	(0.067)
3photo	0.176*	-0.020
	(0.104)	(0.085)
4photo	0.132	-0.131
	(0.097)	(0.081)
5photo	0.290***	0.005
	(0.075)	(0.076)
file num (number of types of files uploaded)	0.005	0.049**
	(0.028)	(0.021)
phy num (number of physical attributes listed)	0.041***	0.010
	(0.011)	(0.011)
right num (number of property-rights items listed)	-0.008	0.032
	(0.037)	(0.025)
Observations	15,723	15,723
R-squared	0.887	0.671
Control Variables	YES	YES
County-Year-Month FE	YES	YES

Table 16 Robustness check: Differentiated photo numbers

This table replicates the baseline model by adding the variables *2photo*, *3photo*, and *4photo* (similar to the definition of variable *5photo*). The outcomes are the number of reminders (in the natural log) in column (1) and the number of registered bidders (in the natural log) in column (2). For each specification, we control for the county-year-month fixed effects. Robust standard errors are two-way clustered at county and year-month level. * indicates significance at the 0.1 level; ** indicates significance at the 0.01 level

Table 17 Robustness check: Endogeneity of officers' capability	s' capability									
	(1)	(2)	(3)	(4)	(5)	(9)	(7)	(8)	(6)	(10)
Variables	ln(reminder)	ler)				ln(registration)	ation)			
<i>video</i> (if a video is uploaded)	0.018 (0.080)					0.157* (0.091)				
5photo (if the number of photos reaches 5)	~	0.237***				~	0.098*			
file num (number of types of files uploaded)		(con.n)	0.010				(1+cu.u)	0.049 **		
4			(0.029)					(0.019)		
phy num (number of physical attributes listed)				0.035***					0.014	
				(0.011)					(0.013)	
right num (number of property-rights items listed)					-0.011					0.032
					(0.036)					(0.025)
Observations	15,700	15,697	15,719	15,718	15,717	15,700	15,697	15,719	15,718	15,717
R-squared	0.890	0.890	0.889	0.888	0.888	0.679	0.681	0.676	0.674	0.674
Control Variables	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
County-Year-Month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Other information variables FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
This table tests the endogeneity of officers' capability following Eq. (3). The outcomes are the number of reminders (in the natural log) in column (1) to column (5) and the number of registered bidders (in the natural log) in column (6) to column (10). For each specification, we control for the county-year-month fixed effects and the fixed effects of the other information variables. Robust standard errors are two-way clustered at county and year-month level. * indicates significance at the 0.1 level; *** indicates significance at the 0.05 level; *** indicates significance at the 0.05 level; *** indicates significance at the 0.01 level	lity followin () in column standard errc gnificance at	g Eq. (3). The (6) to columr ors are two-wa : the 0.01 leve	e outcomes n (10). For e ay clustered 1	are the numl ach specifica at county ar	oer of remin ttion, we cor id year-mont	ders (in the ntrol for the th level. * ii	natural log county-year ndicates sig) in column month fixe nificance at	(1) to colum d effects and the 0.1 leve	in (5) and the fixed ; ** indi-

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Declarations

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