Journal of Computational Science 25 (2018) 1–15

Contents lists available at ScienceDirect

Journal of Computational Science

journal homepage: www.elsevier.com/locate/jocs

An agent-based model for investigating the impact of distorted supply–demand information on China's resale housing market

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ARTICLE INFO

Article history:
Received 14 July 2017
Received in revised form 5 November 2017
Accepted 9 January 2018
Available online 10 January 2018

Keywords:
Agent-based modelling
Resale housing market
Distorted information
Broker

ABSTRACT

Trading participators suffer from information disadvantage in China's resale housing market, where brokers are able to distort supply–demand information and thus mislead their clients in price negotiation. In this paper, we propose an agent-based resale model to examine how brokers' distorted market information affects the market performances. Experimental results show that brokers are truly able to influence market trade count, resale price per size, and the benefits and costs of buyers and sellers. We find that no matter what the actual market condition is, assisting sellers is always the dominating policy for rational brokers. We also find that both buyers and sellers are likely to gain more surplus from transactions if they sign an "Exclusive Right To Buy/Sell" agreement with the broker, but the sellers are less bothered by the increased trade time. Coupled with these findings, managerial implications are discussed for China's resale housing market.

1. Introduction

The resale housing market is an important part of real estate industry, where brokers play a starring role in deals. Although the actions and liabilities of brokers vary across different countries, all the brokerage services can be broadly divided into two stages: matching stage and bargaining stage. In the first stage, the broker searches for potential buyers and sellers. Once a match is made, the broker usually assists her clients during negotiation. If the deal is achieved, the broker will be compensated by a commission, which is often a percentage of the sale price in most countries [1].

Understanding how brokerage participation affects the market performance is recognized as one of six critical topics in brokerage research [2]. Previous studies have primarily concentrated on the impact of brokerage on house prices in the matching stage. However, little attention has been paid to brokers' effects on bargaining process.

Arnold [3] indicates that, transaction prices are commonly established in three ways: posted (non-negotiable) prices, auctions and bargaining. It is bargaining that eventually determines the prices of most real estate deals. In a typical bilateral bargaining, the buyer's and the seller's reservation prices for a house are called willingness-to-pay (WTP) and willingness-to-accept (WTA), respectively. In other words, WTP is the maximum price that a buyer is willing to pay for the house; while the WTA is the minimum price that a seller is willing to sell. If WTP is less than WTA, the deal cannot be made. The transaction price is bounded by WTP and WTA and it could also be influenced by many factors including bidding and asking strategies, latest comparable deals, time on market (TOM), price changes, and perceived market conditions [4]. Among these factors, the most important one could be the market condition, which can be generally divided into three supply–demand situations according to the number of participators: buyer's market, seller's market and balanced market. The price determination model in economics concludes that if demand remains unchanged, increasing supply will result in a lower equilibrium price. This situation is defined as buyer's market. A buyer's resale market put the purchasers in a superior bargaining position since properties are in low demand. However, constrained by limited search time and effort, it is too costly for individual sellers and buyers to survey the whole resale market for obtaining accurate supply–demand information.

In reality, such important market condition information is often supplied by professional brokers, because they may have a sufficient amount of clients to gather supply–demand data. Therefore, it seems that brokers are able to exert impact on the bargaining decisions of buyers and sellers by taking advantage of the market information they delivered. However, intelligent buyers and sellers could doubt the truth of market situation, and thus attempt to

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https://doi.org/10.1016/j.jocs.2018.01.002
1877-7503/

update their beliefs about it if valuable evidences can be observed. Therefore, are the brokers truly able to shape the final resale price if they intentionally provide biased market situation information? If yes, to what extent do their information advantages affect the resale market? Besides, the commission rises along with the resale price, which is the driving force for brokers to help sellers in the bargaining stage. However, given different market situations, is assisting sellers always the dominating policy for rational brokers?

The above questions are paramount research topics in many markets confronted with serious information asymmetry, such as financial market, labour market and resale market. China's resale housing market is a typical one at an early stage of development, where brokers only act as deal-makers and earn a commission of 0.5–3% of the resale price when closing the deal [5,6]. In the literature of real estate brokerage, China's resale housing market is a special case called "one-agent" model, in contrast to the "two-agent" model in which the seller has a broker who works solely on his behalf, while the buyer has a different broker who works only for her [7]. Due to the absence of the real estate market information system (e.g., the multiple listing service in North America, called MLS for short), buyers and sellers tend to simultaneously ask multiple different brokers for their services and information in order to buy/sell homes more efficiently. Such behaviour, however, homogenizes the brokerage services and results in aggressive competition among brokers. To compete for same potential deals and to expedite the bargaining process, commission-hungry brokers could attempt to distort actual market condition information and thus mislead their clients, making themselves less trustful. Therefore, all the players in China's resale housing market suffer from information asymmetry. In view of this phenomenon, there is a compelling need to investigate the above questions.

In this paper we propose an agent-based[1] resale model (ARM) grounded in the complex adaptive system theory, which contains one abstract *market* agent and other three types of heterogeneous agents: *buyers*, *sellers* and *brokers*. Some buyers and sellers in the ARM are Bayesian learners, which means that they will form their bidding and asking prices according to not only the market condition information received from brokers, but also the observed changes of overall market indicators provided by the market. The agent-based modelling and simulation (ABMS) technique is selected due to its outstanding performance in modelling individual-level market interactions like price formations, and non-market feedbacks such as information transfer [4].

The remainder of the paper is organized as follows. In Section 2, we review existing research on the effect of brokerage on housing market, together with some agent-based models relevant to our work. Section 3 describes the overall structure of the ARM and agents' decision rules in detail. Our model is also introduced in a supplementary document using the ODD (Overview, Design concepts, and Details) protocol [9]. We design and conduct a series of experiments under two scenarios in Section 4. Section 5 presents the experimental results and a managerial discussion for China's resale housing market. In Section 6 we conclude the paper and suggest further research directions.

2. Literature review

Beginning in the early 1990s, academic research on the effect of brokerage on housing market has mushroomed. Several theoretical papers with simulation results have examined this research topic in a mathematical way. For example, Bagnoli and Khanna [10] explained that buyers can benefit from using a broker employed by the seller, because they reduced buyers' search costs. Yuvaş [11] investigated the players' search strategies and the equilibrium selling price by modelling the seller's and buyer's search behaviour. It was found that, employing a broker in the model increased the matching probability but caused a commission fee. Nevertheless, interactions among players in bargaining stage were missing. To compare different listing contracts and to understand their impacts, Rutherford et al. [12] stated a theoretical model and also provided evidences observed from the MLS transaction data. Although these early works have enriched our understanding of brokerage service in resale market, its impacts on market performances in bargaining stage are not well studied. A recent exception is the study by Li and Yuvas [13], where the decisions of buyers, sellers and brokers were discussed within a game-theoretic analysis. By solving the game for the equilibrium, they found the optimal size for an MLS and its impact on commission rate and total surplus. However, this theoretical paper also neglected the bargaining stage and the possible information-distorting behaviour of the brokers.

Empirical studies have also contributed a large volume of findings on this issue (see, e.g., [14,15]). Unfortunately, some of them are contradictory. For example, obtained from the historical data from National Association of Realtors, Elder et al. [16] identified that commissions had no independent effect on resale prices. In contrast, Zietz and Newsome [17] showed a positive association between them based on the Utah data. Besides, conclusions drawn from aggregated data mask the different impacts that brokers separately placed in the matching and bargaining stage. Therefore, influence originated from brokers' information advantages is indistinguishable. To the best of our knowledge, it remains a largely unexplored issue whether the broker can affect the market by distorting supply–demand information.

Motivated by the above observations, we set out to examine the aforementioned research questions using the ABMS approach. Agent-based socio-economic studies are mainly built on the complex adaptive system theory proposed by Holland [18], a subdomain of complex systems research. A complex adaptive system is a decentralized system where none of agents inside is able to control the whole system. Instead, agents have to adapt to and co-evolve with the dynamic system in which they exist, allowing us to observe and understand the systematic emergent phenomena. The ABMS technique has been widely used to simulate various systems such as supply networks, waste treatment systems, and transportation systems (see, e.g., [19–22]).

The application of ABMS in housing market research began with a well-known paper by Schelling [23], which studied how agents' individual preferences and simple relocation behaviours leaded to large-scale and complex housing patterns in cities. This successful attempt has triggered a considerable amount of agent-based research on real estate issues. There are several past studies relevant to our work. Amri and Bossomaier [24] adopted spatial attributes, environmental and human factors into fuzzy rules of buyers and sellers. Later in their successive work [25], brokers were considered to construct an estimate of house prices. Parker and Filatova reported a series of works on land price formation using ABMS [4,26], where agents' bidding/asking behaviours were explicitly modelled based on economic theory; the land price was calculated as the result of their interactions. Their influential models have been extended by many following studies (see, e.g., [27,28]). Ettema [29] provided another way to understand price formation by considering subjective probabilities. A Bayesian procedure was embedded in agents behaviours, allowing them to update their perceptions according to market information observed. Additional agent-based models can be found in [30–33], where price negotiation was simulated to produce bilateral trades. Although

[1] In dictionary, word *agent* is synonymous with word *broker* in the business context. To distinguish them, hereafter in this paper the term *agent* only denotes a computing entity with the following characteristics: autonomy, social ability, reactivity, and pro-activeness, as defined by Wooldridge and Jennings [8].

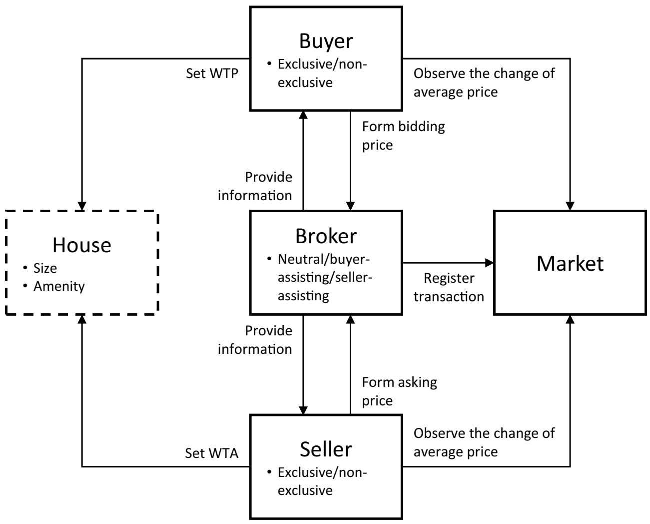

Fig. 1. The overall structure of the ARM, which is assumed to be a complex adaptive system consisting of four types of agents: *the market*, *buyers*, *sellers*, and *brokers*. When delivering the supply–demand information, a broker is either neutral, buyer-assisting, or seller-assisting. An exclusive buyer/seller selects only one broker through the entire trade process and she fully trusts the broker; while non-exclusive buyers/sellers simultaneously ask multiple different brokers for their services.

existing research modelled the agents' bargaining behaviours with many reasonable considerations like imperfect knowledge, learning mechanism and uncertainties, very few studies have examined the brokers' actions in bargaining stage and their impacts on the market performance.

Our model moves beyond previous works in several aspects. First, we propose an agent-based resale model (ARM) to examine how brokers' behaviours affect the market performances, such as price per size and time on market (TOM). Brokers in the ARM serve as deal-makers in searching stage and information providers in bargaining stage, mirroring their real actions in China's resale housing market. Second, buyers and sellers in the ARM not only are heterogeneous in many attributes, but also could be Bayesian learners. we also investigate their impacts on the simulation outcomes. Finally, we generate many competitive markets and conduct computational experiments to examine the performances of brokers who adopt different policies in bargaining stage.

3. Model description

3.1. Overall structure

In the ARM, there are four types of agents: buyers, sellers, brokers and one resale housing market. We explicitly model micro-level interactions among them and macro-level market feedbacks that agent received. The overall structure of the model is presented in Fig. 1.

Underlying the ARM are the following basic but essential assumptions:

1. Buyers and sellers cannot make a trade without a broker. In other words, they have to choose one or multiple broker(s) to buy and sell a house.
2. Both buyers and sellers can be classified into two groups: exclusive and non-exclusive. Exclusive buyers and sellers will select only one broker through the entire trade process and they fully trust the broker, which means they will sign an "Exclusive Right To Buy/Sell" agreement with the broker. In contrast, non-exclusive buyers and sellers simultaneously ask multiple different brokers for their services and information in an open-listing manner. Due to the possible conflicting market information offered by different brokers, non-exclusive agents will observe the changes of overall market indicators to form posterior information about the market situation. The updated belief affects their bargaining powers in negotiation.
3. Overall market indicators are public information, which can be observed by all agents.[2] Besides, actual characteristics of a seller's house are known by the buyers who have visited and viewed it.
4. Each broker gathers supply–demand information from her own clients at current time step. Note that the actual number of her clients is private information that cannot be obtained by others. Therefore, a broker only knows the number of buyers/sellers who have signed agreements with her.
5. In bargaining stage, a broker is able to deliver biased/unbiased market condition information to her clients. Neutral brokers inform their clients with unbiased information. On the contrary, a broker who attempts to help buyers/sellers will offer distorted information in order to swap the bargaining positions of buyers and sellers.

In the following we describe all components of the model in detail and explain the behaviours of each agent at a static time step t as a snapshot of the ARM.

3.2. Brokers' behaviours

Brokers in the ARM are responsible for the following tasks: match buyers and sellers, gather and deliver market condition information, and register successful trades.

3.2.1. Match buyers and sellers

Suppose that at time step t, a broker (e.g., R_k) is selected by $NB_{k,t}$ buyers and $NS_{k,t}$ sellers.[3] Since the sellers usually adopt the passive search pattern and wait for buyers' counteroffers [5], broker R_k in the matching stage only serves buyers. Zhang et al. [6,Section 2] have explicitly demonstrated how the buyers and brokers interact in matching stage in China's resale housing market. Here we copy the interactions to the ARM as follows.

At each time step, R_k will randomly recommend several available houses to each buyer (e.g., B_i) and lead buyers to view these houses in person.[4] Due to the visiting cost, the number of properties (denoted by $h_{k,t}$) that buyer B_i can view at one time step is bounded, i.e., $h_{k,t} = \gamma \cdot NS_{k,t} \in [\underline{h}, \bar{h}]$. Here $\gamma \in (0, 1)$ is a global constant.

At the end of this stage, all the buyers have obtained the full knowledge of the houses they have viewed. Therefore, they are able to calculate the utility for each dwelling based on their preferences, which will be discussed in buyers' behaviours.

[2] The National Bureau of Statistics of China publishes a price composite index of resale houses in 70 large- and medium-size cities monthly. For the buyers and sellers in these cities, it is available to obtain such market information.

[3] As a vital mechanism leading to competition among brokers, how to choose a broker is described later in buyers' and sellers' behaviours.

[4] The reader may argue that in practice, the broker usually recommends houses to buyers according to some factors, e.g., the buyers' preferences. Actually, we have tested some recommendation rules like preference-based and utility-based recommendation. The simulation results show that, although the values of some indicators (e.g., TOM) may be slightly different, all the valuable findings and conclusions presented later in this paper still hold. Therefore, this study mainly focuses on the bargaining stage instead of the matching stage, and here we simply introduce the random recommendation mechanism in the ARM.

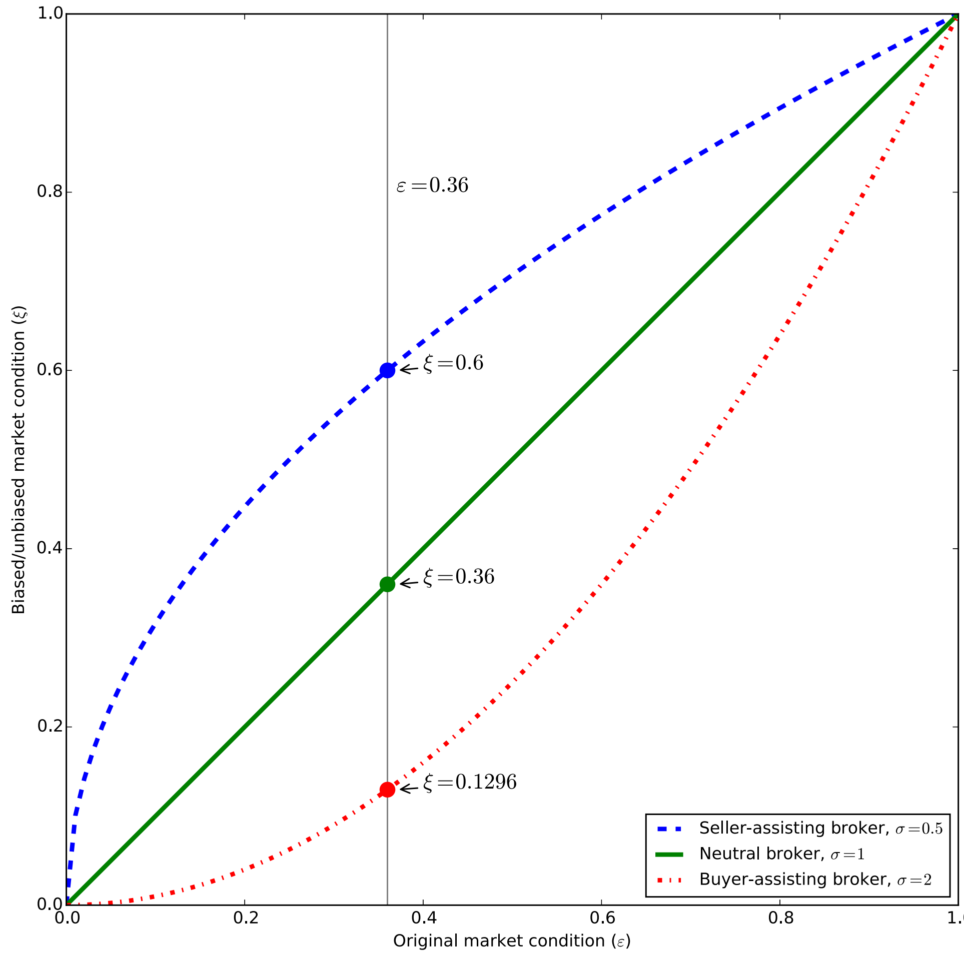

Fig. 2. Three types of brokers and their information-distorting behaviours. The neutral broker reports the true market condition 0.36; while the seller-assisting and buyer-assisting broker will distort the information and deliver 0.6 and 0.1296, respectively.

3.2.2. Process market information

This task is the most important part of brokers' behaviours in the ARM. After gathering buyers and sellers, broker R_k can compute the market tightness ratio $\varepsilon_{k,t}$ as follows:

$$\varepsilon_{k,t} = \frac{NB_{k,t}}{NB_{k,t} + NS_{k,t}}. \tag{1}$$

In previous works [26,5], $\varepsilon_{k,t}$ is formulated in similar forms. Variable $\varepsilon_{k,t}$ is commonly used to indicate the market condition. If the number of buyers $NB_{k,t}$ exceeds the number of sellers $NS_{k,t}$, we have $\varepsilon_{k,t} \in (0.5, 1]$, which means that it is a seller's market. Correspondingly, $\varepsilon_{k,t} \in [0, 0.5)$ implies a buyer's market. As mentioned in Section 1, indicator $\varepsilon_{k,t}$ is a piece of important information that can affect the pricing decisions of trading participants, thus it is known as "bargaining power" [27]. In the ARM, however, buyers and sellers cannot collect such information by themselves, allowing the broker R_k to distort original $\varepsilon_{k,t}$ and deliver biased supply and demand information (denoted by $\xi_{k,t}$) as follows:

$$\xi_{k,t} = \varepsilon_{k,t}^{\sigma_k}, \tag{2}$$

where σ_k is a non-negative constant in this power function. Fig. 2 shows three types of brokers and to what extend they can distort market condition information.

In the ARM, brokers with $\sigma = 1$ are called "honest brokers", since they deliver actual supply and demand information to buyers and sellers without distortion ($\xi_{k,t} = \varepsilon_{k,t}$). It is worth noting that in most cases, even "honest brokers" cannot provide accurate whole market situation information, because some participants, especially exclusive ones, may not choose these brokers for trade. Therefore, variable $\varepsilon_{k,t}$ can be viewed as an indicator which measures the likelihood of broker R_k's belief at time step t: *current market is a seller's market*.

The brokers whose $\sigma < 1$ are called "seller-assisting brokers", because they attempt to deliver "it is a seller's market" information to buyers and sellers even though $\varepsilon < 0.5$, which means current market is more likely to be a buyer's market. For the brokers, it is a nature choice that they help sellers by telling the buyer "it is a seller's market at present", because the commission rises along with the resale price. As illustrated in Fig. 2, when the actual market condition $\varepsilon_{k,t} = 0.36$, "seller-assisting brokers" with $\sigma = 0.5$ will report to both buyer and seller that, the market situation $\xi_{k,t}$ is 0.6, i.e., it is a seller's market. For sellers/buyers, this information will be treated as the priori probability of seller's market (see Eq. (6)) when forming their asking/bidding prices. By providing such distorted information, brokers anticipate a higher selling price in order to earn more commission after concluding this transaction. Therefore, as $\sigma \to 0$, the negotiating power of sellers will be much more exaggerated by the brokers.

Other brokers whose $\sigma > 1$ are called "buyer-assisting brokers", in contrast to the "seller-assisting brokers".[5] Given $\varepsilon_{k,t} = 0.36$ and

[5] The reader may argue that there could be some brokers who over-report the supply–demand information to sellers, and under-report it to buyers. In both the ARM and the China's resale housing market, however, a broker's buyers and sellers often need to repeatedly interact and provide new information such as their

$\sigma = 2$, these brokers will put the buyers in a superior bargaining position by claiming $\xi_{k,t} = 0.1296$. It seems that this type of brokers does not exist in China, where brokers working on behalf of buyers are missing. However, a broker is compensated by a commission only in the case of a successful transaction. When competing for the same on-going resale trade, the broker should expedite the bargaining process and then receive the commission before any other rivals did. If the seller believes that "demand exceeds supply" at present, she may expect a higher selling price and thus reject existing acceptable bids. Under such circumstances, helping buyers could be an alternative policy for brokers to lower the seller's asking price, shorten the negotiation process, and thus win the competition. Therefore, modelling "buyer-assisting brokers" is a meaningful investigation, which also complements this research.

3.2.3. Register successful trades

In the ARM, if both the buyer and the seller eventually decide to trade at a certain price, a transaction takes place. The broker, who brings together two parities and hosts the negotiation, will register this transaction to the market. The market agent will record trade data and remove trade participators from the ARM except the broker, as described later in the market agent's behaviours. At next time step, the seller, buyer and traded house will leave the market, and will not be counted by any brokers when computing the market condition ε.

3.3. Sellers' behaviours

Unlike brokers with few key attributes, sellers in the ARM have many features and thus their behaviours are more complicated. To sell the house, the seller chooses a broker, sets her WTA, forms the asking price and makes final decision on whether or not to accept a buyer's bid.

3.3.1. Choose a broker

All sellers and buyers share the same principle to choose a broker: a broker is more likely to be selected if she has achieved more transactions at previous time step. For brokers, increasing number of clients produces more accurate market condition information (i.e., ε) and, more importantly, higher probability that they can conclude more transactions at this time step. Therefore, this principle creates a positive feedback loop and thus results in the Matthew effect, i.e., the rich get richer [34]. Similar mechanism can be found in many heuristic and learning algorithms, such as genetic algorithm and reinforcement learning, revealing that it is a reasonable rule to identify good brokers.

As mentioned in Section 3.1, if exclusive sellers and buyers have selected a broker at the first time step, they will not choose another one through the entire trade process. In contrast, non-exclusive buyers and sellers pick one broker at each time step, no matter if this broker has been selected by the client before. Given the same amount of buyers/sellers, one would expect that increasing number of non-exclusive agents will enlarge nominal demand/supply, as they broadcast same demand/supply information to many brokers. We examine the impacts of trading participators' exclusive ratios on the performance of the ARM in computational experiments.

bidding/asking prices. It is very likely that they will share the market condition information obtained from the same broker. In that case, this trick will be easily discovered by clients, and the broker will be punished by the competitive market due to her bad reputation. Therefore, we suggest that this strategy is unsustainable and thus this type of broker is excluded in the ARM. However, such brokers may exist in some markets where buyers and sellers have no chance to communicate. Interested readers may consider modelling more types of brokers in their studies if necessary.

3.3.2. Set willingness-to-accept

In the ARM, each seller only owns one house for sale, which means the number of sellers is always equal to the number of available houses. Following previous models [29], house characteristics are public information for visitors. In the ARM, two independent features are considered: size and amenity. The latter one represents all intrinsic valuations of a dwelling except size. Suppose that there is a house owned by seller S_j, whose size is $z_j \in (0, 1)$ and amenity is $a_j \in (0, 1)$. The seller's WTA (willingness to accept) is defined as follows[6]:

$$\mathrm{WTA}_j = (1 + a_j) \cdot z_j \cdot \theta, \tag{3}$$

where θ is the base price per size (BPPS), a constant in the ARM. The BPPS in reality could be price per square foot (PSF) or price per square meter (PSM) according to different size units used. Here we assume that all sellers have same BPPS. Eq. (3) denotes that the bigger/better the house, the higher the seller's reservation price. Note that a seller's WTA remains unchanged over time.

3.3.3. Form asking price

When entering the bargaining stage, it is unlikely that the seller will immediately propose the WTA as her asking price. Instead, sellers will publish an asking price higher than WTA, and thus anticipate a positive surplus which depends on the bargaining power. In other words, if sellers are empowered to dominate the negotiation, they could gain much more surplus by increasing the asking price; and vice versa for buyers. Therefore, both buyers and sellers will dynamically adjust their bidding and counter-bidding based on their relative bargaining powers. For seller S_j, her asking price (denoted by $P_{j,t}$) at time step t will be calculated as follows:

$$P_{j,t} = \mathrm{WTA}_j \cdot (1 + g(\xi_{k,t}) \cdot f_j(\tau_{j,t})). \tag{4}$$

Eq. (4) indicates that seller's bargaining power in the ARM contains two components. The first one $g(\cdot)$ is the *perceived market condition* as in [4,26], which is viewed as an external factor in the ARM. For exclusive sellers who fully trust the broker, their external bargaining powers are consistent with original market information provided by the broker:

$$g(\xi_{k,t}) = \xi_{k,t}. \tag{5}$$

Eqs. (3) and (5) ensure that, the larger the probability of a seller's market, the higher the asking price based on the information offered by the broker. Therefore, the broker R_k is capable of influencing the seller S_j's asking price by distorting the market condition $\xi_{k,t}$ in the ARM.

However, due to the possible conflicting $\xi_{k,t}$ offered by different brokers, a non-exclusive agent will observe the changes of overall market indicators to form her posterior belief about the market situation. Following Ettema [29] and Pooyandeh and Marceau [35], we introduce the Bayesian updating procedure based on the Bayes Theorem. Fig. 3 demonstrates the cause and effect relationships in the ARM. Once seller S_j has received the priori information $\xi_{k,t}$ from the broker, she will observe the change of average price per size (i.e., $E \in \{E1, E2, E3\}$) and update her belief about the market condition (e.g., $P(C2|E)$ where $C2$ means the cause "it is a seller's market at present") as follows:

$$P(C2|E) = \frac{P(E|C2)P(C2)}{P(E|C2)P(C2) + P(E|C1)(1 - P(C2))}. \tag{6}$$

To apply the Bayesian updating procedure, both the prior probabilities and conditional likelihoods need to be determined. For the

[6] In Appendix A we justify our implement of WTA and WTP by comparing with other approaches in the literature. We thank an anonymous referee for this helpful suggestion.

- $P(E1|C1) = P(E2|C2) = 0.1$
- $P(E3|C1) = P(E3|C2) = 0.2$

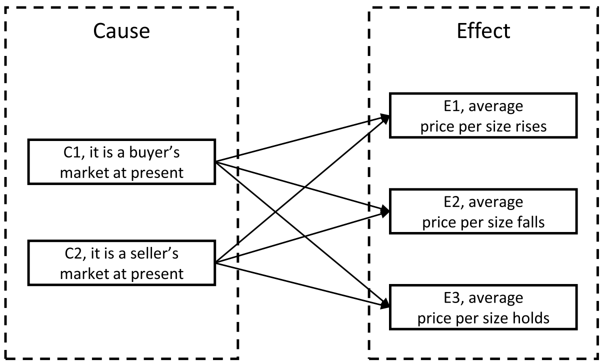

Fig. 3. The cause and effect relationships in the ARM. The two causes are probabilities that measure the agent's belief about the market condition. The three effects are observable events whereby non-exclusive buyers and sellers are able to update their beliefs. An arrow from a cause C to an effect E denotes the conditional probability of "effect E occurs" given that "the reason is cause C", i.e., $P(E|C)$. Although each cause may lead to all effects, the conditional probabilities are different.

prior probabilities $P(C1)$ and $P(C2)$, we use $1-\xi_{k,t}$ and $\xi_{k,t}$ as proxies, respectively. For example, the percentage of buyers in the market naturally measures the probability that "it is a seller's market at present". The likelihood values, shared by all trading participators, are predefined[7] as follows:

- $P(E2|C1) = P(E1|C2) = 0.7$
- $P(E1|C1) = P(E2|C2) = 0.1$
- $P(E3|C1) = P(E3|C2) = 0.2$

For example, broker R_k delivers distorted market condition $\xi_{k,t} = 0.6$ to seller S_j. However, the market publishes the evidence that the average price per size is decreasing (effect $E2$ occurs). According to Eq. (6), the posterior probability $P(C2|E2) = 0.06/(0.06+0.28) = 0.1765$, which means that it is probably a buyer's market. Therefore, for non-exclusive agents, their external bargaining powers can be formulated as follows:

$$g(\xi_{k,t}, E) = P(\xi_{k,t}|E). \tag{7}$$

The second part of Eq. (4) (i.e., $f(\cdot)$) is *urgency*, an internal factor of the bargaining power. Arnold [3] and Zhang et al. [28] suggested that, if the house cannot be traded at time step t, the buyer/seller will iteratively increase/decrease the bidding/asking price until the gap is eliminated. Quan and Quigley [36] defined this phenomenon as *urgency* and found that if buyers/sellers are urgent to buy/sell a property, the transaction price will be significantly affected, which means that the trading participators will consider their time-on-market (TOM) in price negotiation. Therefore, we assume that both sellers and buyers have their different maximum TOMs ($\bar{T}$). Given current TOM ($T_{j,t}$), seller S_j's *urgency* is expressed as follows:

$$f_j(\tau_{j,t}) = \frac{\ln(2-\tau_{j,t})}{\ln 2}, \tag{8}$$

where

$$\tau_{j,t} = \min\left\{\frac{T_{j,t}}{\bar{T}_j}, 1\right\}. \tag{9}$$

When seller S_j enters the market, $T_{j,t} = 0$, thus $f_j(0) = 1$ and $P_{j,t} = \mathrm{WTA}_j \cdot (1 + g(\xi_{k,t}))$, which means that S_j will not discount her asking price at the beginning of the negotiation. However, failed deals make her more cautious and thus her asking price is declining. When $T_{j,t}$ approaches or exceeds $\bar{T}$, $\tau_{j,t} \to 1$, thus $f_j(1) \to 0$ and $P_{j,t} \to \mathrm{WTA}_j$, which means that S_j's internal bargaining power is diminishing in price negotiation. Under such circumstances, seller S_j will also give up her external bargaining power and wish to sell her house as soon as possible. This is a reasonable behaviour which could partly explain why few transactions exist in a seller's market even though the housing price is increasing [37].

To sum up, sellers in the ARM possess two types of bargaining power. The external power is *perceived market condition* provided by the broker. Exclusive sellers form their asking prices based on this information without doubt. In contrast, non-exclusive sellers will update perceived market condition using a Bayesian procedure. The internal factor is *urgency*, which is diminishing as negotiation continues. When selling duration exceeds seller's maximum TOM, the seller has to give up all bargaining powers and possible surplus. Because both bargaining powers are non-negative, seller S_j' asking price is always greater than or equal to her reservation price, i.e., $P_{j,t} \geq \mathrm{WTA}_j$.

3.3.4. Make final decision

Suppose that broker R_k has collected several bids from buyers (denoted by set $\{P_{i,j,t}\}$), seller S_j will first update the highest bidding price she has received since joining the ARM, i.e., $\bar{P_{j,t}}$. The seller will accept a new peak price if the buyer is still tradable. If the buyer offering this new highest price has bought a dwelling from other sellers, the deal is unsuccessful. If current highest bidding price ($P^*_{j,t} = \max\{P_{i,j,t}\}$) is less than historical peak price $\bar{P_{j,t}}$, the seller could still accept with a probability, which is the ratio of these two prices (i.e., $P^*_{j,t}/\bar{P_{j,t}}$). Once both the buyer B_i and the seller S_j eventually decide to trade at this price, a transaction takes place. The seller will gain a surplus from the deal, i.e., $\pi_j = P^*_{j,t} - \mathrm{WTA}_j \geq 0$.

3.4. Buyers' behaviours

To buy a house, the buyer also needs to choose a broker, sets her WTP, forms the bidding price and waits for the sellers' final decisions or counter bids. When selecting a broker, the buyer's behaviours are exactly the same with seller's. Therefore, we skip repeating this process here.

3.4.1. Set willingness-to-pay

Once the buyer B_i has picked a broker (e.g., R_k), broker R_k will provide $h_{k,t}$ dwellings for buyer B_i, as mentioned in brokers' matching behaviours. For different houses, a buyer's willingness-to-pay (WTP) varies as follows:

$$\mathrm{WTP}_{i,j} = \min\{(1+a_j)\cdot z_j \cdot \beta, G_i\}, \tag{10}$$

where the constant β is the base price per size of all buyers and G_i is the buyer B_i's budget. Eq. (10) denotes that a buyer's WTP is based on not only house characteristics, but also her budget for purchasing a dwelling.

Due to the heterogeneity across buyers, we introduce a Cobb–Douglass utility function, following Filatova et al. [26], to measure buyer B_i's preference for a given house as follows:

$$U_{i,j} = z_j^{\lambda_i} \cdot a_j^{1-\lambda_i}, \tag{11}$$

[7] The values of these probabilities are chose based on the law of supply and demand in economics. For example, when the demand curve moves right (toward a seller's market), the price will increase. Therefore, we let $P(E2|C1)$ and $P(E1|C2)$ be large numbers. We have also tested other values and found that our findings are robust to small changes in these probabilities. We thank an anonymous referee for this helpful suggestion.

where λ_i is an exogenous constant to weight house characteristics for buyer B_i. Since both WTP and utility are computed according to house characteristics, they are highly and positively related, i.e., the higher the utility, the higher the WTP.

After visiting many dwellings, buyer B_i will record the utility for each house, and calculate a changing utility ratio (denoted by $\mu_{i,j,t}$) as follows:

$$\mu_{i,j,t} = \frac{U_{i,j}}{\max_t\{U_{i,j}\}}. \tag{12}$$

This utility ratio ($\mu_{i,j,t} \in (0, 1]$) is used in two ways. First, the buyer B_i generates a random number comparing with $\mu_{i,j,t}$, in order to stochastically filter some houses with low utilities. Second, buyer B_i will offer a higher bidding price for the house with larger $\mu_{i,j,t}$, as described later.

3.4.2. Form bidding price

For buyer B_i, her original bidding price ($P'_{i,j,t}$) for seller S_j's house at time step t will be computed as follows:

$$P'_{i,j,t} = \mathrm{WTP}_{i,j} \cdot g(\xi_{k,t})^{f_i(\tau_{i,t})}. \tag{13}$$

We have $P'_{i,j,t} \le \mathrm{WTP}_{i,j} \le G_i$ because both buyer's external and internal bargaining power are less than or equal to 1. Buyer's "urgency" is calculated as follows:

$$f_i(\tau_{i,t}) = 1 - \tau_{i,t}, \tag{14}$$

Eqs. (13) and (14) denote that at the beginning of bargaining, the buyer B_i tends to offer a bid with relatively low price, because $\tau_{i,t} = 0$, $f_i(0) = 1$ and $P'_{i,j,t} = WTP_{i,j} \cdot g(\xi_{k,t})$. As $\tau_{i,t} \to 1$, the internal bargaining power is decreasing since $f_i(0) \to 0$, thus $P'_{i,j,t} \to \mathrm{WTP}_{i,j}$, which means that the buyer is increasing her bidding price and losing her bargaining powers.

It is worth noting that $P'_{i,j,t}$ is not the actual bidding price proposed by buyer B_i at time step t, because the seller S_j's asking price $P_{j,t}$ is also considered. In the ARM, buyer B_i's final bidding price $P_{i,j,t}$ is defined as follows:

$$P_{i,j,t} = \begin{cases} P_{j,t} + \mu_{i,j,t} \cdot (P'_{i,j,t} - P_{j,t}), & \text{if } \ P'_{i,j,t} > P_{j,t}; \\ P'_{i,j,t}, & \text{otherwise}. \end{cases} \tag{15}$$

There are two cases when the buyer compares her own initial bidding price with the seller's asking price. The first case is that the initial bidding price is higher than the seller's asking price, which means that the house is preferred by the buyer because it can provide more utility than other dwellings. In this case, the buyer will increase her bidding price so that she can outcompete other buyers in the auction-like bargaining process [26]. The other case is that the initial bidding price is lower than the seller's asking price. Then the buyer will reduce the seller's asking price to her initial bidding price.

After proposing a bid via the broker, the buyer will wait for the seller's response. If the seller rejects the bid, the price negotiation continues unless the seller has traded with other buyers. If the seller S_j decides to accept the bid, the final resale price is $P^*_{j,t}$ as mentioned in sellers' last behaviour. The buyer B_i's surplus is denoted by $\pi_i = \mathrm{WTP}_i - P^*_{j,t} \ge 0$.

3.5. The market's behaviours

The market agent in the ARM has several responsibilities. First, the market will collect and record all the transaction data and release valuable information, such as each broker's trade count at last time step and the price fluctuation information, i.e., which effect listed in Fig. 3 occurs at the last time step. Second, if the model was initialized with predefined numbers of buyers and sellers and some of them decided to trade at last time step, the market will remove them and replenish the corresponding number of agents to the ARM at the beginning of new time step, in order to keep the overall supply–demand situation unchanged. The last task of the market agent is to check if the model meets the stop criteria. The ARM can run endlessly because of the agent-replenishing mechanism. Therefore, we terminate the simulation after 1000 time steps. This maximum time step is an arbitrary setting. However, we have tested many choices and found that obtained findings and conclusions still held.

Table 1
Values of exogenous parameters in the simulation experiments.

Parameter	Remark	Value
K	Number of brokers	25
γ	Proportion of viewable houses	0.2
$\underline{h}$	Minimum number of houses viewed	1
$\bar{h}$	Maximum number of houses viewed	5
a	Amenity of seller's house	$U(0, 1)$
z	Size of seller's house	$U(0, 1)$
θ	Sellers' base price per size	50
β	Buyers' base price per size	100
$\bar{T}$	Agents' maximum TOM	$U(100, 150)$
G	Buyers' budget	$U(150, 200)$
λ	Buyer's preference for house size	$U(0, 1)$
I	Number of buyers	$\{100, 300, 500, 700, 900\}$
J	Number of sellers	$1000 - I$
ω_b	Probability of creating an exclusive buyer	$\{0.0, 0.25, 0.5, 0.75, 1.0\}$
ω_s	Probability of creating an exclusive seller	$\{0.0, 0.25, 0.5, 0.75, 1.0\}$
σ	Constant to determine the type of broker when distorting information	$\{0.3333, 0.5, 1, 2, 3\}$

3.6. Summary

In this section we explicitly define each agent's attributes and behaviours interacting with the other agents mainly based on three types of theories and concepts. (1) The WTA, WTP and surplus are from the microeconomics theory. (2) The Bayesian decision-making process of buyers and sellers is a popular approach in the decision theory, which has been widely used to simulate negotiation process. (3) Other concepts like TOM are extensively examined in brokerage studies.

Before we start the simulation experiments, the agents' behaviours should be scheduled in a time step for implementation in the computer simulation programs. Fig. 4 summarizes the sequence of events in the ARM in the form of a unified modelling language behaviour diagram.

4. Numerical simulation

4.1. Experimental design

We conduct thousands of experiments using the ARM under two different scenarios, namely Scenario A and Scenario B. Table 1 presents all the exogenous parameters in the ARM, whose values remain unchanged in all the experiments. Due to the lack of space, we cannot examine the impact of all exogenous parameters; instead, to investigate the research questions of this paper, we focus on some important variables which are listed in the below part of Table 1. It can be found that three types of brokers, five supply–demand situations, and exclusive/non-exclusive buyers/sellers are considered in numerical experiments. To generalize the experimental results, some model parameters (e.g., house characteristics and individuals' preferences), which may vary across different markets, are normalized.

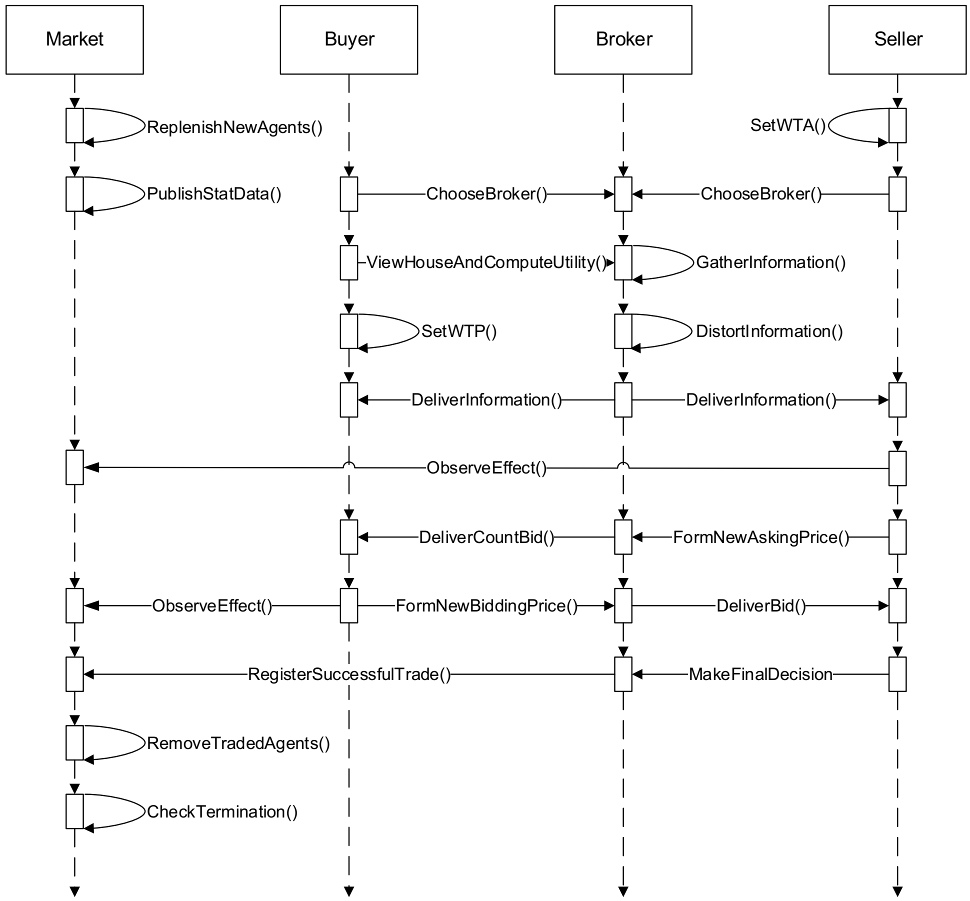

Fig. 4. The time sequence diagram of the ARM. The four big rectangles represent involved agents. The small rectangles below and horizontal solid lines demonstrate the events and interactions among agents, respectively.

Scenario A is designed to answer the first research question: are the brokers truly able to shape the final resale price if they intentionally provide biased market situation information? Under this scenario, all 25 brokers have the same σ which is selected from set $\{0.3333, 0.5, 1, 2, 3\}$. As mentioned in Section 3.3.2, if $\sigma < 1$, brokers will help sellers in bargaining stage. A smaller σ means that the brokers have distorted the original market condition information more heavily for sellers. As σ increases in excess of 1, the brokers will intensify their assistance to buyers in the ARM. Besides, the number of buyers determines the real supply–demand situation of the market, because the total number of buyers and sellers always equals 1000 at each time step in all simulation experiments. We are also interested in how buyers' and sellers' choices (i.e., being exclusive or not) affect the market.

Scenario B diversifies the broker types in terms of the way they distort information. Since there are 25 brokers in the ARM, we divide them into five groups and assign the five values of σ to these groups. We denote these groups as R^{s+}, R^s, R^-, R^b, R^{b+}, whose $\sigma = 0.3333, 0.5, 1, 2, 3$, respectively. Each group has five members, and they share the same σ that remains unchanged during simulation.[8] Due to the Matthew effect among the brokers, we can observe which group will eventually win the competition and thus answer the second question: is helping sellers always the dominating policy for brokers in any market?

4.2. Implementation and performance measures

The ARM is developed using the Repast Simphony, a commonly-used open-source platform for agent-based modelling and simulation. Each experiment is performed 30 times to ensure robust outputs against randomness in agents' initial attributes and behaviours. To comprehensively measure the market performance, we design the following indicators of all transactions during the 1000 time steps under Scenario A:

1. Average surplus of buyers and sellers: π_b, π_s.
2. Average current TOM ratio of buyers and sellers when closing deals: τ_b, τ_s.
3. Transaction count: C.
4. Average price per size: $\rho = \frac{\sum_{j \in \mathcal{S}} P_j^* z_j}{\sum_{j \in \mathcal{S}} z_j}$, where $\mathcal{S}$ denotes the set of all traded sellers.

The π_b (or π_s) is defined as the absolute value of the difference between resale price and WTP (or WTA). The τ_b and τ_s record the time consumed before reaching a successful trade, and thus reflect the market efficiency or liquidity [38]. The following two indicators,

[8] As mentioned before, the value of σ determines broker's distorting behaviour when providing market condition information. In this version of the ARM, σ is designed as an exogenous parameter that cannot be adaptively altered by the broker. Therefore, the reader may expect to examine the effect of changing σ, e.g., what is the best σ selected by most of intelligent brokers in different market situation. However, due to the lack of necessary theoretical foundations and empirical individual-level data, we cannot reasonably model the brokers' adaptive behaviours. In fact, Scenario B also creates a competitive market where competing brokers have different but fixed σ. We suggest that the experimental results are still able to discover which type of information-distorting behaviours is more promising for brokers.

C and ρ, are basic but important metrics because they can measure the activity and status of the resale market.

Under Scenario B, the following two groups of indicators are used to show the brokers' performances affected by their different information-distorting behaviours.

1. Transaction count of each broker group: C^{s+}, C^s, C^-, C^b, C^{b+}.
2. Total transaction price of each broker group: P^{s+}, P^s, P^-, P^b, P^{b+}.

5. Results and discussion

To provide a better readability, all the tables of simulation results are presented in Appendix B. The values in these tables are averaged across 30 samples, and the standard deviations are given in brackets.

5.1. Scenario A

Before analysing data, we first set up a benchmark experiment under Scenario A, which is configured as follows: $I = J = 500$, $\omega_b = \omega_s = 0.5$ and $\sigma = 1$. The following experimental results are comparable to that of the benchmark experiment, because only one or two variable(s) change(s) in each sensitivity analysis.

5.1.1. Impacts of brokers' information-distorting behaviours

We vary the buyer count I and brokers' σ from the benchmark case to examine how brokers' information-distorting behaviours affect the experimental results in different markets. Fig. 5 illustrates that the brokers are able to intentionally shape the market in the ARM. Take the surplus stacked chart, Fig. 5(a), for example, the seller's surplus expands dramatically as the buyer count increases, implying that the overall surplus of traders is fundamentally determined by the actual supply–demand situation. This observation is fully consistent with the common knowledge and the corresponding economic conclusion, revealing that the ARM is a suitable agent-based model for studying the resale housing market. An more important finding is that, the seller's surplus rises when the broker assists her more heavily in price negotiation. For instance, in Table B.2, given a buyer's market with 100 buyers and 900 sellers, the broker with $\sigma = 1/3$ can help seller to gain a surplus (13.06), almost six times greater than that obtained in the benchmark case (2.25). Also, a buyer-assisting broker can enlarge the buyer's surplus in a seller's market ($I = 900$) from 1.73 ($\sigma = 1$) to 5.63 ($\sigma = 3$). Therefore, the brokers are still able to make their efforts by providing biased information, even though about half of their clients do not firmly believe such information.

Similar effects can be also found when investigating the changes of other indicators. However, the broker's power varies under different market conditions. For example, in the buyer's market with $I = 100$, only a few transactions can be produced as shown in Fig. 5(d), leading to the high TOM ratios for trading partners, especially for the sellers (see Fig. 5(b) and (c)). Compared with the remarkable improvement of transaction count in other market, the seller-assisting brokers can only raise this number to a lesser extent. On the other hand, the buyer-assisting brokers can put the buyers in a superior bargaining position and help them to gain more surplus as displayed in Fig. 5(a). The side effect for these buyer-assisting brokers, however, embraces the less successful deals, lower average closing price and possible complaints from their clients because the TOM ratio is very high as demonstrated in Fig. 5(b). Therefore,

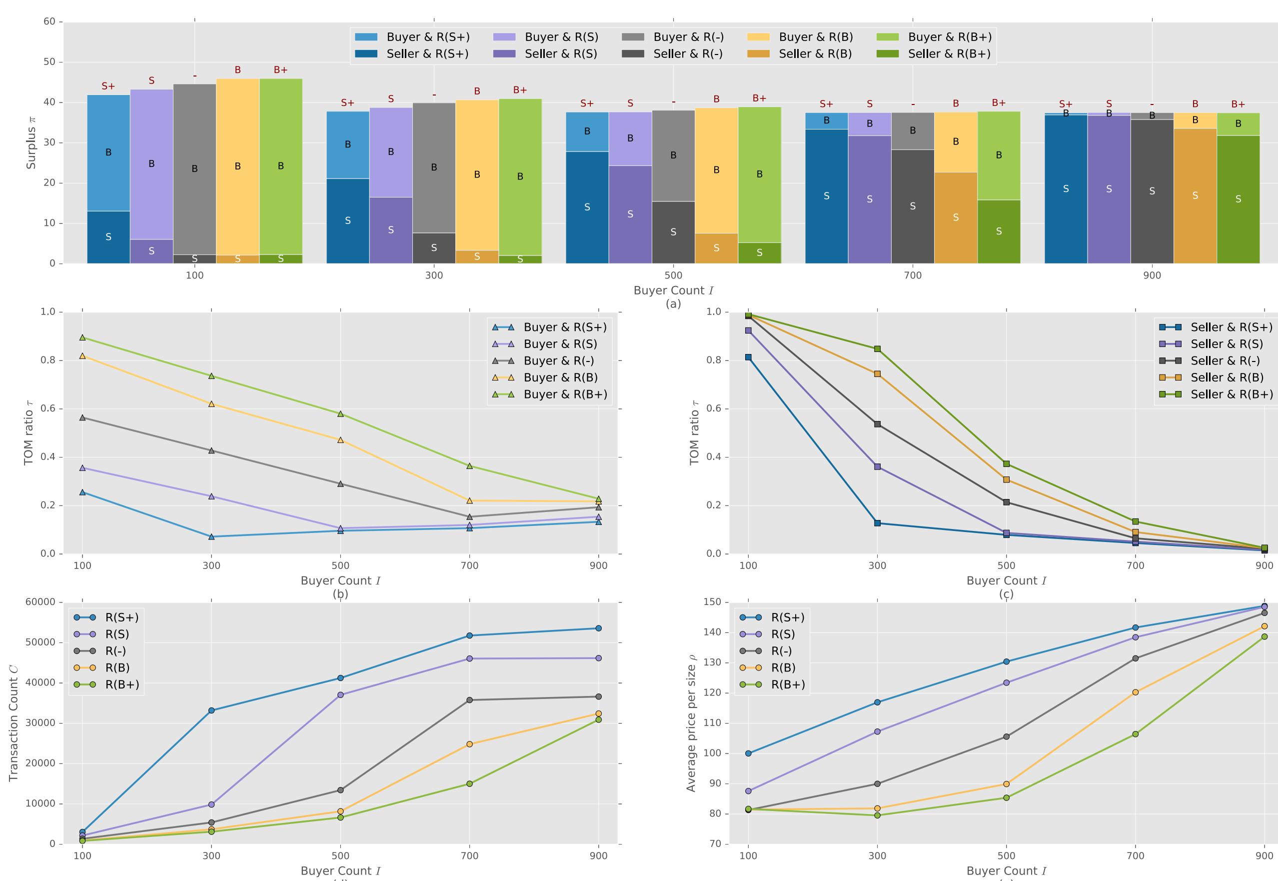

Fig. 5. Impacts of brokers' information-distorting behaviours. The sub-figure (a) is a stacked chart, each column of which is comprised of the average surpluses of sellers and buyers. The types of brokers' behaviours can be distinguished by different colours or the markers on the curves.

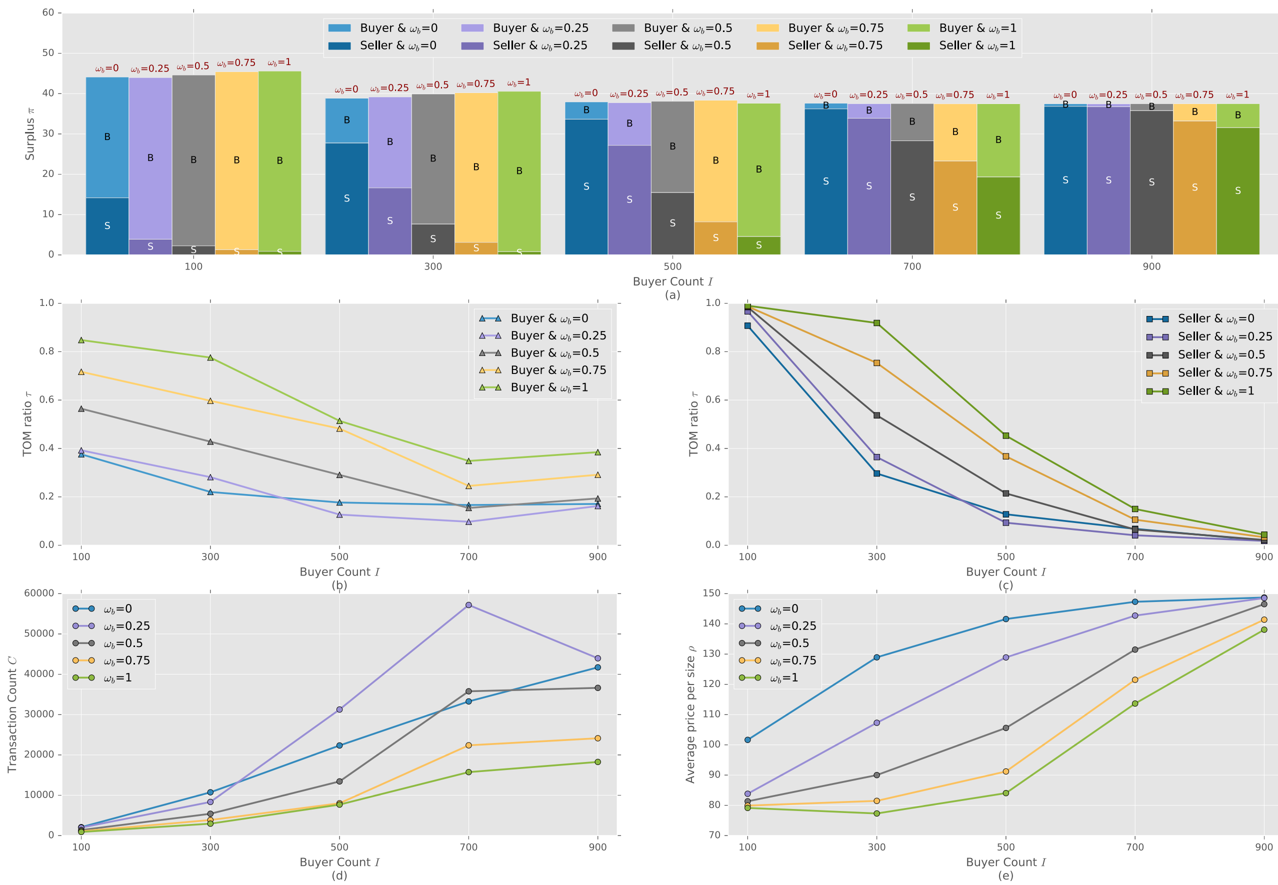

Fig. 6. Impacts of buyers' exclusive probability. The sub-figure (a) is a stacked chart, each column of which is comprised of the average surpluses of sellers and buyers. The types of buyers' exclusive probabilities can be distinguished by different colours or the markers on the curves.

the rational brokers are unlikely to help buyers in most cases under Scenario A.

Another interesting finding is that, the curves in Fig. 5(d) share the same trend with that in Fig. 5(e), which means there exists a positive correlation among the transactions count, average price per size and buyer count. In other words, when there are many buyers in the market, they have to compete for limited houses and thus offer more attractive bids to sellers. Consequently, more transactions are concluded with higher housing price in a faster way, revealing that it is a buoyant market. These rules also work in a reverse manner, leading to a recession in the resale housing market. Based on these practical observations, we suggest that the ARM provides a promising framework for policy-makers to understand the emergent phenomena of the resale housing market. More realistic models can be built upon the ARM for policy development.

5.1.2. *Impacts of agents' exclusive probability*

By altering the agents' exclusive probabilities ω_b and ω_s from the benchmark experiment, we explore how these factors affect the indicators. In other words, from the perspective of buyers or sellers, can they benefit more from being exclusive? Simulation outcomes are reported in Tables B.3 and Table B.4, based on the assumption that all brokers will not distort market situation information.

It can be observed from Fig. 6 that, if a buyer decides to be exclusive and relies on one broker to purchase a dwelling (i.e., with larger ω_b), she would expect a lower price (see Fig. 6(e)) and thus reap greater surplus from the resale deal (see Fig. 6(a)); because the existence of *silent* exclusive buyers essentially reduces the overall visible demand in the market. However, she also has to tolerate a long-time *see-saw battle* with sellers (see Fig. 6(b)) and a higher likelihood of failed transactions caused by her inactivity (see Fig. 6(d)). Therefore, the buyer faces a trade-off between surplus (trade benefit) and time (trade cost).

According to Fig. 7, we may provide different suggestions for sellers. Fig. 7(a) and (e) shows that both the seller's surplus π and average price per size ρ rise along with the sellers' exclusive probability ω_s. In other words, an exclusive seller can also gain more leftovers from price negotiation. However, the exclusive sellers suffer less from the side effects. Fig. 7(c) and (d) imply that in most markets, being exclusive will only cause a slight difference in the sellers' TOM and trade count. For these exclusive sellers, the transaction count is smaller in the seller's market (e.g., with $I = 900$) than that of non-exclusive peers. However, both two groups are still able to sell their houses rapidly with an equally high price. Therefore, it is a wise choice for the seller to be exclusive under this scenario. A possible reason for the different performance between buyers and sellers is that, it is the sellers who make the final decisions instead of the buyers. This rule allows the sellers to determine when to close the deal and thus it saves the trade costs like TOM of the sellers.

5.2. *Scenario B*

All the 25 brokers under Scenario A are identical; while under Scenario B, there are five different groups of brokers in the ARM, which are denoted by R^{s+}, R^s, R^-, R^b, R^{b+}, respectively. We aim to investigate which group will win the competition in different market. Fig. 8 and Table B.5 provide the performances of these groups. It can be observed that, the champion is R^{s+} and the second place is R^s, as their performances of transaction count and total price are much larger than other three groups. Therefore, we can draw the

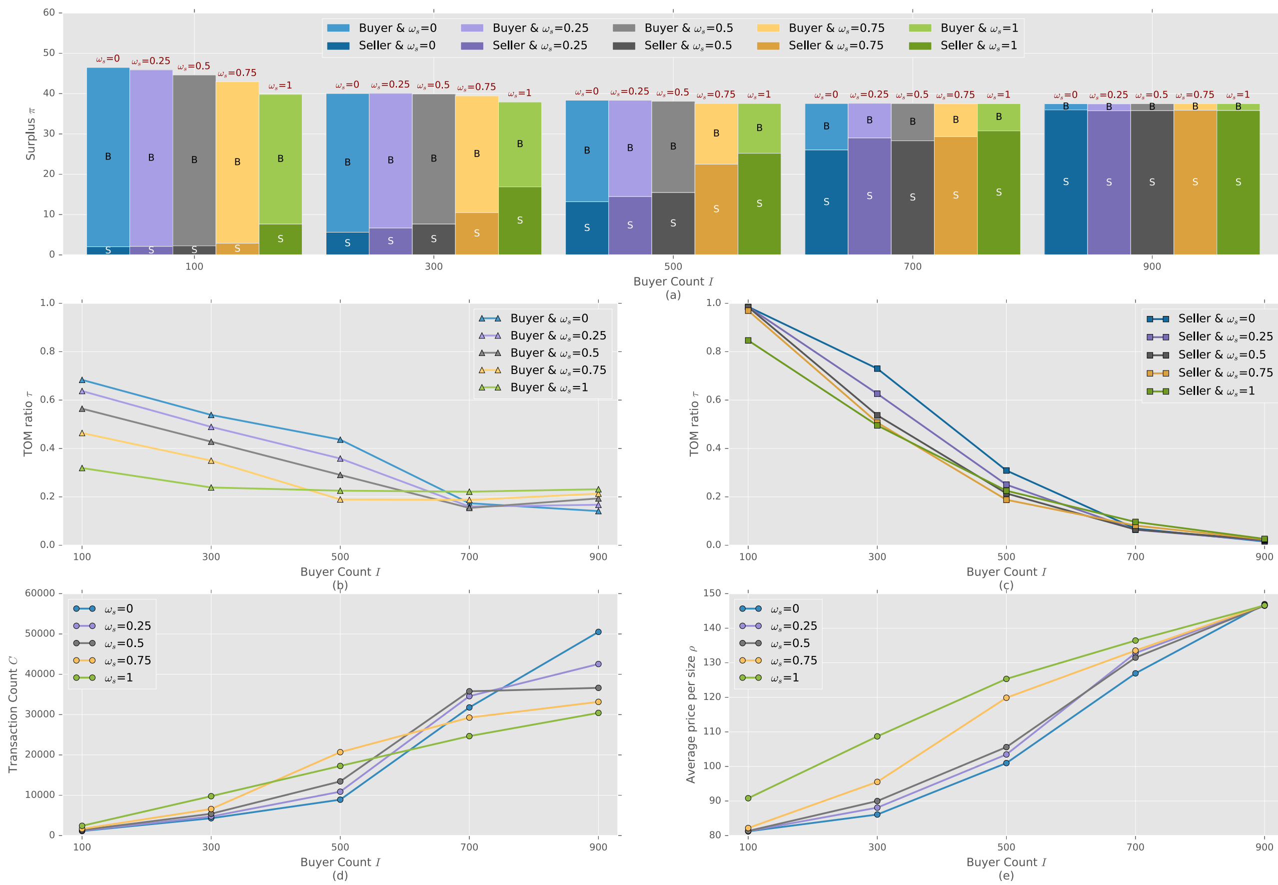

Fig. 7. Impacts of sellers' exclusive probability. The sub-figure (a) is a stacked chart, each column of which is comprised of the average surpluses of sellers and buyers. The types of sellers' exclusive probabilities can be distinguished by different colours or the markers on the curves.

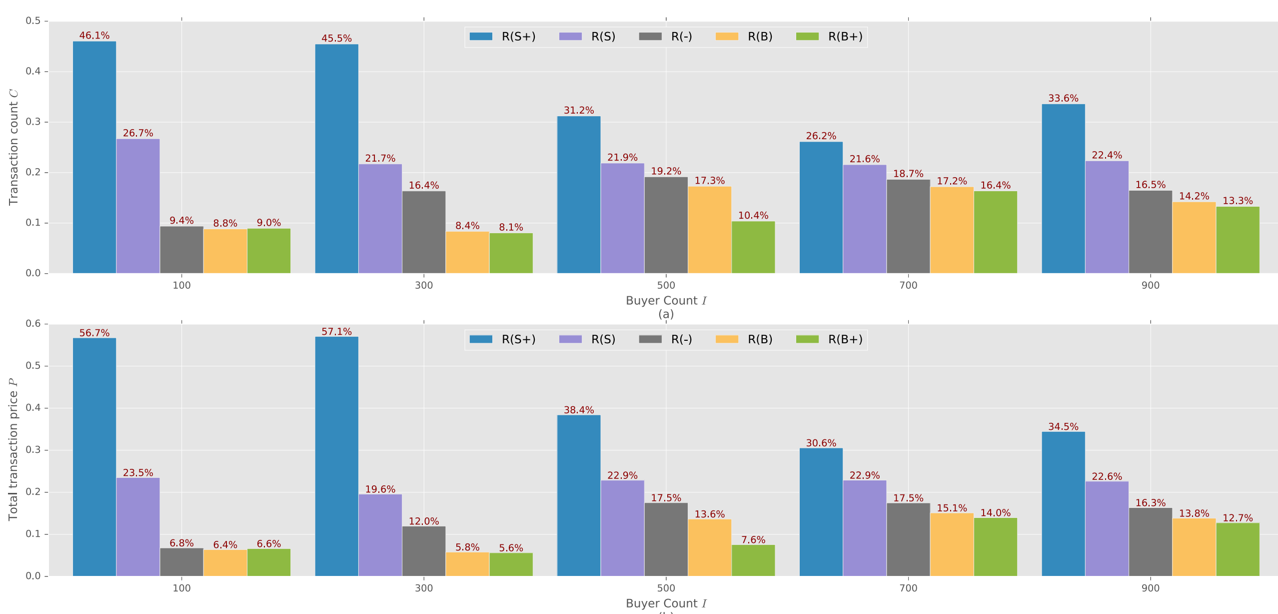

Fig. 8. Performances of competing brokers with different information-distorting behaviours.

conclusion that the dominating policy for rational brokers in the ARM is to assist sellers in any situation. The main reason can be found in Fig. 5. The seller-assisting brokers outperform other types of brokers in terms of transaction count and average resale price (see Fig. 5(d) and (e)). Therefore, more commission can be earned by the seller-assisting brokers in a buoyant market. Another reason is that, the seller-assisting brokers and the sellers share similar interests such as higher surplus and lower TOM of the sellers (see Fig. 5(a) and (c)). Motived by the interests and expectations of the sellers, the brokers will always choose to assist the sellers.

5.3. Managerial discussions

In this section, we have obtained the following findings:

1. The brokers are truly able to influence the trading participators' benefits and costs, as well as the market performances such as transaction count and average price per size. Therefore, the brokers have a strong incentive to raise the resale housing price and thus to earn higher commissions.
2. The impacts of the brokers' behaviours vary across different market situations. However, no matter what the market condition is, assisting sellers is always the dominating policy for the rational brokers.
3. For the buyer and seller, being a Bayesian learner is not very helpful; instead, being exclusive and relying on the broker can actually reduce the overall demand or supply, and thus gain more surplus from transactions.
4. Unlike the buyers who have to balance trade benefit and time cost, the sellers are less bothered by the side effects. Therefore, it is a wise choice for the sellers to be exclusive except in a seller's market.
5. A positive feedback loop among transactions count, average price per size and buyer count is discovered, revealing that the ARM has a good potential to simulate the changes in policies and to evaluate their effectiveness.

Empowered by the last conclusion, we attempt to shed some lights on China's resale housing market by coupling these experimental findings with managerial implications for the practitioners and policy-makers. The first two findings disclose the reason that China's extensive brokerage industry requires regulation. As mentioned in Section 1, all players in China's resale market have to pay extra cost due to the existence of *crisis of confidence* between brokers and their clients. To avoid such a prisoners' dilemma, the government or trade association should ameliorate the information disadvantages of buyers and sellers. One of possible solutions is to construct a MLS-like platform providing accurate and timely listing information for the public, which can significantly reduce the searching costs of buyers and sellers. Actually, the supply information provided by the MLS is also very valuable and helpful in price negotiation. For the buyers who are relatively powerless according to the third finding above, they could be more confident about their bargaining powers after accessing the properties pool. Meanwhile, by observing competitors' responses, the sellers could also adjust their listing prices in a more reasonable way, and thus reduce their trading time.

A key condition to build a successful MLS is that, a seller is willing to sign an "Exclusive Right To Sell" agreement with the broker. By agreement, the seller cannot list the dwelling with any other broker, which ensures that the commission is owed to the broker. In this case, the seller's broker would list the property in the MLS and co-operate with other brokers. However, the fourth finding above implies that in a seller's market, the seller prefers to sign an "Open Agency" contract which allows many brokers to list the house. Unfortunately, some of China's resale housing markets are typical seller's markets due to the huge and continuing demand caused by China's massive urbanization. Under such circumstances, a MLS can hardly be created in a spontaneous manner at present. Therefore, we suggest that external influences are the prerequisites for constructing MLS, including the government planning, public concerns and promotion from the trade association.

6. Conclusions

Many markets confront with serious information asymmetry, such as financial market, labour market and resale market. China's resale housing market is a typical one at an early stage of development, where the brokers are able to distort supply–demand information and mislead their clients in price negotiation due to the absence of the public real estate market information system. However, intelligent buyers and sellers could doubt the truth of market situation, and thus attempt to update their beliefs about it if valuable evidences can be observed. Therefore, we propose the following research questions: are the brokers truly able to shape the final resale price if they intentionally provide biased market situation information? If yes, to what extent do their information advantages affect the resale market? Besides, the commission rises along with the resale price, which is the driving force for brokers to help sellers in the bargaining stage. However, given different market situations, is assisting sellers always the dominating policy for rational brokers?

In this paper we propose an agent-based resale model (ARM) grounded in the complex adaptive system theory, which contains one abstract *market* agent and other three types of heterogeneous agents: *buyers*, *sellers* and *brokers*. Some buyers and sellers in the ARM are Bayesian learners, which means that they will form their bidding and asking prices according to not only the market condition information received from brokers, but also the observed changes of overall market indicators provided by the market. We conducted thousands of experiments using the ARM under two different scenarios to examine how brokers' distorted market information affects the market performances. Experimental results show that the brokers are truly able to influence market trade count, resale price per size, as well as the benefits and costs of buyers and sellers. We find that no matter what the actual market condition is, assisting sellers is always the dominating policy for rational brokers. We also find that if signing an "Exclusive Right To Buy/Sell" agreement with the broker, both buyers and sellers can gain more surplus from transactions, but the sellers are less bothered by the increased trade time compared with the exclusive buyers. Coupled with these findings, managerial implications are discussed for China's resale housing market.

We suggest several future directions for this work. First, new elements, such as spatial factors, can be taken into account to make the ARM more realistic. Second, the agent's behaviours can be improved. For example, the brokers' behaviours are relatively simple and inflexible in the ARM. They can be modelled as autonomous agents which may compete for clients, provide different information for different types of clients, or even attempt to maximize/minimize some objectives under some constraints. This requires us to understand more about the operations of a brokerage company/individual. Finally, we plan to conduct behavioural experiments and collect individual-level data of participators, which can be used to calibrate the parameters of the ARM.

Acknowledgements

We thank the anonymous referees for their helpful comments on earlier versions of our paper. This work is supported by grants from the Key Program of National Natural Science Foundation of China (NSFC No. 71433001, 71532013), the National Natural Science Foundation of China (NSFC No. 71573244, 71202115 and 71403260), the Youth Innovation Promotion Association of CAS, the National Program for Support of Top-Notch Young Professionals, the Fundamental Research Funds for the Central Universities and Beijing Advanced Innovation Center for Soft Matter Science and Engineering.

Appendix A. The implement of WTA and WTP

In the literature, the papers most similar to our study are Parker and Filatova [4], Filatova et al. [26] and Zhang et al. [28]. These papers only focus on the interactions between buyers and sellers, without considering brokers. The WTA is implemented in many ways, e.g., modeling as a constant, the trading price of last transaction, or the seller's WTP for another house. For our study, however, we cannot follow these approaches because: (i) the WTA should not be a constant; instead, it should be positively related to house characteristics; (ii) it is not reasonable to assume that the sellers can track the trading price of last transaction in China where the MLS is missing; (iii) the sellers in our study will not buy new houses after selling, and thus they have no WTPs for another houses.

For the WTP, the most popular approach is the function used in [26], which can be expressed as follows:

$$\mathrm{WTP} = \frac{Y \times U^2}{b^2 + U^2},$$

where Y is the buyer's budget, U is the utility computed using house characteristics, and b is "a proxy for the prices of other goods" [4]. However, the main disadvantage of this approach is that we cannot choose the value of b reasonably. For example, $b = 70$ in [26] while $b = 5$ in [28] without describing how it was calculated.

In view of these disadvantages, we have designed a new approach for implementing both WTA and WTP, i.e., by introducing the concept of base price per size (BPPS). It is reasonable to assume that the seller's BPPS is lower than that of the buyer, otherwise no deals would be made. As described by Eqs. (3) and (10), both the WTA and WTP are computed based on full-size price (i.e., BPPS * size). Meanwhile, the house's amenity serves as a multiplicator of full-size price. We suggest that our implement of WTA and WTP is consistent with what people usually do in practice. The disadvantage of our implement, however, is the assumption that the BPPS is identical among all buyers/sellers. Other researchers may vary BPPS if more empirical evidence are available.

Appendix B. Tables

Experimental results are reported in Table B.2, Table B.3, Table B.4 and Table B.5.

Table B.2
Impacts of brokers' information-distorting behaviours.

Buyer count I	Distort weight σ	π_b	π_s	τ_b	τ_s	C	ρ
100	0.3333	28.88(0.48)	13.06(0.44)	0.26(0.01)	0.81(0.01)	3048.07(70.57)	100.05(0.79)
	0.5	37.26(0.61)	6.04(0.39)	0.36(0.01)	0.92(0.01)	2162.43(40.55)	87.60(0.69)
	1	42.37(0.49)	2.25(0.19)	0.56(0.01)	0.98(0.00)	1363.53(18.01)	81.33(0.63)
	2	43.81(0.76)	2.15(0.12)	0.82(0.00)	0.99(0.00)	927.83(8.20)	81.47(0.69)
	3	43.70(0.56)	2.28(0.12)	0.90(0.00)	0.99(0.00)	845.00(4.77)	81.69(0.60)
300	0.3333	16.68(0.23)	21.13(0.23)	0.07(0.00)	0.13(0.00)	33195.43(945.47)	116.96(0.45)
	0.5	22.26(0.33)	16.50(0.27)	0.24(0.01)	0.36(0.01)	9852.23(278.57)	107.27(0.56)
	1	32.27(0.33)	7.64(0.27)	0.43(0.00)	0.54(0.01)	5410.37(55.37)	90.00(0.56)
	2	37.35(0.33)	3.32(0.13)	0.62(0.01)	0.74(0.01)	3707.77(38.84)	81.87(0.33)
	3	38.94(0.40)	2.04(0.11)	0.74(0.00)	0.85(0.01)	3112.60(25.93)	79.55(0.34)
500	0.3333	9.82(0.26)	27.84(0.28)	0.10(0.00)	0.08(0.00)	41247.27(653.43)	130.42(0.55)
	0.5	13.34(0.25)	24.34(0.26)	0.11(0.00)	0.09(0.00)	37060.20(843.05)	123.44(0.53)
	1	22.63(0.42)	15.46(0.30)	0.29(0.01)	0.21(0.01)	13431.67(414.62)	105.59(0.62)
	2	31.15(0.38)	7.57(0.39)	0.47(0.01)	0.31(0.01)	8180.67(136.96)	89.93(0.76)
	3	33.70(0.28)	5.24(0.23)	0.58(0.01)	0.37(0.01)	6634.43(77.68)	85.38(0.54)
700	0.3333	4.14(0.07)	33.37(0.10)	0.11(0.00)	0.05(0.00)	51773.30(768.32)	141.69(0.23)
	0.5	5.76(0.12)	31.76(0.16)	0.12(0.00)	0.05(0.00)	46067.43(971.93)	138.47(0.28)
	1	9.24(0.21)	28.30(0.23)	0.15(0.00)	0.06(0.00)	35781.07(734.48)	131.50(0.46)
	2	14.92(0.45)	22.71(0.49)	0.22(0.01)	0.09(0.00)	24827.10(928.72)	120.28(0.93)
	3	21.98(1.26)	15.83(1.15)	0.36(0.02)	0.13(0.00)	15008.37(690.55)	106.44(2.32)
900	0.3333	0.55(0.01)	36.93(0.10)	0.13(0.00)	0.01(0.00)	53585.77(249.95)	148.85(0.15)
	0.5	0.73(0.02)	36.81(0.10)	0.15(0.00)	0.02(0.00)	46176.57(345.97)	148.53(0.16)
	1	1.73(0.10)	35.77(0.18)	0.19(0.00)	0.02(0.00)	36628.50(263.76)	146.52(0.29)
	2	3.93(0.21)	33.58(0.25)	0.22(0.00)	0.02(0.00)	32424.47(367.20)	142.13(0.46)
	3	5.63(0.25)	31.82(0.28)	0.23(0.00)	0.03(0.00)	30905.77(507.80)	138.68(0.61)

Table B.3
Impacts of buyers' exclusive probability.

Buyer count I	Exclusive ratio ω_b	π_b	π_s	τ_b	τ_s	C	ρ
100	0	29.96(0.56)	14.16(0.51)	0.38(0.01)	0.91(0.01)	2082.20(49.09)	101.65(0.96)
	0.25	40.10(0.50)	3.89(0.29)	0.39(0.01)	0.97(0.00)	1979.13(33.39)	83.82(0.68)
	0.5	42.37(0.49)	2.25(0.19)	0.56(0.01)	0.98(0.00)	1363.53(18.01)	81.33(0.63)
	0.75	44.14(0.75)	1.29(0.13)	0.72(0.01)	0.99(0.00)	1066.40(12.27)	79.91(0.62)
	1	44.71(0.73)	0.88(0.02)	0.85(0.00)	0.99(0.00)	896.60(4.17)	79.14(0.55)
300	0	11.11(0.14)	27.75(0.21)	0.22(0.00)	0.30(0.01)	10731.63(168.68)	128.94(0.33)
	0.25	22.56(0.36)	16.62(0.37)	0.28(0.00)	0.36(0.01)	8336.70(103.82)	107.30(0.78)
	0.5	32.27(0.33)	7.64(0.27)	0.43(0.00)	0.54(0.01)	5410.37(55.37)	90.00(0.56)
	0.75	37.11(0.35)	3.11(0.10)	0.60(0.00)	0.75(0.01)	3857.60(34.68)	81.47(0.30)
	1	39.76(0.47)	0.81(0.02)	0.78(0.00)	0.92(0.01)	2955.43(8.91)	77.31(0.28)
500	0	4.30(0.12)	33.65(0.21)	0.18(0.00)	0.13(0.00)	22343.63(226.78)	141.60(0.30)
	0.25	10.59(0.21)	27.17(0.23)	0.13(0.00)	0.09(0.00)	31261.30(526.10)	128.91(0.46)
	0.5	22.63(0.42)	15.46(0.30)	0.29(0.01)	0.21(0.01)	13431.67(414.62)	105.59(0.62)
	0.75	30.17(0.44)	8.19(0.42)	0.48(0.01)	0.37(0.01)	8009.73(190.55)	91.20(0.84)
	1	33.06(1.15)	4.55(1.00)	0.51(0.05)	0.45(0.03)	7678.63(740.95)	84.04(2.00)
700	0	1.41(0.04)	36.22(0.16)	0.17(0.00)	0.07(0.00)	33268.70(409.65)	147.30(0.19)
	0.25	3.63(0.05)	33.88(0.11)	0.10(0.00)	0.04(0.00)	57183.60(1478.84)	142.73(0.19)
	0.5	9.24(0.21)	28.30(0.23)	0.15(0.00)	0.06(0.00)	35781.07(734.48)	131.50(0.46)
	0.75	14.19(0.19)	23.28(0.21)	0.25(0.00)	0.11(0.00)	22384.27(396.58)	121.52(0.42)
	1	18.16(0.26)	19.33(0.22)	0.35(0.00)	0.15(0.00)	15738.00(204.68)	113.66(0.48)

Table B.3 (*Continued*)

Buyer count I	Exclusive ratio ω_b	π_b	π_s	τ_b	τ_s	C	ρ
900	0	0.66(0.01)	36.83(0.13)	0.17(0.00)	0.02(0.00)	41717.97(179.36)	148.71(0.15)
	0.25	0.72(0.01)	36.75(0.09)	0.16(0.00)	0.02(0.00)	43965.80(327.71)	148.54(0.16)
	0.5	1.73(0.10)	35.77(0.18)	0.19(0.00)	0.02(0.00)	36628.50(263.76)	146.52(0.29)
	0.75	4.29(0.06)	33.20(0.13)	0.29(0.00)	0.03(0.00)	24134.30(196.71)	141.39(0.19)
	1	5.95(0.05)	31.56(0.14)	0.38(0.00)	0.04(0.00)	18261.37(85.46)	138.08(0.27)

Table B.4
Impacts of sellers' exclusive probability.

Buyer count I	Exclusive ratio ω_s	π_b	π_s	τ_b	τ_s	C	ρ
100	0	44.46(0.62)	2.03(0.19)	0.68(0.01)	0.99(0.00)	1120.33(15.20)	81.22(0.56)
	0.25	43.77(0.63)	2.11(0.17)	0.64(0.01)	0.99(0.00)	1206.50(17.34)	81.29(0.55)
	0.5	42.37(0.49)	2.25(0.19)	0.56(0.01)	0.98(0.00)	1363.53(18.01)	81.33(0.63)
	0.75	40.04(0.47)	2.89(0.22)	0.46(0.01)	0.97(0.00)	1661.43(26.99)	82.18(0.62)
	1	32.15(0.82)	7.65(0.63)	0.32(0.01)	0.85(0.02)	2420.37(68.22)	90.81(1.29)
300	0	34.40(0.38)	5.62(0.17)	0.54(0.00)	0.73(0.01)	4294.90(33.54)	86.09(0.45)
	0.25	33.40(0.35)	6.66(0.24)	0.49(0.00)	0.63(0.01)	4733.27(46.93)	88.08(0.54)
	0.5	32.27(0.33)	7.64(0.27)	0.43(0.00)	0.54(0.01)	5410.37(55.37)	90.00(0.56)
	0.75	28.95(0.68)	10.48(0.63)	0.35(0.01)	0.51(0.01)	6591.77(111.52)	95.53(1.23)
	1	21.03(0.31)	16.88(0.27)	0.24(0.00)	0.50(0.01)	9769.57(94.66)	108.70(0.52)
500	0	25.16(0.26)	13.19(0.32)	0.44(0.00)	0.31(0.00)	8903.67(77.89)	100.97(0.65)
	0.25	23.88(0.30)	14.46(0.26)	0.36(0.00)	0.25(0.00)	10883.20(123.58)	103.46(0.48)
	0.5	22.63(0.42)	15.46(0.30)	0.29(0.01)	0.21(0.01)	13431.67(414.62)	105.59(0.62)
	0.75	15.09(0.15)	22.49(0.13)	0.19(0.00)	0.19(0.00)	20687.07(289.53)	119.88(0.23)
	1	12.36(0.08)	25.19(0.12)	0.23(0.00)	0.23(0.00)	17269.97(121.87)	125.33(0.23)
700	0	11.51(0.15)	26.03(0.15)	0.17(0.00)	0.07(0.00)	31773.20(728.86)	126.94(0.29)
	0.25	8.58(0.25)	29.00(0.27)	0.16(0.01)	0.06(0.00)	34571.30(1366.59)	132.82(0.57)
	0.5	9.24(0.21)	28.30(0.23)	0.15(0.00)	0.06(0.00)	35781.07(734.48)	131.50(0.46)
	0.75	8.16(0.08)	29.31(0.14)	0.19(0.00)	0.08(0.00)	29260.27(253.29)	133.52(0.23)
	1	6.74(0.09)	30.76(0.12)	0.22(0.00)	0.10(0.00)	24663.17(133.70)	136.43(0.23)
900	0	1.51(0.05)	35.97(0.10)	0.14(0.00)	0.02(0.00)	50511.10(835.90)	146.95(0.17)
	0.25	1.72(0.08)	35.74(0.14)	0.17(0.00)	0.02(0.00)	42540.83(668.58)	146.53(0.22)
	0.5	1.73(0.10)	35.77(0.18)	0.19(0.00)	0.02(0.00)	36628.50(263.76)	146.52(0.29)
	0.75	1.63(0.12)	35.87(0.13)	0.21(0.00)	0.02(0.00)	33160.43(412.78)	146.72(0.30)
	1	1.70(0.10)	35.81(0.14)	0.23(0.00)	0.03(0.00)	30421.60(296.65)	146.59(0.30)

Table B.5
Performances of different broker groups.

Buyer count I	Distort weight σ	C	P
100	0.3333	0.46(0.02)	0.57(0.02)
	0.5	0.27(0.02)	0.24(0.02)
	1	0.09(0.01)	0.07(0.01)
	2	0.09(0.01)	0.06(0.01)
	3	0.09(0.01)	0.07(0.00)
300	0.3333	0.45(0.01)	0.57(0.01)
	0.5	0.22(0.01)	0.20(0.01)
	1	0.16(0.01)	0.12(0.01)
	2	0.08(0.00)	0.06(0.00)
	3	0.08(0.00)	0.06(0.00)
500	0.3333	0.31(0.01)	0.38(0.01)
	0.5	0.22(0.00)	0.23(0.00)
	1	0.19(0.00)	0.18(0.01)
	2	0.17(0.01)	0.14(0.01)
	3	0.10(0.01)	0.08(0.00)
700	0.3333	0.26(0.00)	0.31(0.00)
	0.5	0.22(0.00)	0.23(0.00)
	1	0.19(0.00)	0.17(0.00)
	2	0.17(0.00)	0.15(0.00)
	3	0.16(0.00)	0.14(0.00)
900	0.3333	0.34(0.02)	0.34(0.02)
	0.5	0.22(0.00)	0.23(0.00)
	1	0.16(0.01)	0.16(0.01)
	2	0.14(0.01)	0.14(0.01)
	3	0.13(0.00)	0.13(0.00)

Appendix C. Supplementary data

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.jocs.2018.01.002.

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