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An agent-based modeling for housing prices with bounded rationality

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Abstract. This study proposes an agent-based model to investigate major stakeholders' behaviors in the housing market. The proposed model mimics the heterogeneous behaviors of individual buyers and sellers in a housing market considering bounded rationality. The simulation results of case study in Shanghai are robust and reproduce stylized facts including as volatility clustering, absence of autocorrelations, heavy tail, loss asymmetry, and aggregational gaussianity on the absolute return.

1. Introduction

Research into the times series of financial returns demonstrate the existence of typical statistical properties of asset returns, such as distributional properties, tail properties and extreme fluctuations, leverage effects and downside correlations, pathwise regularity, and the linear and nonlinear dependence of returns [1, 2, 3, 4]. These statistics are also known as stylized facts, which deal with the difficulty of justifying the level of large variability (positive and negative) in asset returns in terms of fundamental economical variables.

In China, the real estate business plays a crucial role in the economy. Housing prices and its inflation illustrate the stylized facts of financial time series[5]. Simutaneously, the housing market features heterogeneity and bounded rationality.

Kain[6] pointed out that the usefulness of a housing market theory explicitly depends on how it deals with the heterogeneity that influences the behavior of multiple stakeholders in the housing market. Especially in China, researchers should pay more attention to the inter- and intra-municipality differences in housing because of the country's significant heterogeneity in its emerging urban housing market [7]. A better description of the behaviors in the housing market require a clear understanding of the nature and implications of this heterogeneity.

Malpezzi and Wachter (2005) claimed that in illiquid markets, such as in real estate, prices may be very volatile, displaying dramatic price variations that are extremely difficult to explain using rational theory. Rational behavior theory implies that the market participants know the all other participants' beliefs, which seems excessively unrealistic [8]. Arthur (1994) pointed out that this is infeasible, stating "the type of rationality we assume in economics, perfect, logical, deductive rationality, is extremely useful in generating solutions to theoretical problems. But it demands much of human behavior, much more in fact than it can usually deliver" [9]. This provides a new perspective to modeling market behaviors: an inductive approach with bounded rationality, which refers to the phenomenon that individual rationality in decision-making is limited by the availability of information, the cognitive limitations of minds, and the limited time to make decisions [10]. The idea of bounded rationality was widely used in decisions behind policies[11], and economics and finance [12] since its introduction.

With the development of computational capacity and the availability of big data, financial markets and researchers have used computer-based models, such as the agent-based model. Ferreira proposed a grand canonical minority game agent-based model that reproduces stylized facts including volatility clustering, fat tails, uncorrelated returns, and slowing decay [13]. Similarly, Challet presented and studied a minority game-based model of a financial market with adaptive agents reflecting some stylized facts such as the fat tailed distribution of returns and volatility clustering [14]. Lux build a multi-agent model of a financial market with two groups of agents adopting differing strategies to value assets and making decisions (purchase, sell, hold) based on market prices and their own appraisals [15]. These studies reveal promising potential for intelligent computing models, such as an agent-based model, in financial markets ([16]; [17]; [18]).

Thus, this study aims to develop a new agent-based model to mimic the heterogeneous individual behaviors of major stakeholders (sellers and buyers) in a housing market that includes bounded rationality to capture the systematic behavior of the housing market and reproduce stylized facts. This paper is organized as follows. In the next section, we introduce the proposed model. In Section 3, we describe the simulation of our proposed model and discuss the results in section 4. Finally, we present conclusions in Section 5.

2. The model

Psychology researchers indicate that when humans face complicated problems, they tend more toward looking for patterns rather than using deductive logic, that is, "as feedback from the environment comes in, we may strengthen or weaken our beliefs in our current hypotheses, discarding some when they cease to perform, and replacing them as needed with new ones" [9]. This process coincides with the agent-based modeling process, in which each agent starts from simplified models, learns from the feedback, and adapts the model over time. The stakeholders in a real-world system usually have no access to complete information. Therefore, people make decisions based on the information they can obtain. When making decisions, people integrate limited historical information with their expectations for the future market with bounded rationality, heavily influenced by personal preferences and emotional sensitivity.

The proposed housing market model consists of N interacting agents, where Nb are buyers and the remaining $Ns{=}N\text{-}Nb$ are sellers. The agents act in a given region R (e.g. a rectangular region sized by $X{*}Y$) and interact with other agents in the neighborhood. We describe each detail of the proposed model in the following.

Agents

There are two types of agents: sellers and buyers. Sellers have two types of activities: selling and holding. In each time interval, the seller's decision about the housing price is based on the costs and expected profit. Here, the expected profit is not derived from theoretical models, but based on the individual's memory of limited historical information and bounded rationality. The seller will make a sale if the buyer offers a price meeting their proposed price. Otherwise, the seller will hold. Buyers either purchase or hold. Buyers have similar decision mechanisms,

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and will decide upon the upper bound of the price based on memories of limited historical information and bounded rationality. Only when the seller proposes a price that is no higher than buyer's upper bound will the buyer make the purchase.

Neighborhood

Our model assumes incomplete information. A seller or buyer cannot obtain all information about the market, but rather relies on information from close associates (neighborhood). This closeness includes both physical distance or the social distance in a social network. Incomplete information also means that the historical information, such as prices and volumes, expires after a certain time. Therefore, it is important to define each agent's ''neighborhood" that supplies the agent with information. The model also requires a definition for information expiry, meaing that the information is deleted from the memory pool and is invalid for future decision-making.

Pricing Mechanism

The pricing mechanism for a certain commodity varies with people, location, and time. It is stochastic even for one person at a given time and location. To avoid loss of generality, we set a pool of strategies for agents in the proposed model.

Option Pool

Bounded rationality means that agents will not theoretically deduce the so-called ''optimal option" (though it may not be optimal as other agents dynamically evolve). Instead, agents will select an option from an "option pool". As an example, a option pool for a seller can be:

(i) The price with the most sales according to memory in the last 12 months;
(ii) The price most suitabile to the neighborhood in the last 12 months;
(iii) The weighted average price in the neighborhood in the last 12 months;
(iv) The maximum of the prices of options 1-3.

The suitability of a price S_i is the number of purchases at this price. The weighted average price in neighborhood P_{mean} can be calculated by Eq. (1).

$$P_{mean} = \frac{\sum_{i=1}^{Nb} S_i P_i}{\sum_{i=1}^{Nb} S_i} \tag{1}$$

where Nb indicates the total number of buyers and S_i represents the price offered by the ith buyer.

Similarly, buyers will decide their upper bound of offered prices based on limited historical information. Here, we propose 6 buyer strategies:

1. The same price as in the last month;
2. The average price in the last 12 months;
3. The projected price based on the last 12 months;
4. The average price in the last 4 months;
5. The average price in the last 6 months.

The probability an agent selects an option from among their option pool follows a probability distribution that will evolve over time.

Evolution mechanism

Perception will heavily influence decision making. The perception of a "good" price or "good" strategy will increase the possibility that this price or option will be used in the future. In the beginning, we may have no preference for a certain option, but the preference will develope and the probability of using a specific option will change based on evaluations over the previous time interval. Buyers and sellers will increase or decrease the probability of selecting an option based on the perception of the option, and judgments of how promising this option is.

For example, in the first time interval, an agent sets the selection probability of the 4 strategies at (1,1,1,1). After the first time interval, the agent finds that the second strategy is the one closest to the deal price. He would then change the selection probability in the second time interval to (1,2,1,1). Thus, the second strategy will have a better chance of selection in the second time interval.

Emotional factor

Humans are emotional. If a buyer has a demand and cannot not be satisfied for a long time, he will be influenced by the number of consecutive time intervals with unsatisfied demand, and is willing to increase the purchasing price. Assuming the emotional factor conforms to a sigmoid function, if the ith buyer has unsatisfied demand of N in the last month, the emotional factor is expressed as in Eq. (2).

$$E_i = \frac{K * P_i}{1 + e^{Nt}} \tag{2}$$

Here, K is a multiplier and t indicates the number of consecutive months with unsatisfied demand.

Compared to the standard economic theory assuming that agents are rational and often try to pursue maximum profit in the housing market [19], a significant difference in this model is that each agent will have incomplete information and make random selections based on bounded rationality.

3. SIMULATIONS

We developed a simulation platform with MATLAB 2012b to illustrate the simulation results of the case study under different scenarios.

We use the real-world monthly average housing prices for Shanghai in 2013 as the input for the initial condition: 27,369; 27,399; 25,826; 26,452; 26,552; 26,635; 26,692; 26,913; 26,927; 2,7053; 27,464; and 27,508 (unit: RMB/m^2)(Source: www.soufun.com)

In our simulation, there are N=100 agents, Nb=80 buyers and Ns=20 sellers, randomly located in a a (100, 100) lattice network, as illustrated in Figure 1. The Euclidean distance determines the neighborhood size. Two agents within Euclidian distance D are defined as neighbors. To test the influence of information incompleteness, we consider 5 values for D: 25, 50, 75, 100, 125, and 150. The threshold of D is based on the diagonal distance of the lattice network, which is 100*sqrt(2) in our case study. A seller must estimate buyers' future demand to make sure to meet the demand and reduce stocking costs. Thus, there will be a lag of Δt for sellers, meaning that houses will be ready for sale after construction time Δt (Here, we set $\Delta t = 1$). Each buyer has a demand, uniformly distributed across (1,10). The strategy pool and evolution mechanism for sellers and buyers are as discussed in Section 2.

The simulation is terminated after reaching iteration number tn=1000.

4. Results and analysis

4.1. Stylized facts

To test and analyze the simulated results of our model, we defined the price return *r(t)* as:

$$r(t) = \log P_t - \log P_{t-\delta} \tag{3}$$

Where, P_t denotes the price at time t; and δ is the time delay of no less than 1.

For financial time series, the major statistical properties of asset returns are described using distributional properties, tail properties and extreme fluctuations, pathwise regularity, and linear and nonlinear dependence of returns in time and across stocks [1]. Thus, we focus on these features to analyze our simulation results in terms of price returns *r(t)*.

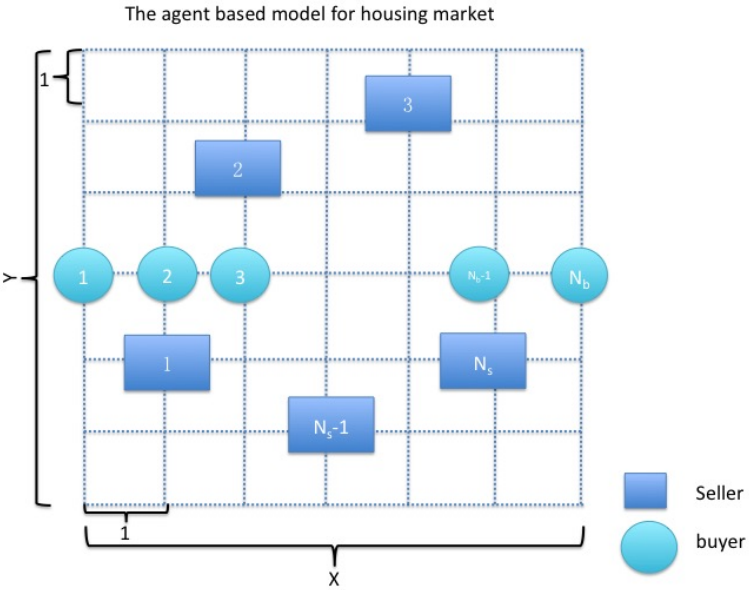

Figure 1. The agent based model of the housing market

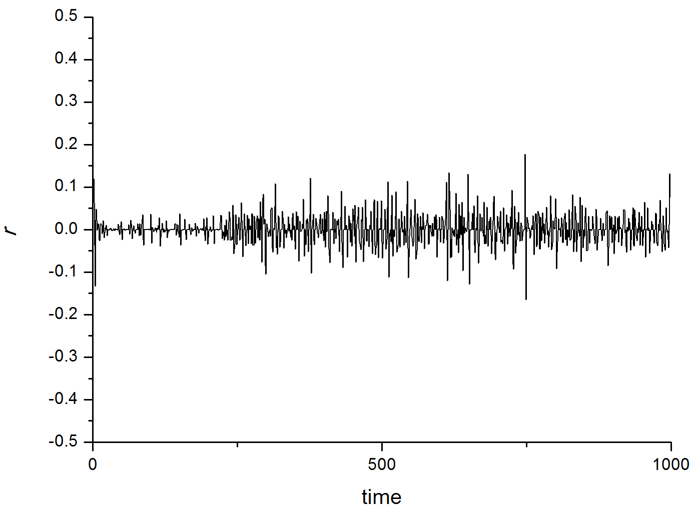

Figure 2. Time series of housing price returns

After 1,000 iterations, we obtain a time series of returns for simulated housing prices, as shown in Figure 2. This housing price time series illustrates 6 stylized facts of financial assets.

Absence of autocorrelations

The return autocorrelation $C(\delta)$ can be defined as:

$$C(\delta) = \frac{< r(t+\delta)r(t) > - < r(t+\delta) >< r(t) >}{r(t)^2} \tag{4}$$

Where $< ... >$ denotes the time average of price returns. Figure 3 shows that there is a slow

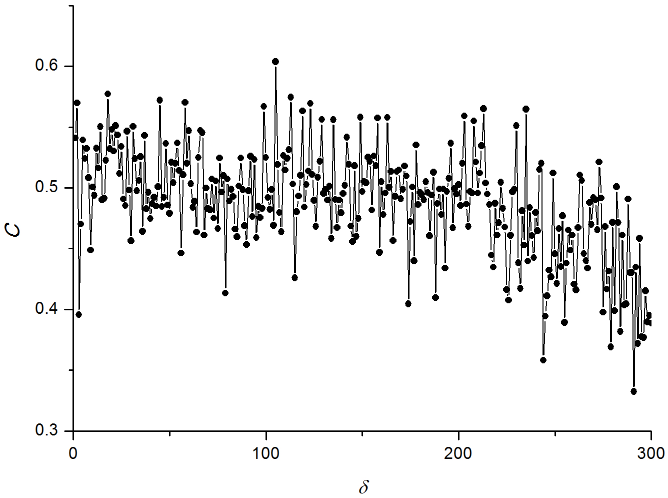

Figure 3. Autocorrelation (dotted line) as a function of δ

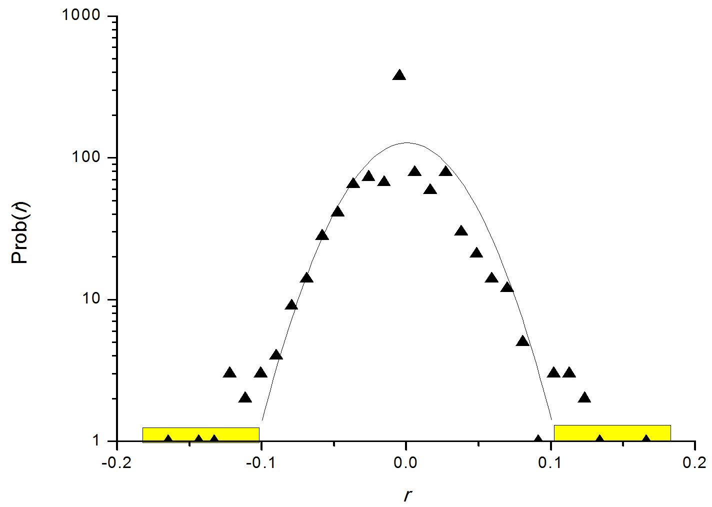

Figure 4. Comparison of probability distribution of returns and fitted normal distribution.

decay decay in C that can be interpreted as a long-range correlation in the returns. This is evidence of a sort of memory in the series.

Heavy tails

To illustrate the heavy tail of the returns calculated from the simulated results, we plot the logarithmic value of the probability mass function (PMF) of r in solid triangles and the logarithmic value of the PDF for the fitted normal distribution in a solid line in Figure 4. The figure shows that the probability distribution of the simulated results exhibits a fat tail, as indicated in the yellow zones.

Loss asymmetry

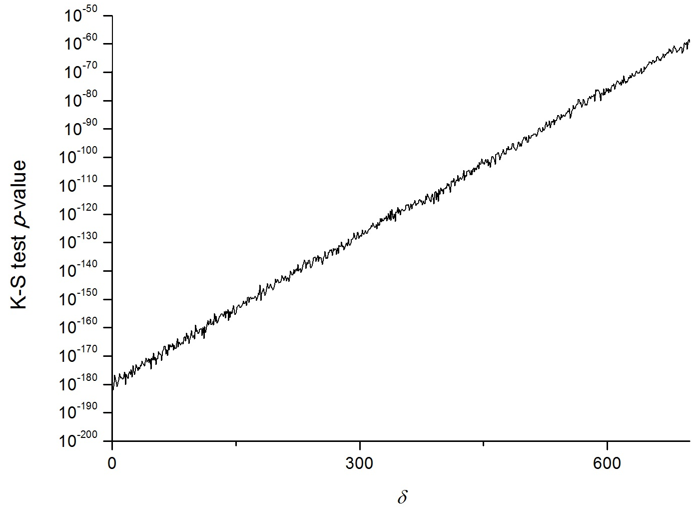

Figure 5. Kolmogorov–Smirnov test (K-S test) p–value as a function of δ

Loss asymmetry is the phenomenon wherein there are significantly large downward movements in the time series but not equally large upward movements [1].

Kurtosis measures how outlier-prone a distribution is. The kurtosis of a normal distribution is 3, and more more outlier-prone distributions have kurtosis greater than 3.

The kurtosis of our simulated result is 6.2803, indicating that the simulated results show loss asymmetry.

Aggregational Gaussianity

When increasing the time scale over which we calculate returns, the distribution of the price returns look increasingly like a normal distribution, indicating aggregational Gaussianity [1]. The Kolmogorov–Smirnov test determines whether a price return distribution fits a standard normal distribution. As shown in Figure 5, when the time delay increases, the p–value increases correspondingly, implying that the corresponding price return distribution is closer to a normal distribution.

Volatility clustering

Volatility clustering has a quantitative signature, that is, large price variations probably have subsequent large price variations.

In Figure 2, we observed this phenomenon in the time intervals [280,320] and [360 380].

These stylized facts prove that the simulation results from the proposed model possess common features of financial time series. The flexibility of this agent-based model can effectively represent the complexity and adaptive capacity of the housing market. Thus, we can apply this model to analyze other systems with similar characteristics or further explore the complex behaviors in those systems.

4.2. Incompleteness of information

Incomplete information is one root cause of bounded rationality. To explore the influence of information incompleteness on our model, we performed a sensitivity analysis of the neighborhood size D using a range of 25 to 150 with a step size of 25.

When the Euclidian distance is set to be 25, the logarithmic value of the PMF of the price return shows heavy tails with a Kurtosis of 40.5082, volatility clustering, and loss asymmetry

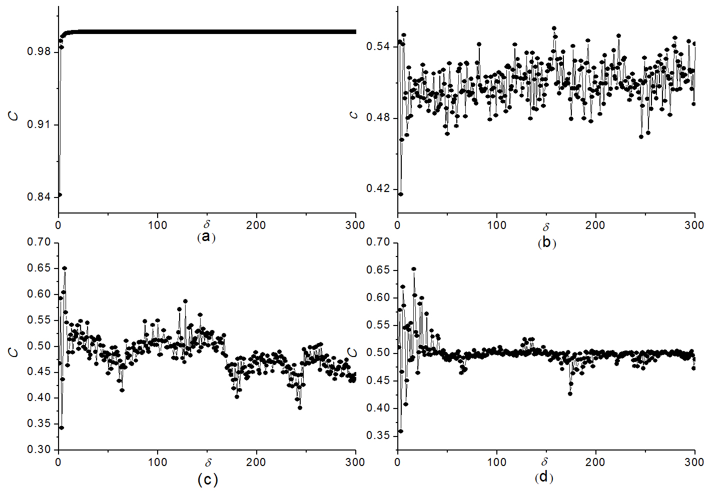

Figure 6. Euclidian distance at 25 (a), 75 (b), 125 (c), and 150 (d) where the absence of autocorrelation does not hold.

with skewness of -3.6175. Autocorrelation (dotted line) as a function of δ shows that C gradually approaches and stabilizes around 1, indicating the obvious presence of autocorrelation. The Kolmogorov- Smirnov test for price returns shows that p equals 0. However, both the absence autocorrelation and the aggregational Gaussianty do not hold when the Euclidian Distance is 25.

When we increase the Euclidian distance to 50, volatility clustering also exists, with Kurtosis equal to 7.3095, showing heavy-tails. Skewness equals 0.3338, indicating loss asymmetry. However, for autocorrelation, we observe a slow increase in C, which does not meet the stylized facts of financial assets.

When the Euclidian distance is set at 75, 125, and 150, respectively, the stylized facts of financial assets on volatility clustering, heavy tails, and loss asymmetry hold, with Kurtosis equal to 7.1207, 22.2322, and 63.7230; and skewness equal to -0.1527, -0.0090, and 0.4480, respectively. For autocorrelation, we observe a fluctuation around 0.5 with no trend of decay or increase when the Euclidian distance is 75. The autocorrelation first decays and then increases and declines again when the Euclidian distance is set at 125,. When Euclidian distance is set at 150, the autocorrelation first decreases and then increases to finally reach a smooth tread near 1, as shown in in Figure 6.

Table 1 shows stylized facts with different neighborhood sizes, where Y indicates that the stylized fact holds with given D, and N indicates that it does not hold. The results show that aggregational Gaussianity and the absence of autocorrelation are more sensitive to the neighborhood size, which represents the incompleteness of information.

5. Conclusion

This study aimed to create an agent-based model to mimic the heterogeneous individual behaviors of major stakeholders (seller and buyers) in a housing market that considers bounded rationality. The model can capture the systematic behavior of the housing market, and the

Table 1. Stylized facts with different neighborhood sizes D.

D	Absence of autocorrelation	Heavy tails	Loss asymmetry	Aggregational Gaussianity	Volatility clustering
25	N	Y	Y	N	Y
50	N	Y	Y	N	Y
75	N	Y	Y	N	Y
100	Y	Y	Y	Y	Y
125	N	Y	Y	N	Y

statistical properties of the data generated by a simulation are in line with the stylized facts expected from the financial data, such as volatility clustering, heavy tails, and loss asymmetry. etcetera. It is especially noteworthy that the aggregational Gaussianity and the absence of autocorrelation are sensitive to the incompleteness of information. This model provides an applicable tool to analyze complicated systems with incomplete information and heterogenous behaviors.

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