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Determinants of Housing Liquidity in Chinese Cities: Does Market Maturity Matter?*

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Abstract: Housing liquidity measures the ability to convert housing to cash as an important characteristic of housing stock. A simple model of buyer offers' distributions was used to theoretically explore the determinants of housing liquidity in a search process. An empirical ordinary least squares model of the time-on-market was developed using data collected in four Chinese cities (Beijing, Shanghai, Guangzhou, and Shenzhen). The results show that in these four Chinese cities, market maturity dominates the variation of housing liquidity, with the effects of housing characteristics, seller's search cost, search strategy, and market conditions being less significant to the time-on-market equation. These empirical results indicate that the slow turn-over of housing stock may constrain the overall level of housing liquidity in major Chinese cities.

Key words: housing liquidity; housing stock; time on market; market maturity

Introduction

The concept of financial asset liquidity was introduced by Tobin[1] and soon introduced to the field of real assets. Compared to the markets for normal goods and services, liquidity constraints always exist in a housing market (especially in the resale housing market) due to several factors, such as heterogeneity, decentralized transactions, dispersed information, long search and bargaining processes, and inexperienced buyers and sellers.

Housing liquidity has not been studied in China although it is becoming an important practical issue, along with the rapid development of the resale housing market since the late 1990s in Chinese cities. In some major cities, such as Shanghai and Guangzhou, the transaction volume in the resale housing market has reached or even exceeded that of new completions. However, little attention has been paid to the liquidity of resale housing units, with the transaction price still being the only indicator in the market. In fact, it has been proved that the transaction price and housing liquidity are highly correlated, and price alone without considering the liquidity cannot fully explain market conditions[2-4].

This paper presents a measurement of housing liquidity which is then used to examine the determinants of liquidity in emerging resale housing markets in major Chinese cities. The current literature is mostly concerned with the effects of individual attributes on housing units and market conditions, with few studies discussing the impact of market maturity, since most research is based on developed resale markets. However, although the resale housing markets in Chinese cities are developing rapidly, most are still in a very immature stage, with small transaction volumes and poorly-set institutions, which may significantly affect housing liquidity. Therefore, this paper will focus more on the effect of market maturity than on the individual attributes and market conditions.

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1 Definition and Measurement of Liquidity

Although much literature on housing liquidity exists, the studies do not agree on the exact definition of housing liquidity. This paper does not compare these definitions, but only reviews the key, well accepted points. First, housing liquidity measures the ability of housing to be converted to cash. Thus, housing liquidity is an intrinsic characteristic of the housing, rather than of the whole market (but it still may be impacted by market conditions or market maturity). Second, and most importantly, both the time-on-market (TOM) and transaction price should be considered to fully capture the housing liquidity. The transaction price is known to rise as the duration of a seller's search process lengthens. Thus, sellers face the trade-off of maximizing the selling price and minimizing the TOM, so neither the price nor the TOM alone can fully capture the housing liquidity.

Although some researchers take the relative probability of sale in a particular instant of time as the measure of housing liquidity, the expected TOM or similar concepts are more generally used as measures because the TOM is an indicator easily available in the search process and the seller's search cost is highly correlated with the search process duration, allowing a direct connection between the housing liquidity and the search process.

Therefore, the housing liquidity measurement provided by Lippman and McCall[5] is used in this paper. They define liquidity as "the optimal expected time to transform an asset into money with optimality determined by the seller's search strategy". This measurement makes it possible to conveniently examine the impacts of many factors on liquidity based on the seller search theory.

2 Seller's Search Process and an Expected TOM Model

2.1 Seller's search process

In a housing market, property sellers search for buyers at the same time as buyers search for properties until a transaction is completed[3]. This search process may last for a very long time because of imperfect information. Unlike the active search process buyers usually conduct, sellers usually more passively wait for receiving offers and then decide whether to accept or not. Offers may be random and follow a specified probability distribution, for example, a normal probability distribution with certain parameters. Thus, the seller's search process can be viewed as a sampling without recall from the pool of potential buyers and their offers[6].

This sampling process lasts until the seller accepts one buyer's offer. A seller lists the property for sale at a stated price, P_{ls}. Generally speaking, the buyers' offers, P_b, would be no more than P_{ls}; otherwise, the search process will not start. The seller also has a reservation price, P_{rs}, meaning that the seller will accept an offer only if the offer is no less than P_{rs}[4]. That is,

$$P_{rs} \leqslant P_b \leqslant P_{ls} \tag{1}$$

2.2 Simple excepted TOM model

The sampling process above can be simplified as shown in Fig. 1. The distribution of buyers' offers is assumed to be a normal probability distribution, with the transactions approached if and only if any offer falls in the "effective range" (that is, the shadow area defined by P_{ls} and P_{rs}). According to Fisher et al.[4], the final transaction price always exceeds the average offering price, so here both P_{ls} and P_{rs} are assumed to be on the right half of the distribution.

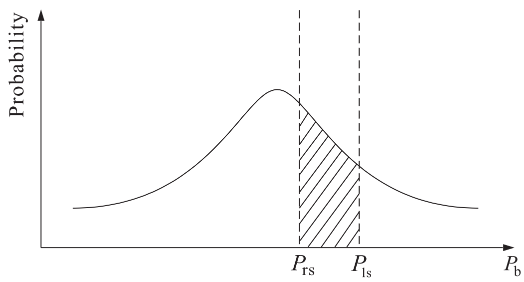

Fig. 1 Distribution model for buyers' offers

Changes of several parameters in the distribution model will affect the expected TOM. Increasing the mean value of the distribution, μ_b, when controlling for other variables, will lead to a right-side shift which then raises the probability that an offer falls into the effective range. An increase in the variance of the distribution, σ_b^2, will reduce the probability in the effective range. An increase in the seller's list price, P_{ls}, will increase the probability. A decrease of the seller's reservation price, P_{rs}, will also raise the probability.

Besides these four elements, a fifth factor that affects the expected TOM, although it does not affect the effective range, is the frequency of offering, ν_b, with the increase of ν_b reducing the expected TOM.

2.3 Market factors affecting the expected TOM

Many factors in the residential market affect the expected TOM of a property through their effects on μ_b, σ_b^2, P_{ls}, P_{rs}, or ν_b. Those factors can be classified as individual factors, market conditions, and market maturity.

2.3.1 Individual factors

Since the liquidity is an intrinsic characteristic of housing, the attributes of a housing property and its seller affect the liquidity. Those individual factors are believed to be the key determinants of liquidity in most studies.

Housing attributes If a dwelling for sale has certain attributes that attract buyers, such as a good location or architecture design, the distribution of buyers' offers shown in Fig. 1 will shift to the right, which increases the probability in the effective range. The offering frequency, ν_b, will also be higher. Therefore, more attractive houses are likely to have a higher liquidity.

Sellers' search cost Zheng[7] separates the buyer's search cost into the activity cost and the duration cost, while the seller's search cost is mainly composed of the duration cost. As the TOM becomes longer, the seller needs to make a trade-off between a higher transaction price and a higher duration cost. Thus, sellers with higher duration costs may set a lower P_{rs} to sell this property more quickly.

Sellers' search strategy Search strategy here refers to how a seller sets P_{ls}. The literature has many possible search strategies with very divergent conclusions[8-11]. Some authors insist that although overpricing appears to raise the probability in the effective range, it significantly reduces the number of potential buyers, leading to a much lower ν_b, which increases the expected TOM. However, other authors disagree, emphasizing not only that overpricing enlarges the bargaining space, but also that buyers in imperfect markets tend to judge quality by P_{ls}, which makes overpriced properties sell with shorter TOM. Therefore, the effect of overpricing on the expected TOM is uncertain.

2.3.2 Market condition

The effect of market conditions has been emphasized in many recent studies and is believed to affect housing liquidity in two ways. First, according to the theories of housing equity constraint and nominal loss aversion in recent studies[12-14], buyers are more sensitive to changes of the market condition than sellers. Especially when the nominal housing price begins to decline, buyers will immediately reduce their offering price, which means that the distribution of buyers' offers shifts to the left. However, sellers are reluctant to change P_{ls} or P_{rs} because they do not want to realize the nominal loss or because they could not afford a new house without getting enough money from this transaction. As a result, the probability in the effective range drops significantly, along with the liquidity level. Second, ν_b is also impacted by the market condition. For example, a recession market has fewer buyers interested in certain houses, leading to a lower ν_b.

2.3.3 Market maturity

The market maturity also affects ν_b to a large extent. In an underdeveloped market with a small transaction volume and poorly-set institutions, inactive transactions result in a lower ν_b and a longer expected TOM, which is typical in China at present.

Thus, individual factors, market conditions, and market maturity all affect housing liquidity. The first two groups are emphasized in the existing literature, but the latter may be more important in Chinese cities. Therefore, an empirical model was developed to test these conclusions.

3 Survey Data

The data used in this research was obtained from a specially designed survey of sellers in the resale housing markets in Beijing, Shanghai, Guangzhou, and Shenzhen, conducted by the Institution of Real Estate Studies at Tsinghua University in early 2004. These four cities are among the most developed cities in China. The resale housing markets in Shanghai, Guangzhou, and Shenzhen are more active than in Beijing.

This survey was conducted in Housing Trade Centers in these cities which register all resale housing transactions. All the sellers coming to the Trade Centers during the 10 day survey period were interviewed to avoid bias in the sampling. The data was filtered based on the following rules: First, transactions before 2000 were not included. Second, some special dwelling types were excluded, such as single family houses, villas, and mixed-residential-retail spaces. Thus, only condominium transactions were included in the data with a total of 731 transactions. The data distribution across the four cities is shown in Fig. 2 with the distribution by listing time shown in Fig. 3.

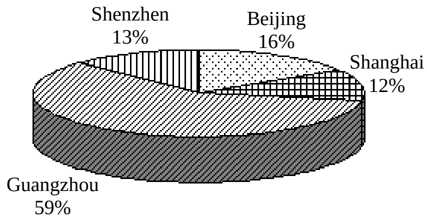

Fig. 2 Sample distribution across the four cities

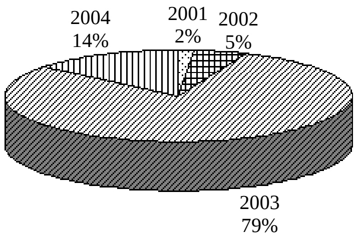

Fig. 3 Sample distribution by listing time

4 Empirical Results

4.1 Empirical approach and variable selection

An empirical model of the expected TOM was developed based on the factors listed in Section 3. Although recently many studies have used the hazard ratio model[13,15,16], this model was not used here because all the transactions involved in the survey had already finished by the time of the survey. Instead, an ordinary least squares model was used:

ln(TOM)=*f* (individual attributes, market condition variables, market maturity variables) (2)

The dependent variable in the model is the natural logarithm of TOM, while the independent variables include three groups of factors.

4.1.1 Individual factors

Housing attributes Several variables were included to represent individual factors, HYEAR, TCBD, TRAIL, AMENITY, ENVIRO, MANAGE, SOUTH, FLOOR, and COMMER. The expected TOM is expected to be shorter if the property for sale is newer (HYEAR), closer to the central business district (TCBD) or subway station (TRAIL), or in a community with higher levels of amenities (AMENITY), more pleasant environment (ENVIRO), and better property management (MANAGE). In addition, south facing (SOUTH) and apartments on higher floors in a residential tower (FLOOR) are also expected to reduce the expected TOM. Finally, the expected TOM for commodity-housing may differ from that of economy-housing (COMMER). The effect of the buyers' preference for dwelling size (HSIZE) is uncertain, and thus it may have an ambiguous impact on TOM.

Sellers' search cost The first variable affecting the sellers' search cost is whether the dwelling is vacant during seller's search process, VACANT. The seller of a vacant house would suffer rent loss or nominal rent loss, which greatly increases the search duration cost. Thus, the expected TOM for vacant dwellings should be shorter. BROKER represents whether the seller employs a broker for the search. A broker can greatly reduce the search cost and, therefore, result in a higher P_{rs}[11,17], but should also increase ν_b, so the impact of broker on TOM is uncertain and needs to be tested in the empirical regression. Some variables representing the seller's household characteristics are also introduced, such as the average annual household income (INCOME) and the age of the respondent (AGE), which may affect the seller's search cost and expected TOM.

Sellers' search strategy The magnitude of overpricing was measured using a hedonic pricing equation model to derive the "theoretical values" of the dwellings. The results are shown in Table 1.

Then, the magnitude of the overpricing can be calculated as

$$\text{OVERPRICING} = (\text{LISTPRICE} - \text{THRPRICE})/\text{THRPRICE} \quad (3)$$

where LISTPRICE is the listing price of a dwelling as reported by the respondent and THRPRICE is the theoretical value of the property calculated from the hedonic regression. The OVERPRICING variable was included in Eq. (2).

4.1.2 Market condition variables

There are two sets of variables for the market conditions. First, the variables, SPRING, SUMMER, FALL, and WINTER, indicate the seasons included in the search process to represent the seasonal effects on liquidity. The market is expected to be more active in some months than in others. Second, GROWTH indicates the growth of the nominal housing price in the market. The expected TOM is expected to be shorter in a hot market and longer in a market recession. Since there is no reliable price index for resale housing in China, the price growth rate for new completions shown in Table 2 was used here as a proxy. GROWTH was the value of the price growth rate in each city and each year when the unit was listed for each observation.

Table 1 Regression result of hedonic pricing equation (Dependence: ln(SELLPRICE))

Variable	Coefficient	*t*
C	1.820***	15.846
BJ	0.486***	11.545
SH	0.720***	13.293
SZ	0.216***	6.351
HSIZE	0.003**	2.088
BEDROOM	0.227***	5.031
LIVINGROOM	0.133***	3.102
FLOOR	0.009***	3.362
SOUTH	0.071**	2.526
AMENITY	0.063***	3.473
ENVIRO	0.017	0.657
MANAGE	0.052**	2.525
TCBD	–0.003***	–4.584
TRAIL	–0.004***	–3.391
COMMER	0.085***	2.840
HYEAR	–0.017***	–4.950
Statistics		
F	89.267***	
Adjusted R^2	0.712	
Log likelihood	–122.720	
White heteroskedasticity *F*	12.698***	

Notes: (1) ***, significant at 0.01 level; **, significant at 0.05 level.

(2) The white heteroskedasticity consistent covariance was used because the white heteroskedasticity *F* is significant.

Table 2 Values of GROWTH in Eq. (2) (%)

	2001	2002	2003	2004
Beijing	26	42	11	30
Shanghai	26	11	21	47
Guangzhou	–8	20	17	12
Shenzhen	14	13	21	15

Source: China Real Estate Index System (CREIS)

4.1.3 Market maturity variables

IMMATURE is introduced as a proxy to indicate the level of the resale market's maturity. This variable was calculated as the ratio of the resale transaction volume to the total housing transaction volume (resales plus new completions) in the city, as shown in Table 3. The increase of this variable will improve the overall liquidity.

Table 3 Values of IMMATURE in Eq. (2) (%)

	2001	2002	2003	2004
Beijing	4	5	12	20
Shanghai	44	48	49	51
Guangzhou	29	37	40	43
Shenzhen	28	32	36	42

Source: Data reported by real estate authorities in the four cities.

4.2 Results

The estimation results of the expected TOM in Eq. (2) are listed in Table 4.

Table 4 Regression results of the expected TOM equation (Dependence: ln(TOM))

Variable	Coefficient	*t*
C	2.379***	3.914
BJ	–1.279***	–3.360
SH	0.378**	2.414
SZ	–0.194**	–1.924
HSIZE	–0.055	–1.376
HYEAR	0.006	1.349
FLOOR	0.002	0.726
SOUTH	–0.007	–0.181
TCBD	0.000	0.343
TRAIL	0.000	0.246
COMMER	0.030	0.710
AMENITY	–0.052*	–1.864
ENVIRO	0.027	0.835
MANAGE	0.010	0.432
VACANT	–0.009	–0.180
BROKER	0.066*	1.718
AGE	0.025	1.294
INCOME	–0.028	–1.302
OVERPRICING	–0.053	–1.083
SPRING	0.527***	11.887
SUMMER	0.695***	14.311
FALL	0.722***	11.467
WINTER	0.958***	8.307
GROWTH	–0.775	–0.997
IMMATURE	–4.527***	–3.245
Statistics		
F	78.731***	
Adjusted R^2	0.794	
Log likelihood	–235.440	
White heteroskedasticity *F*	2.847***	

Notes: (1) ***, significant at 0.01 level; **, significant at 0.05 level; *, significant at 0.1 level.

(2) The white heteroskedasticity consistent covariance was used because the white heteroskedasticity *F* is significant.

The adjusted R^2 is 0.794 and F is significant at the 1% confidence level, both of which indicate that the model has a strong explanation power for explaining the TOM variations in the sample. The adjusted R^2 for most models estimating the TOM in the existing literature are relatively low in the range of 0.3 to 0.5[3,6,9]. Thus, most researchers conclude that housing liquidity is not easily measured because of the transaction heterogeneity. The adjusted R^2 of this model is much larger than in previous studies, indicating that at present the housing liquidity in the Chinese housing market is more affected by the overall market maturity in the cities instead of the individual dwelling characteristics.

The results show that the explanation power of the individual factors is limited. Only one variable (AMENITY) in this group is significant. Thus, units in communities with more amenities are more attractive to buyers and thus, have a higher liquidity. The other variables in this group are all insignificant although their signs are mostly consistent with the expectations. For the variables related to the sellers' search costs, the coefficient of BROKER is both positive and significant; thus, while brokers effectively reduce the sellers' search cost, they also encourage sellers to pursue higher prices and to set higher reservation price, which leads to a longer TOM. The coefficient of VACANT is negative, consistent with the initial analysis, but not significant. The coefficient of OVERPRICING is also insignificant, so the different views regarding the role of overpricing in the seller's search process cannot be tested with this data set.

For the market condition variables, the variables of SPRING, SUMMER, FALL, and WINTER are all quite significant, with TOM being the shortest in spring, followed by summer and fall. The coefficient of GROWTH is negative but not significant, which may be partly due to measurement errors caused by using the price growth rate in the new completion market as a proxy for that in the resale market.

Most importantly, the market maturity variables dominate the variations of the TOM. The coefficient of IMMATURE is negative and significant at the 1% confidence level, which means that housing liquidity would be greatly improved if the market were more mature with active resale transactions. Taking Guangzhou as an example, from 2001 to 2003, the percentage of resale transactions among the total transactions rose from 29% to 43%, with the average expected TOM decreasing by 39% according to the coefficient of IMMATURE, when holding other variables constant.

In addition, all the three city dummy variables, BJ, SH, and SZ, are significant to at least the 5% level. Therefore, besides the maturity level and price growth, other location or city specific factors may affect the TOM.

5 Conclusions

Housing liquidity is an important characteristic of housing. This study analyzed housing liquidity and its determinants using a simple model of the buyer offers' distribution in the search process, taking "the optimal expected time to transform an asset into money with optimality determined by the seller's search strategy" as the measurement of housing liquidity. Then, a least squares analysis of the TOM was used to analyze the data collected in a survey in four Chinese cities.

The empirical results show that market maturity dominates the housing liquidity variations. Housing attributes, seller's search cost, search strategy, and market conditions have less significance. However, there are still some interesting findings among the individual attribute variables. For example, a broker encourages sellers to pursue higher prices and set higher reservation prices, thus leading to longer TOM.

The findings to some extent depart from the widely accepted argument in the existing literature that housing liquidity is an intrinsic characteristic of housing. The immature nature of the resale housing market in these cities constrains the overall housing liquidity. Therefore, a developing resale market is essential to improve the overall housing liquidity in these housing markets.

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TUM Vice President Visits

Vice President Meng Liqiu of Technical University of Munich (TUM) visited Tsinghua University on July 7, 2008. Tsinghua Vice President Kang Kejun had a discussion with Professor Meng. VP Kang briefed Professor Meng on Tsinghua's recent developments in aerospace, energy, electrical engineering, life science, and management. They also exchanged ideas on further enhancing cooperation between Tsinghua and TUM.

Professor Meng visited the School of Aerospace, the Institute of Nuclear and New Energy Technology, the Department of Engineering Physics, and the Department of Chemistry after the talk.

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