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Title: Reference Dependence, Loss Aversion and Residential Property Development Decisions

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Reference Dependence, Loss Aversion and Residential Property Development Decisions

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Abstract

We analyse land transaction and residential development data from Beijing, China and identify that developers' evaluation of land transaction exhibits reference dependence and loss aversion. Developers with prior land transaction losses set higher house prices than those without prior losses. This effect is strongest at the beginning and towards the end of the property sales period. It is moderated by developers' ownership structure and listing status. Privately-owned firms experience stronger effects than their state-owned counterparts, whereas unlisted firms are more strongly affected than their listed counterparts. Results have implications on the relationship between the land and the housing markets in China. In a booming land market where land acquisition entails a high price, developers will transfer excess land price to house prices, thereby increasing the latter. The land market plays an integral role in managing housing prices in China.

Keywords: reference dependence, loss aversion, behavioural economics, real estate development, housing market

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1. Introduction

Hedonic price models are routinely used to price residential properties. In such models, the pricing decision is assumed rational, and they only consider attributes that add value to properties. However, extant literature identified numerous behavioural factors influencing house prices, such as anchoring [1; 2], inattention [3; 4] and loss aversion [1; 5; 6]. Although these studies vary greatly in terms of geographic regions and behavioural factors, they have reached two consensuses: the inclusion of behavioural factors significantly enhances the performance of hedonic price models, and prospect theory is the most widely used and applicable behavioural model in this stream of research (see, for instance [6; 7; 8]). In this paper, we push the boundary of behavioural research in real estate studies along these directions.

We focus on the behavioural factors of reference dependence and loss aversion, two well-documented concepts from prospect theory [9; 10]. Reference dependence refers to people's tendency of deriving utility from a comparison with a reference point; loss aversion refers to people's tendency of stronger reaction to losses than to equal-sized gains[1]. In the real estate market, the two concepts are helpful in explaining real estate market cycles [1; 5; 6; 14; 15], household mobility decisions [8] and mortgage lender and borrower's behaviour [16; 17], amongst others. However, most of the existing studies investigate individual or household decisions. Little is known if other market participants, such as real estate developers, are prone to such biases.

A typical residential property development project starts with real estate developers buying a plot of land and ends with them selling the properties developed on the plot. If developers price the properties rationally, then they would consider only the market value of the attributes in hedonic price model at the time of sales. Hence, land acquisition cost is irrelevant sunk cost. However, evidence from behaviour economics corroborates that people are likely to evaluate consecutive events together if they experience prior losses in the first event, in the hope of breakeven [18; 19]. If real estate developers are also affected by loss aversion due to previous land acquisition losses, then they are likely to pursue breakeven by setting the asking prices of

[1]Evidence from various fields has confirmed the key roles of reference dependence and loss aversion in human decision-making processes [11; 12; 13]. For an excellent review about the applications, see Barberis [7].

their housing units above the fair market prices. The study of such behaviours are of economic and policy importance. Firstly, a developer should not pursue project-specific breakeven, but rather he must push for firm-level breakeven. Thus, the sunk cost of a specific project, i.e. losses due to excessive payment for a plot of land, should be written off and ideally offset by profits from other projects. This behaviour is closely related to myopic loss aversion and narrow framing in the behavioural literature, and the adverse impacts of such behaviours are well documented [20; 21]. Secondly—and more importantly—loss aversion leads to disposition effect and, subsequently, long time-on-market and potentially high final transaction prices [22; 23; 24; 25]. In the real estate development context, any pricing mistake (e.g. overpaying for a plot of land) is not corrected fully and timely in the subsequent sales of complete housing units. Therefore, policymakers should be wary of any loss aversion effect resulting from the land acquisition stage. Housing price regulations would most probably be effective if policies target the source of the issues, such as the overpricing of land.

We choose Beijing, China as our study area because it offers an ideal setting to test our hypotheses. The state owns all urban lands in China. Real estate developers can only obtain the right to use residential lands through public auctions of land leases from local governments. This institutional setting offers two benefits to our analysis. Firstly, land prices are transparent and recorded accurately through the public auction platforms. Secondly, land prices can be separated clearly from house prices. These features facilitate the reliable identification of loss aversion effect due to land transaction losses.

We analyse land and house transaction records from 2003 to 2014 and find that real estate developers' pricing decisions for newly built properties exhibit reference dependence and loss aversion. When they pay prices higher than the reference land prices, they tend to set 14% higher house prices than developers without such losses. Loss from land acquisition transactions strongly affects developers' pricing behaviour in the first year of the sales period[2]. However, developers become rational as sales progresses into the second and the third year and when additional market information is taken in. The loss aversion effect is lowest at the third year of sales period, which is the average time to sell out housing units within a project in our sample. Our findings also confirm previous conclusions on disposition effect. We

[2]Sales period starts from the year when the project started to sell its units to the year when all of the units in the project were sold. Presales are not considered all sales in our database after construction was completed.

contend that the most loss-averse developers took the longest time to sell out their properties, i.e. eight years in our sample. These findings not only add to the fast-growing behavioural literature in real estate research but also highlight the important role of land market in China's housing market.

The rest of this paper is organised as follows. A description of the theoretical framework is presented in Section 2, whereas the background information about real estate development in China is provided in Section 3. The details of our empirical implementations are described in Section 4, followed by the presentation of empirical results and several robustness checks in Sections 5 and 6, respectively. Conclusions and proposals for future research directions are provided in Section 7.

2. Theoretical Framework

We develop our empirical models based on prospect theory [9], which has been applied in a wide range of fields such as finance [20; 23], marketing [26; 27; 28; 29] and real estate economics [1; 5; 6; 8; 30], amongst others[3]. The introduction of reference dependence and loss aversion is the most significant improvement that prospect theory offers to the standard economic literature. Reference dependence means that decision makers asses the value of a bundle of goods or services relative to a reference point rather than their absolute values. Loss aversion is the tendency of disliking losses more than favouring equal-sized gains. In the current study, we focus on these two elements, as illustrated in the following formula:

$$v(x) = \begin{cases} (x - ref)^{\propto}, & x \geq ref \\ \lambda(ref - x)^{\beta}, & x < ref \end{cases} \quad (1)$$

where x is the bundle of goods/services consumed; ref is the reference point; $\propto$ and β take positive values between 0 and 1; and λ is the coefficient that measures the degree of loss aversion.

In the context of real estate development, prospect theory predicts that the reference points of real estate developers will affect their pricing decision. Moreover, their behaviours will be affected by loss aversion. Developers evaluate the outcome of land auctions by comparing transaction prices with reference prices (e.g. their expectation). This comparison will put the developer in either a gain domain if the transaction price is greater than the expectation, or a

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[3] For a comprehensive review on this stream of literature, see Barberis [7]; DellaVigna [31].

loss domain if the transaction price is less than the expectation. Prospect theory then predicts that developers' behaviours are different in the two domains. Decision-makers tend to be risk seekers in the loss domain and risk aversive in the gain domain.

The concept of reference dependence is also related to a long-standing idea in the psychology literature. This idea states that prior outcomes will affect people's decision-making afterwards. In principle, prior costs are sunk costs that are not recoverable. Therefore, future decision-making should not involve them. However, empirical evidence shows that decision-makers are influenced by sunk costs [32; 33]. Behavioural economists further expand the idea of sunk costs to sunk losses and gains (for simplicity, we term both as prior outcomes hereafter). They also use prospect theory to explore the effect of prior outcomes. In the well-known study of Thaler and Johnson [19], lab experiment evidence is obtained to show that people increase their risk-seeking behaviour after a prior gain (house money effect) and tend to pursue breakeven after prior loss. Thaler and Johnson explained the results with quasi-hedonic editing rules. They argued that peole tend to segregate the prior gain from subsequent gains but integrate the gain with subsequent losses (cancel-out). By contrast, they tend to integrate prior loss with subsequent gains (cancel-out) but segregate it from subsequent losses. People follow these rules to reduce pain from the loss. Inspired by this paper, Barberis *et al.* [34] defined loss aversion behaviour with the influence of prior outcomes. According to them, people are less loss averse after prior gain because the gain provides cushion for subsequent losses. Moreover, they experience increased loss averse after a prior loss because the loss heightens their sensitivity to subsequent losses.

This conclusion leads us to another concept for understanding prior loss effect: mental accounting [25; 35]. The term refers to people's cognitive process to think about, evaluate and organise economic outcomes. Therefore, when land transaction takes place, the developer opens a mental account to evaluate the transaction. In the following stage when developers set house prices, they might close the account for land transaction and open a new account for house sales, or they might integrate the two process and evaluate the two transactions in one integrated account. If developers use segregate accounts, then land transaction outcomes should not affect developers' asking price for houses. However, in the presence of integrated account, setting a high house prices would offer developers in the loss domain a chance to breakeven and reduce negative feelings from the land transaction [19]. According to prospect theory, real estate developers are likely to use integrated account, especially in the loss domain.

Losses from previous land transactions (paper/unrealised costs) will be considered in the pricing decisions of housing units. Therefore, their pricing decision can be described by the following formula:

$$P_{it} = \alpha_0 + \boldsymbol{X}_i\boldsymbol{\beta} + \delta_t + f(loss_i), \tag{2}$$

where P_{it} is the house price for properties on land lot i; $\boldsymbol{X}_i = (x_1, x_2, \dots)'$ is a matrix of observable property attributes; δ_t represents the time fixed effect; and α_0 is a constant; $loss_i$ is the truncated differences between land transaction prices and developer's reference points, as defined in Equation (3).

$$loss_i = (refrerence\ point_i - land\ price_i)D(reference\ point_i < land\ price_i)\ , \tag{3}$$

where D(•) is a function that is equal to 1 when the condition in the bracket holds, and 0 otherwise.

A typical hedonic price model includes the first three components. The underlying assumption is that developers consider only the 'house account' when pricing housing units. When developers integrate 'house account' and 'land account', the gain/loss measure also enters the hedonic price model, as given in Equation (4). According to prospect theory and mental accounting, the losses and gains from land transactions affect real estate developers' behaviours differently. If developers are in the gain domain (i.e. land acquisition costs are below their expectations), then they will behave rationally when determining the asking price of housing units completed on that plot. However, if land price is above their reference point, then they will suffer from loss aversion. They will also subsequently set high asking prices for new homes built on the land lot in the hope of breaking even. In sum, standard economic theory predicts that $f(loss_i) = 0$, whereas prospect theory predicts that $f(loss_i) > 0$. We use data from China to test these hypotheses in the succeeding parts of the study.

3. Real Estate Development in China

Before the 1990s, employers provided free housing for urban residents in China. All lands are owned by the state. Hence, a market for land transactions did not exist, and real estate development by private companies or individuals was impossible. In the mid-1980s, land reform successfully implemented the leasehold property right system in China. Under the new system, the government still owns all urban lands, but land use right can be leased to individuals or institutions[4]. Alongside the land reform was the gradual commercialisation of the housing market in China. Housing provision from the public sector gradually and steadily gave way to a fast-expanding private housing sector. Real estate development projects mushroomed, firstly in coastal cities, and then quickly spread to inland areas. Land prices increase as the demand for land for private housing shoots up. In the early 1990s, most lands were leased through private negotiation between the local governments and the buyers, which gave rise to corruption and led to unfair (often at lower prices) transactions. Since 2002, the government has mandated that all land transactions must be conducted publicly and transparently through auctions, tenders or listings. Consequently, information regarding land transactions between local governments and developers is publicly available at government websites in real time nowadays.

In the past decade, the real estate sector has been expanding rapidly as a result of China's economy growth and urbanisation. Figure 1.1 demonstrates the significant growth in the number of real estate developers from 2000 to 2008, especially in the private sector. Figure 1.2 shows the rapid growth of real estate investment in the same period, especially in the residential sector. Figures 1.3 and 1.4 exhibit the land transaction volume and total revenues from land sales between 2008 and 2016. Although the local governments of third-tier cities had leased the largest amount of lands during this period, the revenue from land leasing was lower in comparison to that from second-tier cities. This paleness is due to the low land prices in third-tier cities (see Figure 1.5). Land transaction volume in first-tier cities remains low because most land lots in those cities have been developed already. Thus, available undeveloped land is scarce. The unmet demand in first-tier cities escalated land prices from approximately 3,000 *yuan/m*^{2} to 17,000 *yuan/m*^{2} in less than a decade (see Figure 1.5). Figure 1.6 shows the national-level house and land prices. Whilst both prices increase consistently, land price has compromised much higher proportion in house prices compared with house price in recent years. The land market plays an important role in the fast-growing housing market in China. Outcomes from land transactions can substantially influence real estate developers' decisions in the later stages of the real estate development process.

(Insert Figure 1 Here)

[4]The duration of leasehold varies depending on the land use purpose, i.e. 70 years for residential development land. Land use right can also be transferred within this period.

4. Empirical Implementations

4.1 Data

We collect data from Beijing, the capital of China. Beijing has experienced a rapid population growth and sprawled considerably in the last few decades. The number of registered residents jumped from 2.03 million in 1949 to 21.15 million in 2013, whereas the number of unregistered residents increased from 0.06 million in 1949 to 8 million in 2013[5]. The growing population density pushed the demand for residential property developments. Consequently, land prices and house prices soared rapidly. Figure 2 exhibits the annual residential land and house price indices and their growth rates from 2004 through 2015. House prices maintained high growth rate, except in 2011 when a package of governmental policies to control speculative investment and cool down the market was implemented[6]. Notably, land price rose as rapidly alongside house price. In six years out of the period examined, the growth rate of land price even exceeded that of house price. As such, land acquisition fee has become a major cost in real estate development. In 2000, land purchase cost accounted for only approximately 15% of the total investment in real estate development. The number reached 50% in 2015[7].

(Insert Figure 2 Here)

The first part of the dataset is the land transaction data from Beijing Municipal Commission for City Planning and Land Resources Management (http://ghgtw.beijing.gov.cn). We collect records of 432 land lot transactions between 2003 and 2010. The information includes location, land area, construction area, floor area, land use type, benchmark price, transaction date, transaction price and the name of the real estate developer. We then match the land transaction data with monthly new home transaction records in Beijing from the Hang Lung Center for Real Estate of Tsinghua University (http://www.cre.tsinghua.edu.cn). The matching gives

[5]Data retrieved from Beijing Municipal Bureau of Statistics (http://www.bjstats.gov.cn). The household registration system, or *Hukou* in Chinese, is the official system that identifies a person's residency in an area.

[6]The examples of the policies are that, the down payment rate increased from 20% to 30% for all first-time home buyers; the mortgage rate discount declined from 30% to 15% of the benchmark interest rate; the same family would have to pay higher down payment and mortgage interest if purchasing second or third properties; mortgage loans to non-residents of a city were suspended unless they could prove that they have had paid taxes in that city for at least one year.

[7]From Beijing Municipal Bureau of Statistics (http://www.bjstats.gov.cn).

4,899 home transaction records for 198 residential property development projects after dropping observations with missing values and incorrect records[8]. Given the time lags from land transaction to property sales, the matched sales records are in the time range of 2006 and 2014. For each land lot, we calculate the distance to the city center, the nearest underground station, the nearest park, the nearest hospital and the nearest primary school with the location information. We also obtain real estate developers' ownership structure and listing status information from https://www.qichacha.com.

The dataset covers 11 out of 16 administrative districts in Beijing[9]. Figure 3 demonstrates the distribution of the observations amongst administrative districts[10]. The total number of land transactions recorded in each district between 2003 and 2010 is represented by different shades of blue, with dark colors representing high transactions. The four districts in the city core, i.e. Xicheng District, Dongcheng District, Xuanwu District and Chongwen District, have the smallest land transaction volume during the sampling period. Land transactions—as a proportion of the total land sales in the whole city—range between 0.01% (Dongcheng District) and 1.5% (Xuanwu District) in these districts. This result is because the majority of the land in the city core has already been fully developed or occupied with cultural heritages that are not allowed for redevelopment. Land transactions increase as the distance from the city center lengthens, such as in Daxing District (16.8%) and Fangshan (15.3%). We then overlay our sample points on the map with yellow crosses. The distribution of our sample points not only covers the most active parts of the land markets in Beijing but also resembles the geographical patterns of the population distribution closely. Hence, the sample is representative.

(Insert Figure 3 Here)

Table 1 exhibits the descriptive statistics of variables that measure the characteristics of land, project and real estate developers. The average land price is 5,617 RMB/m2 which is about one-third of the average house prices (19,721 RMB/m2). The standard deviations are high for

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[8]More specifically, we exclude records that have missing values and outliers (land prices or house prices three standard deviations away from the average price in the same development projects). We also exclude records that have house sales date earlier than land leasing dates.

[9]Five districts, i.e. Mentougou, Yanqing, Huairou, Miyun, and Pinggu, are omitted due to data availability.

[10]*Chongwen* and *Xuanwu* were independent administrative districts before 2010, and they were merged into *Dongcheng* and *Xicheng,* respectively in 2010. In Figure 3, we still treat them as independent districts because our sample period is mostly before 2010. Thus, samples distribute amongst 13 districts in Figure 3.

most of the variables and in some cases even higher than the mean, thereby indicating the high heterogeneity amongst the development projects and developers.

(Insert Table 1 Here)

4.2 Model Specification

Following the theoretical framework, we describe developers' asking price for residential real estate development project i (P_i) as a linear function of an indicator of loss ($LOSS_i$), the observable attributes ($\boldsymbol{X}_i$), the indicator of the year when house sales take place ($Year_i$), a constant (α_0) and the error term (ε_{it}). This specification is given in Equation (4). The definition of $LOSS_i$ can be found in Equation (5), where L_i is the actual land price; ref_i is the reference land price. $\boldsymbol{X}_i$ summarises a vector of hedonic attributes for house prices, including decoration level when sold (*DECO*), floor to area ratio (*FAR*), property management fee (*FEE*), average size of properties (*SIZE*), distance to city center (*DIST_CCT*) and distance to subway station (*DIST_SUB*). $Year_{i,t}$ equals one in the year of sales in project *i*, and zero otherwise. Note that all sales in our database occurred between 2006 and 2014, and $Year_{2006}$ is dropped as the base category. All measurements are at the project level. For instance, P_i is the average asking price of all saleable housing units in project *i* in the year of investigation.

$$P_i = \alpha_0 + \alpha_1 LOSS_i + \boldsymbol{X}_i\boldsymbol{\beta} + \sum_{t=2007}^{2014} \delta_t Year_{i,t} + \varepsilon_{it} \quad (4)$$

$$LOSS_i = \begin{cases} 1, ref_i - L_i < 0 \\ 0,\ ref_i - L_i \geq 0 \end{cases} \quad (5)$$

In this specification, if α_1 is substantially greater than zero, then prior losses are associated with high asking prices that developers set in the later stage of home sales.

Real estate development is a long and complex process, during which developers generally make constant adjustments to their strategies. This condition is particularly true during the sales stage of this process. Developers commonly sell housing units within the same project in phases, even if all units have already been completed. This approach allows developers to adjust listed prices such that any mispricing in previous sales could be corrected. Investigating if developers can overcome loss aversion as additional market information comes in (i.e. as sales progresses through multiple phases) is important. Therefore, we adopt two variations of

Equation (4) to investigate the initial effect of loss aversion and the overall effect of loss aversion throughout the sales period.

To investigate the initial effect of loss aversion, we consider sales in the first year of the sales period only. For project i, let t_1 be the first year of the sales period. Section 6 describes the model specification. $P_{i,1}$ is the average asking price of all saleable housing units in project *i* in the first year of the sales period. Coefficient α_1 captures the isolated, net effects of loss aversion. δ_{t1} is the year fixed effects that captures the influences from any other factors that are not included in $\boldsymbol{X}_i$.

$$P_{i,1} = \alpha_0 + \alpha_1 LOSS_i + \boldsymbol{X}_i\boldsymbol{\beta} + \sum_{t1=2007}^{2014} \delta_{t1} Year_{i,t1} + \varepsilon_{i,1} \quad (6)$$

To investigate the overall effect of loss aversion, we augment Equation (4) to include sales in the whole project sales period, as shown in Equation (7). $P_{i,n}$ is the average sales price. In our sample, the maximum length of sales period is eight years (i.e. developers spent up to eight years to sell all units in their projects). We create eight dummy variables (i.e. T_j, where j = 1, 2, 3, … 8) to indicate the different years when sales occurred during the sales period. Note that the dummy variable for the first year of sales period is omitted from Equation (7) because the effect has already been captured by δ_{t1}. We then create interaction terms between $LOSS_i$ and T_j to capture the effect of loss aversion, if any, in each year of the sales period. T_j is also included in Equation (7) to control for any other project-year specific effects other than loss aversion. $P_{i,n}$ is the average asking price of all saleable housing units in project *i* in the *n*th year of investigation. If a project took *N* years to sell out all of its units, then a total of *N* observations will be created for this project, one for each of the year within the sales period.

$$P_{i,n} = \alpha_0 + \alpha_1 LOSS_i + \boldsymbol{X}_i\boldsymbol{\beta} + \sum_{t1=2007}^{2014} \delta_{t1} Year_{i,t1} + \sum_{j=2}^{8} \delta_j T_j + \sum_{j=2}^{8} \alpha_j LOSS_i * T_j + \varepsilon_{i,n} \quad (7)$$

The overall or accumulative effect of loss aversion for the whole sales period can be constructed with the coefficient estimates of $LOSS_i$ and its interaction terms in Equation (7). If it took three years for a project to sell all the completed units, then the accumulative loss aversion effect in year one, two, and three can be calculated as $\hat{\alpha}_1$, $\hat{\alpha}_1 + \hat{\alpha}_2$, and $\hat{\alpha}_1 + \hat{\alpha}_2 + \hat{\alpha}_3$ respectively.

4.3 Reference Point Determination

Identifying reference point is crucial for the estimation of Equations (6) and (7). If the reference point is defined incorrectly, the developers might be placed in the wrong domain, and subsequently the measurement of losses could be wrong. This condition would render the whole analysis invalid. Unfortunately, prospect theory offers no clear guidance regarding the identification of reference points. In real estate loss aversion literature, the most commonly used reference point is previous purchase [See, for instance, 1; 5; 6; 36]. The advantage of such an approach is that previous purchase prices are observable and salient. However, this solution is not feasible for our analysis due to the very nature of land transaction and the land market in China because all of the land auctions in the country are the very first sales. No previous transaction information is available. To circumvent this data availability issue, we estimate the reference point by calculating the inverse distance weighted average price of comparable land transactions in the neighbourhood.

For each land lot i, we firstly implement a radius search to identify comparable land sales. The choice of an appropriate radius is important. Technically, a small radius gives close parcels of land, and thus comparable to land lot i. However, a small radius and searching area sometimes results in an insufficient number of parcels. A trade-off exists between precision and robustness. We tried various radiuses and found that 5 mile is the smallest radius that can offer sufficient sample size for our estimation. We then identify a total of Q_i comparable land transactions for land lot i within the 5 miles radius. Given that not all comparable land sales occurred in the same year, we discount the prices to year 2003. The discount rate, denoted as r_{year}, is the cumulative land price growth rate between the year of land transaction (*year*) and 2003. For instance, for a comparable land lot j in 2007, if the transaction price is p_j, then 2003 price is $p_j^* = \frac{p_j}{1+r_{2007}}$.

We also use an inverse distance weighting method to aggregate the prices of the Q_i comparable land transactions. The inverse distance weighting method ensures that closer transactions have high weights, whereas transactions further away have their contributions diminishing with distances. Let $k_{ij} = \frac{1}{distance_{ij}}$, where $distance_{ij}$ is the distance between land lot i and a comparable land lot j. Accordingly, the 2003 price p_j^* has a weight of $w_{ij} = \frac{k_{ij}}{k_{i1}+k_{i2}+\cdots+k_{iQ_i}}$.

The estimated comparable land price as of year 2003 is the weighted average of discounted land prices of all Q_i comparable land transactions, or $\sum_{j=1}^{Q_i} w_{ij} \times \frac{p_{ij}}{1+r_{year_j}}$.

Lastly, we convert the 2003 weighted average price to the year when land lot i was purchased, with r_{year_i}. In sum, the formula to calculate the reference point is as Equation (8).

$$ref_i = (1 + r_{year_i}) \times \sum_{j=1}^{Q_i} w_{ij} \times \frac{p_{ij}}{1+r_{year_j}} \quad (8)$$

5. Results and Discussions

After matching each land transaction with transactions within 5-miles radius, we drop six land lots that have no comparable transaction. For the remaining 192 land lots, 12 comparable transactions emerge for each lot on average. We identify 82 land transactions in the loss domain and 110 in the gain domain. Table 2 contrasts land prices and house prices in the two domains. Whilst reference land prices are only slightly greater in the gain domain than in the loss domain, i.e. 5,413 yuan/m^2 and 5,241 yuan/m^2, land transaction price differences are much larger, i.e. 7,458 yuan/m^2 and 3745 yuan/m^2. Thus, real estate developers in the loss domain purchase land lots of similar value at higher prices. The difference is great in the average house prices, i.e. 22,920 yuan/m^2 and 16,907 yuan/m^2, which is consistent with our hypothesis that developers in the loss domain set high house prices to pursue breakeven.

(Insert Table 2 Here)

Table 3 presents the Ordinary Lease Square (OLS) estimates of Equation (6). The coefficient estimates of control variables and year fixed effects are significant with expected signs. For simplicity, we present coefficient estimates of key variables only in Table 3. In column (1), we present results by using all sample points. *LOSS* has a positive coefficient that is significant at the 1% level. The coefficient confirms that developers compare land transaction with the reference price, and previous losses from land purchases affect their pricing decisions for houses that are completed later on these land lots. Specifically, developers in the loss domain set asking prices for newly completed houses 10% higher than their counterparts in the gain domain.

(Insert Table 3 Here)

5.1 Ownership

Existing evidence infers that state-owned enterprises (SOEs) and privately owned enterprises (PEs) behave differently, especially in their decisions directly associated with economic profits. Under state controls, SOEs sometimes forgo maximum economic profit in the pursuit of social and political benefits. For instance, SOEs usually have excessive labor inputs [37], and they are pressured to hire politically connected people, rather than those best qualified [38]. Thus, SOEs are less efficient and profit driven than PEs [39]. SOEs typically have soft budget constraints and consequently less pressure from losing money [40; 41; 42]. Even in financial distress, they can always rely on the state to bail them out. Thus, they are not sensitive to financial losses. However, PEs do not have the backing from the state, and have to take responsibility for the bad decisions they made and the resultant losses. They should be responsive to prior losses. SOEs also have better access to external financing and lower cost of credit than PEs. They enjoy direct budgetary support from the government and preferential treatment by government-owned financial institutions [43]. Given the low cost of credit, a painful loss to PEs may not be as painful to SOEs. Consequently, state-owned developers may be less motivated to set high house prices and pursue breakeven. The manner in which firm ownership structure moderates loss aversion effect must be tested.

A Chow Structural Break test on Equation (6) confirms that the coefficient estimates for SOEs and PEs are not identical. Consequently, we estimate Equation (6) using SOEs and PEs sub-samples separately. The results are given in columns (2) and (3) in Table 3. We find that PEs are sensitive to losses. They set 12% higher asking prices when in the loss domain. However, no evidence of SOEs responds to land transaction losses. The results are in line with the existing literature as discussed previously. We conclude that the loss aversion premium estimated in the previous step, i.e. the 10% price increase estimated by using the full sample, is largely driven by the private sector.

5.2 Listing Status

The extensive literature on initial public offering documents the benefits of stock listing. These studies indicate that listed firms enjoy better access to financial resources [44], lower cost of credit [44] and enhanced financial flexibility [43; 45] than unlisted firms. Therefore, we expect that firms that are listed on a stock exchange are less sensitive to losses than unlisted firms. Using the same strategy as outlined in Section 5.1, we test if listed and unlisted firms have different responses to prior losses. Again, a Chow Structural Break test confirms that the two types of firms behaved differently. We subsequently estimate Equation (6) for listed firms and unlisted firms respectively. The results are given in columns (4) and (5) in Table 3. Unlisted developers are more sensitive to losses than unlisted developers. They set asking 16% higher prices when they are in the loss domain. Listed developers, however, do not exhibit substantial loss aversion behaviour. Thus, the financial advantages provide listed companies with improved financial flexibility, and consequently cushions from temporary losses. The correlation between listed status and ownership structure in our sample is not high. For example, the correlation coefficient between the two variables is 0.445; the proportion of listed companies is 77%, 33%, and 52% for SOEs, Pes, and all companies combined, respectively. Therefore, the identified listing status effect is a separated issue from the ownership structure effect.

5.3 Overall Effect of Loss Aversion

In the previous section, we document that prior losses affect developer's pricing strategy when the property enters the market. In this section, we further probe if this effect persists throughout the whole selling period with model specified in Equation (7). We create one observation for each year of the project period, instead of only one observation in the first year of the project period in Equation (6). The total number of observations in this step tripled from 195 to 742 because the average sales period is 2.89 years. Given that observations from the same project are related, we use clustered standard errors to correct any potential biases in the estimation. Similar to the estimation of Equation (6), we have controlled for project, year and sales period duration fixed effects.

Table 4 shows the coefficient estimates of Equation (7). We construct the accumulative effect of loss aversion over the entire project period based on Table 4, and plot the results in Figure 4. SOEs are not included in Figure 4 because the coefficient estimates of $LOSS_i$ are insignificant across the board. The figure reveals a nonlinear relationship between the length of sales period and the effect of loss aversion on asking prices of newly completed apartments. If a project can sell out of its inventory within the first year, then the effect of loss aversion is estimated to be 14% of overpricing. Hence, developers' asking price is 14% higher than the fair market price. If it takes more than one year to clear the housing unit inventory, developers become rational in pricing the apartments in later stages of the sales. This change is evident from the downward slope of all curves from Year 1 to Year 3 in Figure 4. However, if it takes more than three years to sell out the units, developers will become loss averse over the time. This result is not surprising given the average length of sales period in our sample is 2.89 years. When a project takes longer than usual (i.e. 2.89 years or 3 years) to sell out, developers become anxious about recovering land transaction loss. This result is also consistent with the findings in the studies of disposition effect, which is caused by loss aversion. Hence, the ones who are most prone to loss aversion effect are the least likely to sell at a loss, and thus likely to have the longest sales period. Therefore, loss aversion effect is the largest for projects with the longest sales period (i.e. 8 years in our sample).

(Insert Table 4 Here)

(Insert Figure 4 Here)

6. Alternative Reference Point Determinations

In their influential paper, Kahneman and Tversky [9] provided a few candidates for reference point, such as the status quo, the expectations of decision makers and the formulation of offered prospects. However, empirical difficulties arise when applying their theory. Specifically, reference points are often formed under the influence of heuristics and biases; they are unobservable, heterogeneous and possibly nonstationary [46]. As such, the determination of reference points an empirical issue, and no hard and fast rule exists. On the one hand, this situation encourages and enables researchers to identify a wide range of reference points. On the other hand, it requires most behavioural studies to establish the robustness of their findings to different choices of reference points. In this section, we present results using an alternative definition of reference point in the estimation of Equations (6) and (7) to verify the robustness of our findings.

We consider a rational version of reference point, i.e. land price valuation based on hedonic price modelling. Real estate developers are professionals who know their markets and products well. Their knowledge and experience will help them form the reference point based on their implicit estimation of the land prices, especially when land lots are in areas with less frequent transactions. We adopt hedonic pricing technique to capture this implicit valuation process based on land hedonic characteristics. This technique has been widely used in the studies of land prices[11].

We develop the valuation-based reference point by adopting a semi-log model specification as proposed by Mills (1971), Kau and Sirmans [47] and summarised by Colwell and Munneke [48]. The model specification is shown in Equation (9).

$$\text{Ln } L_i = \theta_0 + \boldsymbol{Y}_i\boldsymbol{\theta_1} + \boldsymbol{T}_i\boldsymbol{\theta_2} + \varepsilon_{i,} \quad (9)$$

where Ln $L_i$is the natural logarithm of land price per square meter for land parcel i; $\boldsymbol{Y}_i$ is a k×1 vector of explanatory variables including locational attributes, physical attributes, land use and developer characteristics; $\boldsymbol{T}_i$ is a set of binary dummy variables which equals 1 only in the year of land transaction; $\boldsymbol{\theta_1}$ and $\boldsymbol{\theta_2}$ are coefficients to be estimated; ε_i is identically and independently distributed errors.

The choice of independent variables and the estimates of Equation (9) can be found in Appendix 1. We then use the predicted land value as developer's reference point, i.e. $\widehat{L_i} = ref_i$, and calculate the indictor of losses in Equation (3) accordingly. Table 5 presents the new OLS estimates. Loss coefficients have similar positive signs and are of similar magnitudes as in Section 5. Thus, the presence of loss aversion is confirmed. PEs and unlisted firms are still significantly loss averse, with coefficients of 0.13 and 0.20, respectively. SOEs and listed firms are still less loss averse than their counterparts. Therefore, our conclusion still holds that PEs and unlisted firms are more sensitive to losses than SOEs and listed firms.

The overall effect of loss aversion also exhibits nonlinear relationship with the year in the sales period, as demonstrated in Figure 4. We did not report the estimated overall loss aversion effects for years 6 to 8 because observation numbers are insufficient (i.e. less than 20 data points) to obtain reliable estimations. This condition is an inherent shortcoming for the hedonic price modelling approach, which is more data intensive than the weighted average comparable prices approach used in Section 5. Figure 4 suggests that the overall loss aversion effect

[11] It was developed from theory of consumer behaviour, which suggests that commodities are valued for their individual utility-bearing attributes or characteristics [47]. Various studies have explored this model in terms of attribute selection [48; 49], functional form specification [50] and possible biases involved in the valuation method [51]. For recent applications in land valuation literature, see for example, Wang [52], Sirmans and Slade [53], and Nichols et al. [54].

decreases from year 1 to year 3, and gradually bounces up since the fourth year. The pattern is very similar to that in Figure 3. Overall, our conclusions remain the same when the alternative definition of reference point is used.

(Insert Table 5 Here)

(Insert Figure 5 Here)

7. Conclusions

Using land transaction and apartment sales data in Beijing, this paper shows that prior losses from land transactions affect developer's pricing decisions for new homes. The effects are also moderated by ownership structures and listing status of the developers. We find that SOEs or listed firms are not sensitive to prior losses in land transactions when pricing their newly completed apartments. The loss aversion effect is strong in the first year and towards the end of the sales period. Our findings add to the existing literature in the following ways.

Firstly, whilst the presence of loss aversion in household-level decisions has been proven, behavioural studies on real estate developers' decisions are lacking. Developers play crucial roles in both the land and the housing markets. Cognitive bias in their behaviours, if any, will potentially affect both markets. In comparison with the general public, real estate developers are more experienced and knowledgeable of the market. They work in groups and make decisions with higher stakes. Consequently, they are less likely to be affected by behavioural or cognitive biases [49; 50]. Nevertheless, we identify strong evidence of reference dependence and loss aversion amongst Chinese real estate developers. Thus, the persistence and robustness of reference dependence and loss aversion are confirmed as have been found in other studies [see, for example, 13].

Secondly, our findings also shed lights on ways to mitigate or even eliminate loss aversion effects. As discussed previously, experience and high stakes cannot help real estate developers overcome loss aversion. Nevertheless, SOEs do not exhibit loss aversion effect at all, whilst listed firms are less affected than their unlisted counterparts. Thus an effective way to overcome loss aversion is to write off prior losses as sunk costs, partially or completely. Specifically, SOEs view losses from land transactions as sunk costs and write them off implicitly, knowing that the costs will be bared by the states. Therefore, their decisions about house prices are not affected by prior losses. Similarly, listed firms have better access to financing and are often of much larger scale than unlisted firms in China. They are more likely to recognise prior land transaction losses as sunk cost and behave more rationally in deciding the listing prices of new apartments. As such, the effect of loss aversion is overcome, albeit partially. This finding, once again, confirms the persistent nature of loss aversion. One cannot easily overcome loss aversion through practice or by using willpower. The most effective way is to write off the loss, or move the decision maker out of the loss domain.

Results also have implications for our understanding of the Chinese real estate markets. Whether high land prices are to blame for the overheating in housing market in China or not is a hot topic for debate [51; 52]. Although our paper does not answer this question directly, the findings deduce that land overpricing is likely to spillover to housing market. As developers are reluctant to write off losses from overbidding in land auctions, overpricing mistakes in land market will not be corrected in the pricing decisions in the housing market. This condition will push up the price in housing market accordingly. If the central government of China wants to cool down the housing market—which is one of the strategic priories in the recent five-years plan of the nation—then it should look upstream, i.e. the land market, to find an effective solution. Our findings present yet another evidence that the land and housing markets in China are closely intervened, and should not be studied or regulated in isolation [53; 54].

Appendix

We follow the land valuation literature to select the independent variables in Equation (9). The first group is the locational attributes, including the distance to the city centre, distance to the nearest amenities, i.e. underground station, primary school, park and hospital. They normally affect house prices negatively. The second group comprises two binary variables indicating land use restrictions, i.e. commercial use and public use. All land parcels in our sample are restricted to residential development as the main land use purpose. However, some are allowed/required to have public use or commercial use too. Public and commercial land will, on the one hand, improve the convenience in the neighbourhood which has positive effect on future house prices. On the other hand, they also drive up construction costs. These considerations are taken into account by the developers when they purchase the land parcel. We also include floor area rather than land area in the regression to represent lot size. In China, the maximum floor area ratio is always explicitly provided in any land-leasing contract and developers cannot construct over the floor area stated in the contract. Thus, floor area is more informative than land area in showing the potential of the land parcel.

As for developer characteristics, we use a dummy variable to indicate private ownership, as SOEs normally have stronger financial capability and flexibility to offer high land prices. Another important variable is a dummy variable for joint auction. When two or more developers purchase land parcels jointly, they have improved purchasing power so that they can bid high for favorable land parcels. Therefore, joint auction is a possible signal for high land price.

Table A.1 exhibits the estimates of Equation (9). The models passed all standard diagnostic tests except the VIF (variance inflation factor) test for multicollinearity. The five distance variables are correlated. Multicollinearity leads to inflated standard errors and insignificant p-values. However, given that this issue will not affect prediction, which is our main purpose of this analysis, we do not take further action to address this issue.

(Insert Table A.1 Here)

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Figure 1 Real Estate Development in China

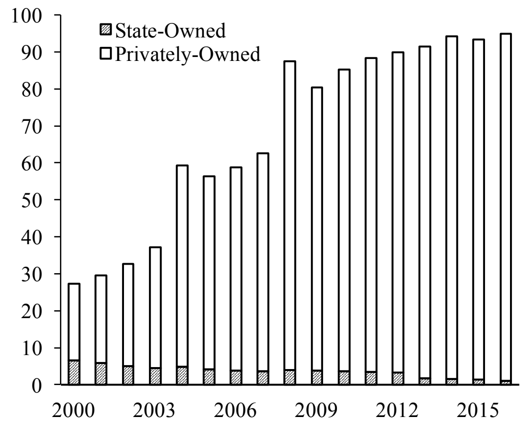


Figure 1.1: # of Real Estate Developers (1,000)

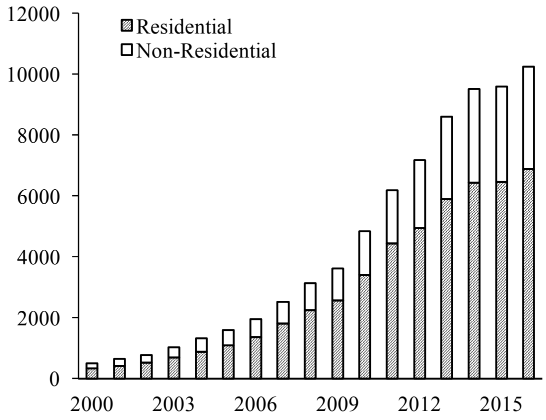


Figure 1.2: Real Estate Investment (Trillion *yuan*)

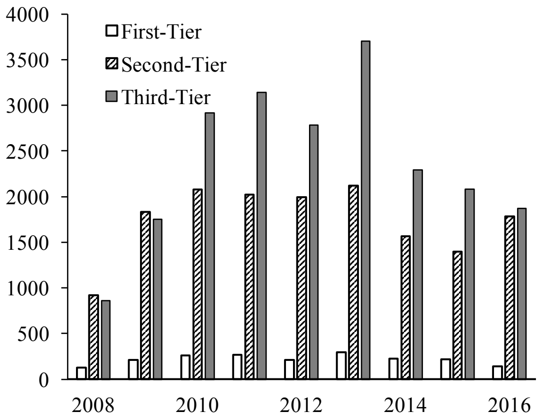


Figure 1.3: Land Transaction Volume

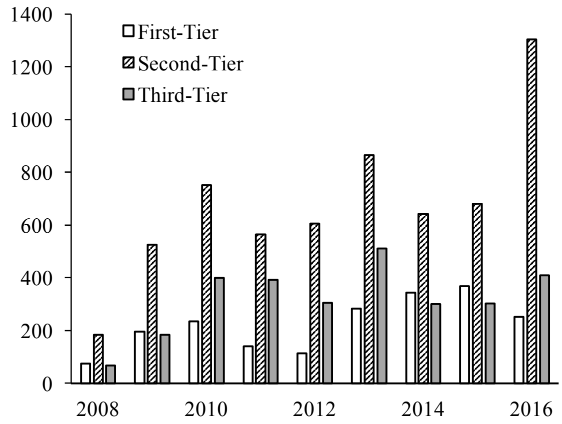


Figure 1.4: Land Transaction Revenues (Trillion *yuan*)

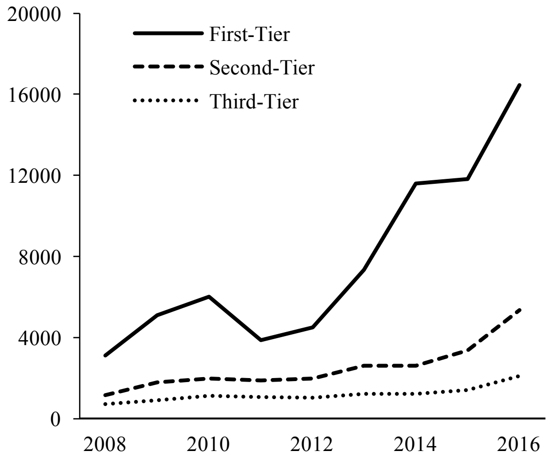


Figure 1.5: Land Price (*yuan/m*^{2})

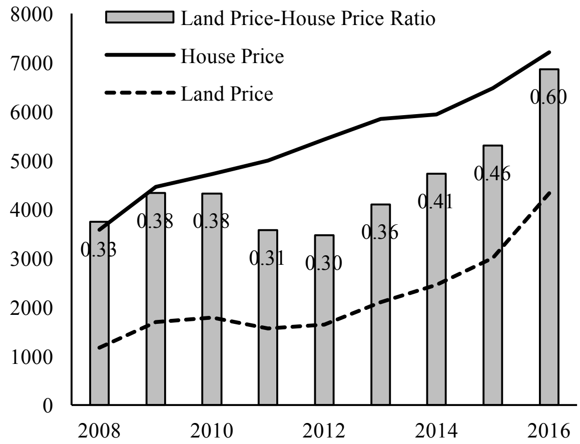
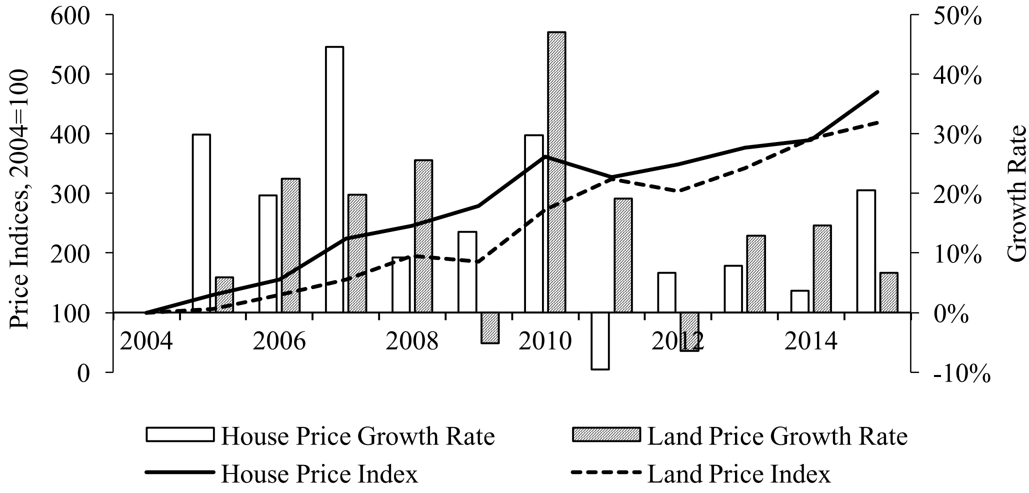


Figure 1.6 House & Land Price (National, *yuan/m*^{2})

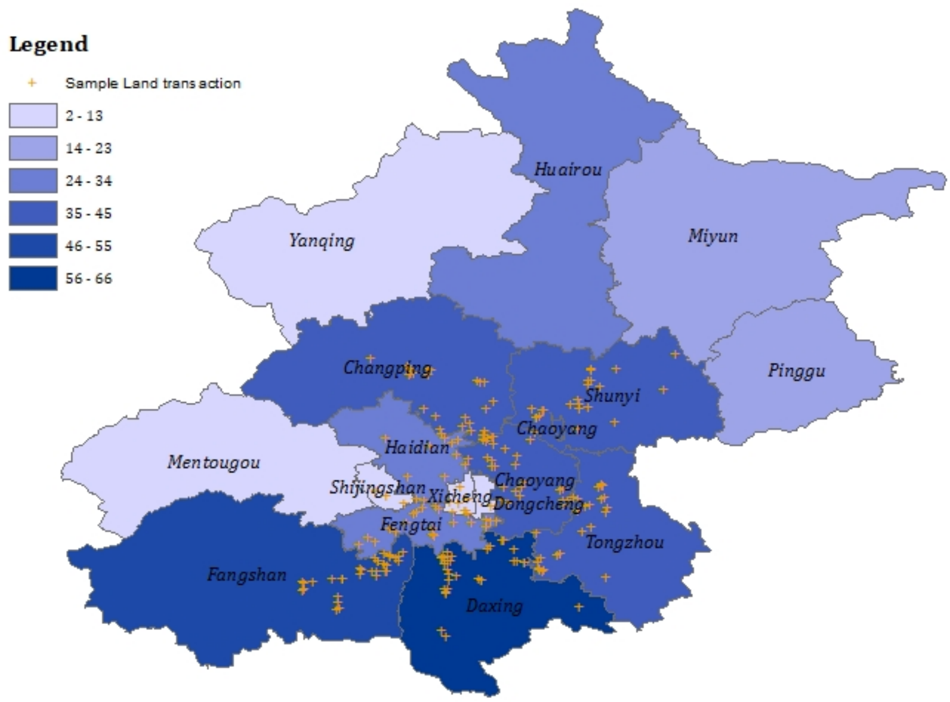
Sources: Wind & National Bureau of Statistics of China

Figure 2 House and Land Price Indices in Beijing (Annual): 2004—2015



Notes: The left axis represents indices; the right axis represents growth rates. For both indices (left axis), 2004 = 100.
Sources: House price indices are retrieved from National Bureau of Statistics of China. Land price indices are retrieved from Jing, Deng and Gyourko, 2012, NBER working paper. Growth rates (right axis) are from authors' own calculation.

Figure 3 Land Transaction in Municipal Districts



Sources: Land transaction records are from Beijing Municipal Commission for City Planning and Land Resources Management (http://ghgtw.beijing.gov.cn).

Figure 4 Overall Effect of Loss Aversion

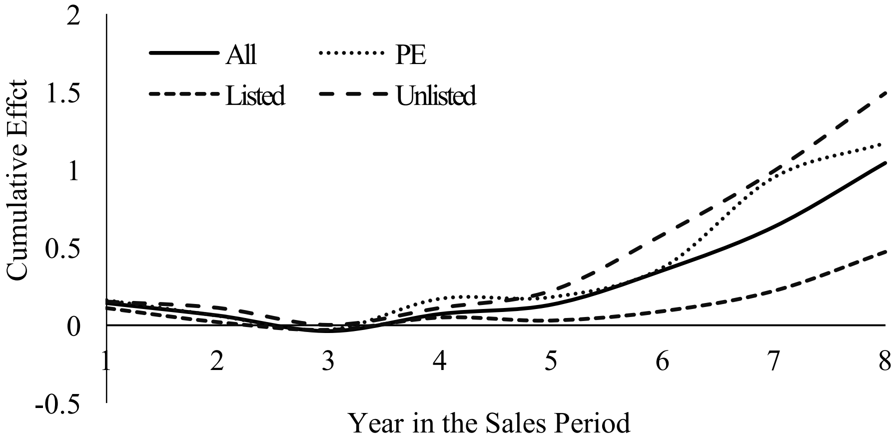


Figure 5 Overall Effect of Loss Aversion (Valuation-Based Reference Point)

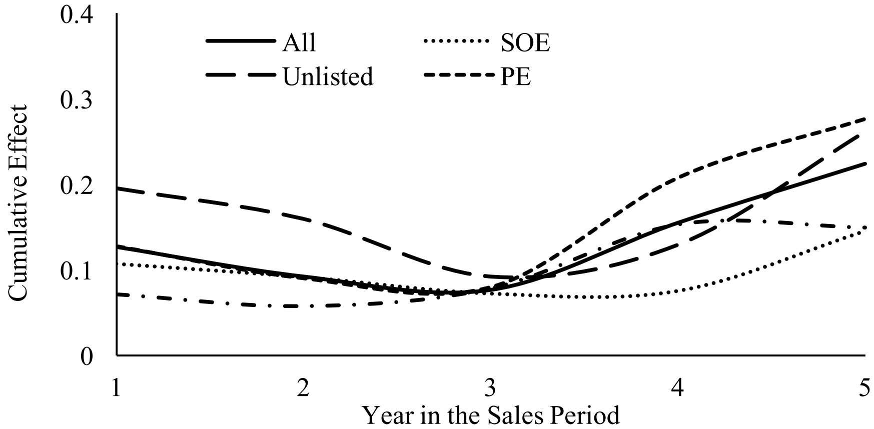


Table 1 Summary Statistics of Key Variables

Variable name	Definitions	Mean	*SD*
Land characteristics			
DIST_CCT	Distance to city centre (km)	21.77	10.12
DIST_UGS	Distance to nearest underground station (km)	2.91	3.42
DIST_EPS	Distance to nearest elementary primary school (km)	12.61	8.71
DIST_HSP	Distance to nearest hospital (km)	12.59	8.25
DIST_PAR	Distance to nearest park (km)	8.11	6.67
LANDAREA	Land area (1,000 m^2)	90.44	79.28
FLOORAREA	Floor area (1,000 m^2)	170.59	127.86
PUBLIC	Commercial use included	0.34	0.48
COMMERCIAL	Public use included	0.25	0.44
LPRICE	Land price (1,000 yuan/m^2)	5.62	4.34
Project characteristics			
DECO	Average decoration cost (yuan/m^2)	858.41	1991.51
FAR	Floor area ratio	2.09	0.79
FEE	Property management fee (yuan/m^2)	3.18	1.86
SIZE	Average unit size (m^2)	121.76	52.22
HPRICE	House price (1,000 yuan/m^2)	19.72	10.88
Developer characteristics			
LISTED	Listed	0.48	0.50
PE	Private enterprise (All PEs in joint purchase)	0.44	0.50
JOINT	Jointly purchased by more than one developer	0.19	0.40

Table 2 Land and House Prices in the Gain and Loss Domains

	Obs.	Mean	*SD*	Min	Max
Panel A. Loss domain					
# Comparable land lots	82	11.35	5.61	1	23
Reference price	82	5,412.66	2,653.26	1,210.38	12,574.76
Land price	82	7,457.50	3,704.49	1,498.00	18,014.00
House price	82	22,920.57	12,379.52	3,217.41	69,970.85
Panel B. Gain domain					
# Comparable land lots	110	12.25	5.19	1	25
Reference price	110	5,241.36	2,650.09	1,268.61	14,619.67
Land price	110	3,745.19	2,240.85	347.00	12,523.00
House price	110	16,906.57	7,457.71	3,688.53	43,420.94

Notes: The unit for prices is 1000 yuan/m2.

Table 3 Coefficient Estimates of Equation (6)

Reference point	Within 5 miles (inverse distance weighted average)				
Sample	(1) All	(2) SOE	(3) PE	(4) Listed	(5) Unlisted
LOSS	0.10***	0.04	0.12**	0.06	0.16***
	(0.03)	(0.05)	(0.05)	(0.04)	(0.05)
DECO	3.97***	3.04*	4.31***	3.34**	4.24***
	(0.98)	(1.58)	(1.33)	(1.35)	(1.18)
FAR	0.03	0.13***	0.01	0.05	0.02
	(0.03)	(0.03)	(0.03)	(0.05)	(0.03)
FEE	0.06***	0.08***	0.06***	0.08***	0.05***
	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)
SIZE	1.03**	0.63	1.01*	0.95	1.11**
	(0.40)	(0.68)	(0.52)	(0.58)	(0.47)
DIST_CCT	-2.33***	-2.43***	-2.17***	-1.81***	-2.83***
	(0.28)	(0.41)	(0.37)	(0.40)	(0.35)
DIST_SUB	-0.44	-0.47	-0.07	-1.66*	0.47
	(0.71)	(1.12)	(0.96)	(0.99)	(0.87)
CONSTANT	8.89***	8.69***	8.96***	8.91***	8.94***
	(0.13)	(0.20)	(0.16)	(0.18)	(0.15)
R-squared	0.86	0.91	0.85	0.85	0.89
Adj. R-squared	0.85	0.89	0.82	0.82	0.87
Number of obs.	191	86	105	99	92

Notes: Standard errors in parentheses. Apart from the variables listed in the table, all regressions also include dummy variables for the transaction year. Their coefficients are significant and omitted from the table for simplicity.

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Table 4 Coefficient Estimates of Equation (7)

Reference point	Within 5 miles (inverse distance weighted average)				
Sample	(1) All	(2) SOE	(3) PE	(4) Listed	(5) Unlisted
LOSS	0.14***	0.09	0.16**	0.11**	0.15*
	(0.05)	(0.07)	(0.07)	(0.05)	(0.09)
*LOSS*T_2*	-0.08*	-0.04	-0.10*	-0.09*	-0.04
	(0.04)	(0.07)	(0.06)	(0.05)	(0.08)
*LOSS*T_3*	-0.10*	-0.10	-0.09	-0.05	-0.11
	(0.06)	(0.10)	(0.08)	(0.06)	(0.11)
LOSS T _4*	0.11	-0.02	0.20**	0.08	0.11
	(0.07)	(0.10)	(0.10)	(0.07)	(0.13)
LOSS T _5*	0.06	0.19	0.01	-0.02	0.11
	(0.13)	(0.15)	(0.18)	(0.12)	(0.19)
LOSS T _6*	0.22	0.24	0.19	0.06	0.36**
	(0.15)	(0.18)	(0.21)	(0.27)	(0.16)
LOSS T _7*	0.28	0.13	0.58**	0.13	0.41**
	(0.22)	(0.33)	(0.24)	(0.42)	(0.19)
LOSS T _8*	0.41**	0.48*	0.22	0.25	0.50**
	(0.17)	(0.26)	(0.15)	(0.21)	(0.25)
CONSTANT	9.90***	9.60***	9.91***	9.94***	9.82***
	(0.15)	(0.24)	(0.21)	(0.18)	(0.22)
Project fixed effect	YES	YES	YES	YES	YES
Year fixed effect	YES	YES	YES	YES	YES
Sales duration fixed effect	YES	YES	YES	YES	YES
R-squared	0.66	0.72	0.65	0.70	0.64
Adj. R-squared	0.65	0.69	0.62	0.68	0.61
Number of Obs.	742	328	414	365	377

Notes: Standard errors in parentheses. Apart from the variables listed in the table, all regressions also include control variables for property attributes, transaction years and sales duration. Their coefficients are significant and omitted from the table for simplicity.

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Table 5 Coefficient Estimates of Equation (7): Alternative Reference Point

Reference point	Within 5 miles (inverse distance weighted average)					Hedonic valuation				
Sample	All	SOE	PE	Listed	Unlisted	All	SOE	PE	Listed	Unlisted
LOSS	0.14***	0.09	0.16**	0.11**	0.15*	0.13**	0.11*	0.13*	0.07	0.20**
	(0.05)	(0.07)	(0.07)	(0.05)	(0.09)	(0.05)	(0.06)	(0.07)	(0.06)	(0.08)
*LOSS*T_2*	-0.08*	-0.04	-0.10*	-0.09*	-0.04	-0.03	-0.02	-0.04	-0.01	-0.04
	(0.04)	(0.07)	(0.06)	(0.05)	(0.08)	(0.04)	(0.06)	(0.06)	(0.05)	(0.08)
*LOSS*T_3*	-0.10*	-0.10	-0.09	-0.05	-0.11	-0.02	-0.02	-0.01	0.02	-0.07
	(0.06)	(0.10)	(0.08)	(0.06)	(0.11)	(0.06)	(0.09)	(0.08)	(0.06)	(0.10)
*LOSS*T_4*	0.11	-0.02	0.20**	0.08	0.11	0.08	0.00	0.13	0.08	0.04
	(0.07)	(0.10)	(0.10)	(0.07)	(0.13)	(0.07)	(0.08)	(0.10)	(0.07)	(0.11)
*LOSS*T_5*	0.06	0.19	0.01	-0.02	0.11	0.07	0.07	0.07	-0.00	0.13
	(0.13)	(0.15)	(0.18)	(0.12)	(0.19)	(0.10)	(0.13)	(0.13)	(0.10)	(0.14)
CONSTANT	0.14***	0.09	0.16**	0.11**	0.15*	9.85***	9.65***	9.82***	9.93***	9.67***
	(0.05)	(0.07)	(0.07)	(0.05)	(0.09)	(0.14)	(0.22)	(0.21)	(0.18)	(0.22)
Project fixed effect	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year fixed effect	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Sales duration fixed effect	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
R-squared	0.66	0.72	0.65	0.70	0.64	0.70	0.75	0.68	0.75	0.67
Adj. R-squared	0.65	0.69	0.62	0.68	0.61	0.69	0.73	0.67	0.74	0.65
Number of obs.	742	328	414	365	377	695	298	397	344	351

Notes: Standard errors are enclosed in parentheses. Apart from the variables listed in the table, all regressions also include control variables for property attributes, transaction years and sales duration. Their coefficients are significant and excluded from the table for simplicity.
*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Table A.1 Land Hedonic Valuation Estimates

Explanatory variable	**Coef.**	**Std. Err.**
Distance to the city centre (*m*)	-1.151	1.179
Distance to the nearest underground station (*m*)	2.398	1.325
Distance to the nearest primary school (*m*)	-3.497	1.705
Distance to the nearest park (*m*)	2.089	1.035
Distance to the nearest hospital (*m*)	-2.101	1.542
Floor-area-ratio	0.002	0.048
Commercial use	-0.062	0.073
Public use	0.012	0.084
Joint action	-0.060	0.084
Listed	0.160	0.075
Private enterprise	0.018	0.073
Constant	7.705	0.288
Number of obs.	198	
Adj. R-squared	0.65	

Notes: Dependent variable is log land price. We also include dummy variables for the year of land transaction. Their coefficients are significant, but they are excluded in the table for simplicity.