Multiple Reference Points and Length of Ownership in the Housing Market

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Abstract:[1]

Reference-dependent utility has been shown to have a significant influence on housing market activity. Sellers facing a nominal loss on their home due to market conditions, tend to inflate the asking price and thus the transaction price of their home, indicative of loss aversion. However, the original purchase price of a home may lose influence as a reference-point as the period of ownership increases, while homeowners rely increasingly on other benchmarks such as neighboring homes' sales prices as reference points. In other words, a homeowner may have multiple reference points in their underlying utility function, whose relative influences shift in importance over time. We use comprehensive administrative data on residential real estate transactions in Singapore's private housing market to test the influences of original purchase price and recent neighborhood price as reference points over the length of homeownership. Purchase price and neighborhood price are each valid reference points based on established empirical methods in the behavioral and housing economics literature. By testing for their relative influences as a function of length of ownership, we find that prior purchase price is more influential for the first years of ownership, while neighborhood price becomes more influential during the subsequent holding years. Finally, we provide a theoretical framework for understanding the relative influences of multiple reference points over time, which supports the empirical findings.

Keywords: reference-dependence, multiple reference points, housing market, length of ownership

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1. Introduction

Housing market transactions are among the most substantial decisions an individual makes in their lifetime. Sellers have been shown to exhibit loss aversion in their pricing and transactions choices (Genesove and Mayer, 2001; Anenberg, 2011; Bokhar and Geltner, 2011; Bucchianeri and Minson, 2013; Liu and van der Vlist, 2019). The evidence for loss aversion in the housing market rests on the phenomenon that when facing a transaction in the loss domain of utility, sellers ask for and sell at higher prices than the market would otherwise predict. Prior studies in this line of research have demonstrated that the prior purchase price of the home (ie. lagged status quo) is a reference point for home sellers, thus serving as the benchmark against which losses and gains are calculated.

However, as time elapses since the purchase of the house, do homeowners continue to hold their original purchase price as the main reference point? In this study, we evaluate the hypothesis that while the prior purchase price is an influential reference point during the initial years of homeownership, homeowners selling their house several years after their original purchase use a different reference point as their benchmark: the recent price of neighboring homes. In other words, after originally purchasing a house, selling that same house shortly thereafter tends to invoke the prior transaction price as the reference point, whereas a longer holding period may drive sales prices towards a price at which neighboring apartments have recently sold.

Some debate exists in the literature regarding whether reference-dependent utility is a robust form of preferences, or whether it can be mitigated with experience. List (2003, 2004) and Tong et al (2006) find evidence that reference-dependent behavior diminishes with experience. However, other studies such as Pope and Schweitzer (2011) and Eil and Lien (2014) find that highly experienced decision-makers still exhibit reference-dependent behavior.[2] One possibility is that while reference-dependence may be fundamental in how decision-makers value outcomes, the actual reference point against which they evaluate outcomes may not be static in nature, but may instead shift over time. For example, in the real estate context, homeowners may eventually stop evaluating possible selling prices based on a comparison to their own original purchase price, but instead start to evaluate offers based on the prices at which their neighbors have recently sold their homes.

To our knowledge, our study is the first to apply the possibility of two reference points of time varying influence in the context of the real estate market. Although a shift in reference points over time holds intuitive appeal, most prior studies of reference-dependence in the housing market and in studies using field data more generally, focus on the influence of a single reference point. In the real estate context, studies have specifically focused on the original purchase price as the reference point of sellers.[3] However, it is reasonable to think

[2] Post, Van den Assem, Baltussen and Thaler (2008) provides evidence that reference-dependent behavior also persists over very high stakes.

[3] A notable recent empirical test of reference-dependence in the housing market is Andersen, Badarinza, Liu, Marx and Ramadorai (2021), which utilizes Danish data to establish reference-dependence, but finds limited influence of loss aversion specifically. Their study shares with ours in terms of examining both distributional and average reference-dependent effects in a housing market using detailed transactions data, while methodologically, their main empirical estimation is structural in nature whereas our distributional analysis is essentially non-parametric. Our study also departs crucially from theirs in that they examine a single reference point (prior purchase price), while our study focuses on establishing both prior purchase price and recent neighborhood price as reference

that over time, homeowners may shift their reference-point from the price level they personally experienced previously, to a price level that is more representative of the current situation in their local neighborhood. Using administrative data on residential real estate in Singapore, we find that sellers shift over time from being reference-dependent around their original purchase price, to being reference-dependent around a recent neighborhood price.

The empirical methodology we utilize is twofold, and for each method, we establish the reference-dependence around prior purchase price and recent neighborhood price separately, then consider the two candidate reference points as competitors in relation to the years of ownership. Using each approach, we find evidence that over time, homeowners shift from holding a reference point based on prior purchase price, to one based on the recent median neighborhood price.

First, we use a distributional approach similar to that in Lien and Zheng (2015), Allen, Dechow, Pope and Wu (2017), Rees-Jones (2018), and Gao, Lien and Zheng (2019), to cross-sectionally identify bunching in the price distribution around the candidate reference point. We examine the distribution of price differences compared to each reference point candidate, focusing on a narrow window to identify irregular changes in empirical likelihood along the relative price level. The distribution of transactions prices bunches around each reference point in the relative likelihood pattern of being in immediate vicinity of the reference point, gains, and losses, generally in that order - typically with a discontinuity in the distribution at the candidate reference point. When incorporating both reference points into the empirical framework, the distributional pattern generally shifts from one of centering around the prior purchase price to one of centering increasingly around the recent neighborhood price with a similar pattern, as years of ownership increase.

In our second empirical approach, we follow Genesove and Mayer (2001) and subsequent related studies in the real estate economics literature by estimating a hedonic model for incurred loss, then evaluating how estimated loss incurred is related to the transactions price. This method focuses on capturing the average treatment effect of the seller's house being in the loss domain at the time of sale, and allows us to control for housing project and observable individual house features.[4] We find that whether evaluating the reference points either separately or together, loss tends to have a positive relationship with price, indicating homeowner aversion to incurring a loss along either reference domain. Extending this empirical approach to account for shifts in loss aversion patterns over years of ownership allows us to test our length of ownership hypothesis based on average effects.

Finally, we propose a shifting reference point theoretical framework to explain the empirical findings, modeling homeowners' selling decisions under multiple reference points, which vary in salience as a function of time. The model is closely related to that in Bhatia and Golman (2019), which suggests attention as a key determinant of reference-point influence. As the time of ownership increases, the original purchase price

points whose relative influences shift over the ownership period. Comparatively, the data utilized in our study is arguably well-suited to our shifting reference point hypothesis due to the relative homogeneity of housing units in Singapore, which facilitates the comparison of sales prices among neighbors in the same housing complex.

[4] A project, also known as a real estate development, which typically includes several buildings and hundreds of units. Neighborhoods, projects, and complexes are used interchangeably in this paper.

becomes less salient due to reduced attention as a function of time passed, while the neighborhood price receives greater attention.

We utilize the complete administrative data of private housing market transactions in Singapore from years 1995 to 2017. The Singapore housing market has several attractive features for the purposes of the analysis. For one, all units within each residential project in Singapore are quite homogenous in terms of the external and internal attributes (Baltagi and Li, 2015; Huang, Li and Ross, 2018), which reduces the heterogeneity of house features and pricing uncertainty in the market. In addition, Singapore's housing market can be described as a small but open market, which undergoes periodic ups and downs based on global conditions, allowing us to test for reference-dependence without a single monotonic trend dictating the pricing patterns over time. Finally, Singapore is a significant real estate market in the context of Asia, being highly transacted given the geographic area and population density, but small enough such that our data contains almost all the transactions in the market over the sample period.[5] These features of the Singapore housing market make it particularly suitable for studying potential changes in reference-dependence over time using our two empirical approaches.

The two main empirical approaches we utilize are complementary to one another in that they both establish reference-dependence, but using different approaches. The distributional approach allows us to visually and empirically observe precise irregularities in the price distribution that are indicative of reference point driven behavior. The benefit is that we are able to observe the price effects of reference-dependence directly from the raw data, without relying on particular empirical methods or specifications. Observable covariates in the data are controlled for, but are assumed to not be fully responsible for irregularities in the price distributions that take the form of sharp local discontinuities or asymmetries. On the other hand, the two-stage hedonic model approach has the benefit of being able to control for housing project and property level characteristics to determine whether the loss domain inflates prices. The shortcoming of this approach being that by focusing on estimating average effects, we are less able to describe precise patterns in the price distribution. Utilizing both approaches enables us to better understand both the overall average effect and the distributional effects in the narrow window over the homeownership period.

The remainder of this paper is organized as follows: Section 2 briefly discusses the institutional details of the housing market in Singapore. Section 3 describes the data and empirical strategies, and in Section 4 we present descriptive evidence and the empirical results. A theoretical framework which can account for the results is presented in Section 5. We conclude and discuss in Section 6.

2. Residential Property Market in Singapore

There are three types of residential properties in Singapore: private non-landed properties (including private apartments and condominiums), private landed properties, and public housing which are locally known as Housing and Development Board (HDB) flats. Based on the 2015 Singapore General Household Survey, about 80.1% of resident households live in HDB dwellings, which are designed to be subsidized

[5] The idea of a neighborhood-based reference-dependence is based on anecdotal practice that homeowners in Singapore check online for recent sales prices within the same housing complex, before deciding on one's own asking price.

affordable housing for Singapore citizens. Private non-landed properties are occupied by 13.9% of resident households, while 5.6% of resident households live in landed properties, and the remaining 0.3% live in other types of properties.[6]

We restrict our sample to the private non-landed residential market for the analysis. Private non-landed properties are those for which the land is leased from the government through either a 99-year lease or a 999-year lease, but the house itself is owned by an individual. We make this restriction for several reasons. First, private residential housing is likely to be affected by market forces that impact the price of housing, unlike HDB flats which are heavily subsidized by the government. While HDB flats make up the largest portion of the overall housing market in Singapore, we exclude these units due to the high subsidy received when purchasing a HDB unit as well as other policies that restrict the supply and demand of these properties.[7] Second, the market for private non-landed housing is much more active compared to the public housing market, although the market share is not as large as that for public housing. Units in landed private properties make up a very small portion of the market, less than 5%, and are not frequently transacted.

Finally, compared to other market segments, private non-landed housing units within each residential project are largely homogenous in terms of the attributes of the units.[8] Typically, all units within the same project have the same type of renovations, the same basic household appliances, outdoor facilities and they are fully furnished (Baltagi and Li, 2015; Huang, Li and Ross, 2018).[9] This provides an opportunity to explore price variation of almost identical units in the same project, after adjusting for hedonic features such as floor and area. The largely homogeneous features of homes once controlling for the main observable characteristics in the data, is one of the key reasons why the housing market in Singapore is ideal for our study.

Since Singapore is a small open economy, its housing market is subject to global economic conditions, and has thus gone through several periods of upswings and downturns during the sample period. As Figure 1 shows, since 1995, the market has gone through four major housing market downturn periods. These correspond to the Asian Financial crisis in the late 90s, the dot-com bubble in the US in the early 2000s, the global financial crisis originating in the US subprime mortgage crisis in 2008, and the most recent time period which corresponds to the Singapore government's cooling policy measures in the housing market. The ups and downs of the market during the sample period allow us to examine how the influence of reference points depends on market conditions, although it is not the main focus of this study.[10]

Finally, as a major metropolitan center, Singapore's housing market is one of the important and active housing markets in Asia. The Singapore housing market serves as a residence and investment source for local

[6] Source: https://www.singstat.gov.sg/docs/default-source/default-document-library/publications/publications_and_papers/GHS/ghs2015/ghs2015.pdf

[7] For more information on the policies and the nature of the subsidy for HDB housing flats in Singapore, see: https://lkyspp.nus.edu.sg/wp-content/uploads/2014/11/Public-Housing-in-Singapore.pdf.

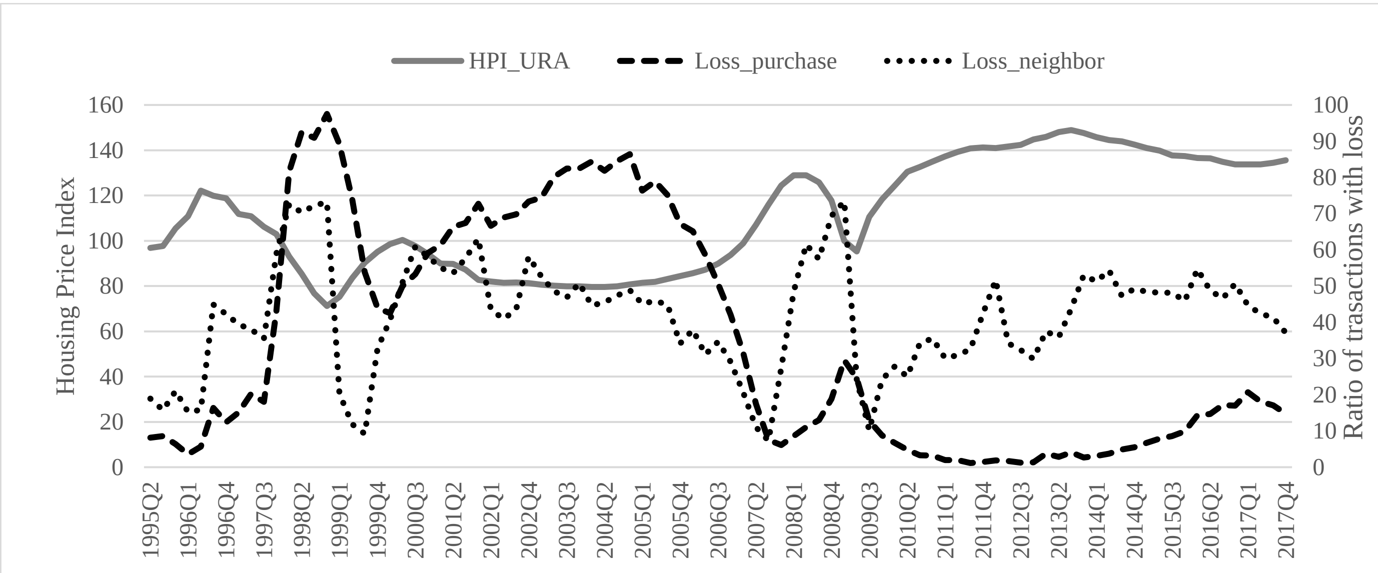
[8] In Singapore, "project" means "real estate development". One project typically includes several buildings and hundreds of units.

[9] Guntermann, Liu, and Nowak (2016) also argue that nearby properties are likely to have similar attributes in the U.S. real estate market.

[10] Genesove and Mayer (2001) have an analogous observation about the Boston condominium market in their study.

buyers and international buyers. In addition, Singapore has a well-established public housing program, which provides affordable public housing to all citizens. Thus, the private housing market that we examine in this paper can be interpreted as the housing market apart from local citizens' affordability constraints. In our data, which consists of all private residential real estate transacted over the sample period, over half of transactions (54%) were by buyers who lived in private property, while around 41% of transactions were by buyers living in public housing.

Figure 1: Housing Price Index



Note: HPI_URA is the housing price index released by the Urban Redevelopment Authority in Singapore, with 2009Q1 is the base time for the index. Loss_purchase represents the ratio of transactions with nominal loss to the total number of transactions and Loss_neighbor represents the ratio of transactions with loss (using recent neighborhood price as reference point) to the total number of transactions.

Figure 1 shows three time series relevant to the Singapore housing market and our analysis. First, the grey solid line displays the housing price index (HPI), the official index of the housing market provided by the Singapore government. The time trend shows that the Singapore private real estate market has undergone several periods of price growth and price declines. The periods of decline mainly correspond to major economic events such as the Asian Financial Crisis (1997 to 1999), the Dot-com bubble (2000 to 2004), the Subprime Mortgage Crisis (2008 to 2010) and Singapore's macro-prudential policies to cool the housing market (2013 to 2016). While the exact formula for calculating the official HPI is not public, several other real estate indices using Singapore housing market data correspond very closely to the official HPI.[11] The black dashed line in Figure 1 corresponds to the number of transactions in the market occurring in the seller's nominal loss domain using prior purchase price as the reference point. We can observe that the frequency of

[11] There are other two housing price indices for Singapore. An alternative index by Jiang, Phillips and Yu (2015), uses data at the building level and employs a methodology similar to a repeat-sales method. Another index is constructed by the Institute of Real Estate Studies at the National University of Singapore, using hedonic matching followed by repeated sales estimation, however the series is available only from March 2009 onward.

transactions in the nominal loss domain is inversely correlated with HPI. The black dotted line shows the ratio of transactions in the loss domain to the total transactions, using median sales price in the same housing project in the previous quarter as the reference point. The frequency of transactions in the neighborhood loss domain shows a less dramatic pattern.

3. Data and Empirical Strategy

3.1 Data Description

We use transaction-level price data for all private residential transactions in Singapore from the Real Estate Information System (REALIS) maintained by the Urban Redevelopment Authority of Singapore (URA).[12] The REALIS database provides proprietary information on all property sales (residential, commercial and industrial property transactions) in Singapore since January 1, 1995 to December 31, 2017.[13] Among the residential property categories, the database includes landed private property transactions (detached houses, semi-detached houses and terrace houses), non-landed private property transaction (condominiums and apartments), and executive condominiums.[14] As mentioned above, we utilize non-landed private properties (private condominiums and apartments) for the analysis. We further exclude transactions that took place under en-bloc sales (collective sales) agreements as they are not conducted in a standard market setting and thus may bias our results.[15] The data contains information on the transaction date, transaction price, unit attributes (project identity, building block, floor level, and living area), and project attributes (project size, location by postal district, completion date, and land title).

Table 1 shows the summary statistics of sample that includes at least a second transaction for the specific housing unit (at least two consecutive transactions in the data for a given property is required for our empirical approach). The variables include price, price per square meter, differences between selling price and reference point(s), holding period, price index at the selling time, changes in price index between the time of selling and that of prior purchase, floor, and area in square meters.[16] We have 120,371 observations when using prior purchase price as a reference point, and 116,006 housing units when using recent neighborhood price as a reference point (in some cases there is no transaction within the same neighborhood within a short time period). The average holding period for a housing unit is 5.62 years - the shortest holding period being less than 1 year, and the longest being 22.67 years.[17] The lowest housing price index (HPI) during our sample period was 71.2 in 1998 Q4 and the highest was 148.90 in 2013 Q3, with 2009 1Q as the base time (HPI = 100) of the index.

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[12] https://spring.ura.gov.sg/lad/ore/login/index.cfm.

[13] Sales are registered with the Singapore Land Authority (SLA) by the purchasers' lawyers shortly after the property is sold.

[14] Executive condominiums are strata-titled apartments built by the private sector has and with facilities comparable to a private condominium. However, like public housing, there are restrictions attached in the initial years such as eligibility conditions and a minimum required occupation period before the flat can be sold. The market share of such apartments is very small.

[15] En-bloc sales refer to the sale of all the units within a housing development to a single party or a consortium/joint venture. The price of housing purchased through an en-bloc sale is usually higher than the market price of individual units.

[16] For neighborhood price as a reference point, because different houses are different in size, we report only differences in price per square meter.

[17] To have more accurate holding years, we first calculate the holding months of each housing unit and then divide the holding months by 12.

As Table 1 indicates, the magnitude of the price difference between current transaction price and original purchase price, compared to the difference between current transaction price and recent neighborhood price are quite different, 2036.74 vs 367.79, respectively. The reason is that as holding period increases, the difference between selling price and purchase price tends to be large due to general inflation and price increase trends in the housing market, over the depreciation of structures and the decreases in leasehold years of the land (Giglio, Maggiori and Stroebel, 2015). The average difference between selling price and recent neighborhood price on the other hand, tends to be smaller mainly because they are transacted within a fairly homogeneous set of apartments in terms of specific residential complex and time period. The corresponding standard deviations of these relative price measures are comparatively more similar in magnitude, 2706.74 and 1460.24, respectively.

Table 1: Summary Statistics

	Observations	Mean	Std. Dev.	Min	10th percentile	50th percentile	90th percentile	Max
Price per square meter (psm) in SGD	120371	10756.78	4927.15	1009.00	5430.00	9821.00	17241.00	51877.00
Price in SGD	120371	1301318.43	1011691.12	107000.00	590000.00	1040000.00	2185000.00	30400000.00
Selling price psm minus purchase price psm	120371	2036.74	2706.74	-22012.00	-954.00	1830.00	5365.00	24680.00
Selling price psm minus recent neighborhood price psm	116006	367.79	1460.24	-21960.59	-1023.00	284.00	1899.00	21690.00
Selling price minus purchase price	120371	246404.32	425632.73	-8000000.00	-111250.00	190000.00	650000.00	12773800.00
Holding years	120371	5.62	4.19	0.08	1.25	4.50	11.58	22.67
Housing Price Index	120371	122.03	20.72	71.20	87.20	130.50	142.50	148.90
Change in HPI btwn selling and purchase	120371	2.43	4.77	-17.80	-1.60	1.60	8.30	15.20
Floor	120371	8.82	7.75	-2.00	2.00	7.00	19.00	68.00
Area in square meters	120371	121.49	52.17	24.00	73.00	114.00	176.00	967.00

3.2 Empirical Strategy

Our general empirical strategy is to first determine whether the distribution of house prices is indicative of reference dependence under each reference point candidate (prior purchase price, and recent neighborhood price) separately, then use the analogous combined specifications to test the relative influence of those reference points as a function of holding years.

Our first main empirical approach relies on focusing on the distributional features of transactions within a relatively narrow range around the reference points. To examine the distributions, we use three complementary sub-approaches: First, we implement a local linear regression discontinuity approach on the frequency of transactions within adjacent price bins based on distance from the reference points, in order to obtain a basic assessment of distributional patterns around the candidate reference points; Next, we employ a logit model to directly test how the likelihood of a transaction occurring within a narrow distance of the reference points varies by holding years; Finally, we implement a multinomial logit approach which jointly tests the relative influences of the two reference point candidates over holding years.

Our second main approach focuses on estimating the average effect of the loss domain on transaction prices. This approach follows much of the literature on reference-dependence in the real estate market by implementing a two-stage regression on transactions price using fitted values from a hedonic regression (Genesove and Mayer, 2001, and others). Using this approach, we test separately and simultaneously for the effects of prior purchase price and median neighborhood price as reference points.

3.2.1 Examining the Distribution of Transaction Prices around Reference Points

To define loss, we use purchase price and recent neighborhood price as reference point, respectively. To do so, we group transactions into price bins denoted by starting point $b_{i,t}$, denoting the count of observations within the bin by $C_{i,t}$.[18] The procedure of aggregating the data into bin frequencies is similar to that used in Rees-Jones (2018) in detecting the influence of loss aversion in tax reporting, and more generally follows the approach of identifying reference-dependence using outcome distributions, such as in slot machine gambling in Lien and Zheng (2015), marathon finishing times in Allen, deChow, Pope and Wu (2017), and auto insurance claims in Gao, Lien and Zheng (2019), among others.

In terms of the fitting of the distribution, we use a local linear regression discontinuity (RD) approach as in Berger and Pope (2011) in detecting loss averse behavior in the NBA, and Lien, Xu and Zheng (2017) in detecting loss aversion in online experiences. We use a local linear regression discontinuity estimation along a narrow window of the running variable (for discussion, see Imbens and Lemieux, 2008).

The specification around each single reference point candidate is given by

$$C_i = \beta_0 + \beta_1 Price\_dif_i + \beta_2 Loss_i + \beta_3 Price\_dif_i \times Loss_i + u_i \qquad (1)$$

[18] Best and Kleven (2017), Slemrod, Weber and Shan (2017) and Rees-Jones (2018) also group observations into bins for the purpose of studying the distributional characteristics.

where C_i is the count of house sales in bin i. The prices in each bin range from $[b_i, b_i + \text{width}]$ for price per square meter, where $Price\_dif_i$ is the middle of the value range within each bin. The price difference is defined as the difference between the actual selling price and the reference point in question. Note that we mainly use a bin width of 20 SGD, we also report results using bin widths of 10 and 50.

3.2.2 Logit regressions

Reference dependence predicts a relatively higher concentration of transactions outcomes within a narrow range of the reference point, particularly in the narrow marginal gains domain. With the general shape of the relative price distributions provided in the previous specifications, we additionally use a logit regression to examine how the likelihood of being within narrow windows of each reference point candidate varies by holding months, controlling for changes in market conditions.

$$\Pr\left(window_{i,t} = 1\right) = \Phi(\rho_0 + \rho_1 Hold\_years_{i,s,t} + \rho_2 \Delta HPI_{s,t} + \varepsilon_{i,t}) \qquad (2)$$

$Hold\_years_{i,s,t}$ is the holding period expressed in years.

For the case of recent neighborhood price as reference point, we use the median of the transaction price per square meter of houses within the same project, transacted one quarter prior to the actual selling quarter t of house i.[19] For all specifications, we include changes in the housing price index between purchase time s and selling time t, $\Delta HPI_{s,t}$, to control for the overall changes in the housing market between the purchase time and selling time.

3.2.3 Multinomial Logit

To provide a comprehensive assessment of the transaction activity in a narrow window of both reference point candidates, we use a multinomial logit approach using the narrow reference window, gain, and loss bins for each of the reference point candidates, as dependent variables. Table 2 below conceptualizes our approach. Using the nominal prior transaction price as one reference point candidate, and recent neighborhood price as the other reference point candidate, we construct narrow bins as depicted, with a total width of less than 6 percent of the average house price in the data. Similar to the previous approach in Section 3.2.2, by examining a small window around the reference point candidates, we focus the analysis on detecting irregular variations in the likelihood of a transaction occurring in each small bin as a function of holding years.

Although the 9 bins are naturally adjacent to each other, without a theoretical foundation, there is no natural ordering among the bins. A multinomial logit approach allows us to test the relative likelihood of

[19] The median neighborhood price of the previous quarter reflects a natural reference point candidate under the case of social comparisons under heterogeneous features, although it is not the only possible reference point candidate. Other possible reference points in the social cross-section domain could include other order statistics or moments of the distribution. Since our detection approach for reference-dependent behavior in the price distribution relies on detecting significant discontinuities and excess likelihood near the reference point, based on our methodology, an affirmative statistical result suffices to validate the median as a reference point. In our hedonic two-stage estimation (Section 3.2.4), we control properly for observable characteristics of each property unit, thus minimizing the effect of heterogeneity between units, and find similar support of the median recent neighborhood price as a reference point.

transactions within these narrow ranges without imposing interpretation on the priority ordering among the bins. Under a shift in reference dependence from one reference point to another, we expect that the relative likelihood of transactions occurring in particular bins shifts accordingly. For example, a shift in reference-dependence from the prior transaction price to the recent neighborhood price will tend to shift the likelihood from the areas of neighborhood loss and nominal reference/gain ranges, to the areas of nominal loss and neighborhood reference/gain ranges.

We implement a multinomial logit as follows, where the independent variables X_i include holding years (our main variable of interest), as well as changes in HPI as a control variable for market conditions.

$$\Pr(y = j) = \frac{\exp(X_i \cdot \beta_j)}{1 + \sum_{k=2}^{9} \exp(X_i \cdot \beta_k)} \qquad (3)$$

where the 8 categories corresponding to the relative price ranges are shown in Table 2 below (comparison group excluded). The detailed assumptions and explanations for the hypothesized likelihood changes from nominal to neighborhood as a function of holding years are derived in Appendix A.

Table 2: Multinomial Logit Bins, Predicted Direction of Coefficient on Holding Years

	Nominal loss	***Nominal reference window***	***Nominal gain***
Neighborhood loss	*(2)*	***(3) (-)***	***(4) (-)***
Neighborhood reference window	***(5) (+)***	*(1) Comparison group*	*(6) (+)*
Neighborhood gain	***(7) (+)***	*(8) (-)*	*(9)*

3.2.4 Two-stage Regression on Transaction Price

Thus far, each empirical approach has focused on the distributional effects of reference-dependence on transaction prices. However, much of the prior literature on reference-dependence in housing markets has focused on the *average* effects on price. The argument is that controlling for other relevant factors, a potential loss faced on a house sale incurs a higher average asking and transactions price in the market. We further implement this method to cross-check our results against those currently in the literature and test our shifting reference point hypothesis.

Following the literature, we implement a two-stage estimation procedure.[20] In the first stage, the expected price at selling time is estimated using the hedonic features of the property. Loss is calculated by

[20] We follow the literature by using log of price as the dependent variable in the two-stage method.

subtracting the predicted price from the hedonic regression at selling time from the reference point.[21] The hedonic regression is given by

$$Lp_{i,t} = \beta x_{i,t} + \xi_n + \delta_q + \psi_a \cdot \pi_y + \varepsilon_{i,t} \qquad (4)$$

where $Lp_{i,t}$ is the log of the price of house i, $x_{i,t}$ are observable characteristics of the house, including size, floor level, and construction status, ξ_n is the housing neighborhood (project) fixed effects, δ_q are year by quarter fixed effects, $\psi_a \cdot \pi_y$ are planning area by year fixed effects, and $\varepsilon_{i,t}$ is the error term.[22]

$$Loss_{i,t}^{GM} = (\widehat{Lp}_{i,t} - RP_{i,t})^{+} \qquad (5)$$

where $\widehat{Lp}_{i,t}$ are the fitted values from the hedonic regression. $RP_{i,t}$ is the reference point, either $Lp_{i,s}$ the log of purchase price at time s, or $Lproj_{i,t}$, the log of the median price square meter within the same project recently, one quarter before the actual selling time t. $Loss_{i,t}^{GM}$ is truncated at zero.

A least squares regression is then implemented with $Loss_{i,t}^{GM}$ as the main explanatory variable of interest.

$$Lp_{i,t} = \alpha Loss_{i,t}^{GM} + \beta x_{i,t} + \gamma Loss_{i,t}^{GM} \cdot Hold\_years_{i,s,t} + \xi_n + \delta_q + \psi_a \cdot \pi_y + \varepsilon_{i,t} \qquad (6)$$

where controls are similar to that in the first stage, besides loss, and its interaction terms with some variables. The variable we focus on is the holding period, although we also examine changes in market conditions.

Although our two-stage method closely follows Genesove and Mayer (2001), our empirical method differs from theirs in the following ways. First, since our hypothesis of this paper addresses a shifting reference point, we first establish each reference point separately following their approach, and then the two reference points simultaneously, while adding the interaction between loss and holding years to test our hypothesis. Second, while their data encounters omitted variable bias due to unobserved characteristics in the first stage, we use homogeneous housing units within a project and control for unobserved project-specific characteristics. We believe that our specification, combined with the relatively homogeneous features of the Singapore housing data, overcomes the omitted variable bias issue. Lastly, we use bootstrapping to obtain the standard errors of the two-stage estimators, which has been commonly used in recent related literature, rather than the method described in Newey and McFadden (1994).

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[21] We note that in Genesove and Mayer (2001), their main analysis focuses on listings data which is a greater reflection of the seller's targeted sales price than the actualized transactions price. In the later section of their paper, they implement an analogous specification based on transactions price, and given that we are working with administrative transactions data, we follow this approach.

[22] There are 55 urban planning areas in Singapore. Each planning area has an average population of approximately 150,000 and is served by an administrative center as well as several commercial centers and shopping malls.

4. Results

We now present the results according to each of the previously described empirical strategies. We begin with the results from the local linear regression discontinuity approach, which serves as a preliminary assessment of whether there is a difference in market pricing activity in the gain and loss domains of each candidate reference point. In order to implement this assessment of the distribution of home sales prices, we conduct a transformation of the data focusing only on the price variable. The distribution of sales prices reflects the frequency of sales occurring at each price level, or in our analysis, price level relative to the candidate reference point. Constructing bins of fixed intervals over the range of price differences relative to the reference point, we tally the sales observations in each bin. With frequency as dependent variable and price-related variables as the explanatory variables, we then use a simple regression to describe the price distribution.

The running variable is *price difference (p_dif)* which is defined as the sales price minus the candidate reference point (ie. purchase price, neighborhood price). The coefficient on price difference reflects the underlying slope of the distribution moving from left to right. *Loss* is an indicator variable for whether the house sales price is in the loss domain relative to the candidate reference point (ie. *price difference* is negative). The coefficient on the interaction term of *price difference* and *Loss* provides the marginal impact of the loss domain on the slope of the distribution. The coefficient on *Loss* indicates whether there is a significant discontinuity in the distribution at the candidate reference point. Although we currently focus on linear estimation of the distribution to the left and right of the candidate reference point, it is useful for obtaining a basic idea of the activity to the left and right of the candidate reference point.[23]

A significant coefficient on *Loss* over a reasonably focused price bracket, whether positive or negative, is an indication of reference-dependence.[24] Such a coefficient indicates that there is a discontinuity in the market pricing of homes at the reference point. In the case of a negative coefficient on loss, the suggestion is that relatively fewer homeowners sold their house in the loss domain in a narrow price range around the reference point than homeowners selling above. The reverse holds for a positive coefficient on loss. In either case, a classical pricing context is unlikely to deliver a sharp discontinuity in the price distribution around any specific price level (let alone house-specific reference price levels) unless an externally imposed policy or rule encourages such behavior in the marketplace. In the setting we examine, there is no such externally imposed policy or rule, which leaves decision-makers' preference as the primary driver of the effect.

The relative magnitude of slopes on the gains side and loss side of the distribution also contains information about potential loss aversion in the market. For example, a steeper slope on the loss side can be indicative of pileup of house sales very close to the reference price. A flatter slope to the distribution indicates

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[23] A more parametric-oriented approach could estimate polynomial coefficients to the left and right of the reference point, which we put aside for now in favor of obtaining a comparison of the basic features of the distribution across different reference point specifications. Imbens and Lemieux (2008) argue for a linear regression discontinuity design around a narrow window, while an alternative is polynomial fitting over a larger window.

[24] Note however, that it is not a necessary condition for reference-dependence to influence behavior. See for example, the two-stage estimation in Section 4.6, which does not require a discontinuity at the reference point.

more home sales spread across different price levels. Under reference-dependent loss aversion, we may observe a slope to the distribution on the loss side which exceeds the slope on the gains side in absolute value.

We conduct this basic analysis in the aggregate, as well as disaggregated by years to compare the features of the distributions based on market conditions and length of homeownership. The analysis is conducted with nominal purchase price, purchase price per square meter, and neighborhood price per square meter as the candidate reference points, respectively.[25]

4.1 Aggregate Evidence – Distribution of Price Differences

We begin with the evidence based on transaction price distributions. Tables 3 and 4 display the results of the narrow regression discontinuity specification for varying sample windows of the running variable (transactions price minus reference), for prior price per square meter and neighborhood price per square meter, respectively. Panel A of each Table contains results for bin width of $10 SGD, while Panel B corresponds to bin width of $20 SGD.

The negative and significant coefficient on loss that generally appears across sample and bin specifications in Table 3 for the prior purchase price as reference point, showing that there is a significant difference in transactions activity immediately to the left and right of the prior price, when allowing for differing linear slopes on either side of the prior purchase price. Table 4 shows a similar pattern for neighborhood price as the reference point. As in Table 3, a significant discontinuity exists at the reference point, such that the linear approximation of the slope on the loss side tends to be steeper than that on the gains side. This corresponds to the typical pattern we expect to see under loss aversion.

In the immediately subsequent sections, we utilize a similar approach while subdividing the sample by holding years to address our main hypothesis about the relationship between the relative reference-dependence of prior purchase price and recent neighborhood price as a function of holding years. In addition, we use this approach subdividing the sample by calendar years, which helps to informally visualize the reference-dependence effects apart from boom and bust periods in the housing market, while also illustrating the reference-dependent pricing phenomena in the transactions distributions.

[25] For the case of prior purchase price as a reference point, using total price or price per square meter is the same because a house has the same size over time. In terms of mental accounting, it is not clear whether homeowners care about total price or price per square meter. We implement all our specifications under both assumptions and find similar results using total price or price per square meter. We report the results for price per square meter in Subsection 4.1 and for total price in Subsection 4.2, while for space considerations, all other results are available upon request.

Table 3: Transactions – Prior Purchase Price per Square Meter as Reference Point

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Sample	±500	±600	±700	±800	±900	±1000	±2000	±3000	±4000	±5000
Panel A: Bin size: 10 SGD										
Loss	-51.174**	-48.123***	-45.172***	-41.339***	-39.224***	-36.368***	-48.324***	-82.919***	-111.290***	-133.709***
	(-2.40)	(-2.69)	(-2.95)	(-3.05)	(-3.25)	(-3.30)	(-7.97)	(-17.09)	(-26.43)	(-35.87)
P_dif	0.008	0.022	0.030	0.039*	0.041**	0.047***	0.028***	-0.001	-0.019***	-0.029***
	(0.14)	(0.61)	(1.10)	(1.88)	(2.47)	(3.47)	(7.63)	(-0.31)	(-14.76)	(-31.26)
Loss × P_dif	0.021	0.008	0.007	0.003	0.008	0.005	0.021***	0.037***	0.049***	0.053***
	(0.28)	(0.16)	(0.19)	(0.11)	(0.34)	(0.24)	(4.04)	(13.19)	(26.96)	(41.06)
Constant	178.548***	175.991***	174.433***	172.074***	171.682***	169.677***	179.426***	203.248***	224.394***	238.366***
	(11.84)	(13.94)	(16.09)	(17.96)	(20.10)	(21.81)	(41.85)	(59.25)	(75.37)	(90.44)
Obs	100	120	140	160	180	200	400	600	800	1000
Adj. R^2	0.227	0.293	0.364	0.438	0.507	0.570	0.831	0.854	0.857	0.859
Panel B: Bin size: 20 SGD										
Loss	-100.863**	-95.354***	-89.619***	-82.235***	-78.042***	-72.366***	-96.560***	-165.810***	-222.576***	-267.420***
	(-2.45)	(-2.78)	(-3.05)	(-3.16)	(-3.37)	(-3.42)	(-8.29)	(-15.98)	(-23.07)	(-30.21)
P_dif	0.020	0.047	0.061	0.079*	0.082**	0.094***	0.057***	-0.001	-0.038***	-0.057***
	(0.20)	(0.67)	(1.18)	(1.99)	(2.60)	(3.63)	(7.95)	(-0.28)	(-12.89)	(-26.33)
Loss × P_dif	0.036	0.014	0.013	0.006	0.015	0.009	0.042***	0.074***	0.098***	0.106***
	(0.25)	(0.15)	(0.17)	(0.10)	(0.34)	(0.23)	(4.20)	(12.34)	(23.53)	(34.58)
Constant	355.765***	351.228***	348.244***	343.753***	342.998***	339.053***	358.783***	406.482***	448.793***	476.740***
	(12.20)	(14.48)	(16.74)	(18.71)	(20.94)	(22.65)	(43.54)	(55.41)	(65.79)	(76.16)
Obs	50	60	70	80	90	100	200	300	400	500
Adj. R^2	0.390	0.476	0.557	0.631	0.693	0.743	0.915	0.911	0.901	0.896

Notes: The dependent variable is the number of transactions in each bin. *t* statistics in parentheses, * indicates significance at the 10% level, ** indicates significance at the 5% level and *** indicates

Table 4: Transactions – Recent Neighborhood Price per Square Meter as Reference Point

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Sample	±500	±600	±700	±800	±900	±1000	±2000	±3000	±4000	±5000
Panel A: Bin size: 10 SGD										
Loss	-69.418***	-80.872***	-92.789***	-105.873***	-116.728***	-126.522***	-185.380***	-187.759***	-175.052***	-160.685***
	(-4.54)	(-5.90)	(-7.58)	(-9.46)	(-11.22)	(-12.99)	(-20.64)	(-18.05)	(-16.19)	(-15.13)
P_dif	-0.181***	-0.228***	-0.270***	-0.303***	-0.320***	-0.329***	-0.286***	-0.201***	-0.143***	-0.106***
	(-4.84)	(-8.17)	(-12.63)	(-17.66)	(-22.63)	(-27.59)	(-52.02)	(-47.33)	(-43.27)	(-40.82)
Loss × P_dif	0.679***	0.712***	0.741***	0.752***	0.750***	0.736***	0.517***	0.343***	0.238***	0.173***
	(12.83)	(18.00)	(24.48)	(31.06)	(37.44)	(43.64)	(66.47)	(57.04)	(50.83)	(47.14)
Constant	596.578***	605.182***	614.257***	622.180***	627.250***	629.993***	603.716***	533.423***	466.801***	411.617***
	(55.22)	(62.43)	(71.00)	(78.64)	(85.25)	(91.50)	(95.08)	(72.53)	(61.06)	(54.82)
Observations	100	120	140	160	180	200	400	600	800	1000
Adjusted R^2	0.854	0.882	0.907	0.921	0.932	0.939	0.930	0.861	0.784	0.712
Panel B: Bin size: 20 SGD										
Loss	-138.240***	-161.556***	-185.459***	-211.726***	-233.550***	-253.146***	-370.840***	-375.550***	-350.125***	-321.382***
	(-4.77)	(-5.91)	(-7.39)	(-8.95)	(-10.46)	(-11.89)	(-15.64)	(-13.04)	(-11.57)	(-10.77)
P_dif	-0.357***	-0.455***	-0.540***	-0.604***	-0.640***	-0.658***	-0.572***	-0.402***	-0.286***	-0.212***
	(-5.03)	(-8.15)	(-12.28)	(-16.68)	(-21.08)	(-25.22)	(-39.40)	(-34.18)	(-30.92)	(-29.05)
Loss × P_dif	1.351***	1.420***	1.480***	1.503***	1.499***	1.471***	1.034***	0.685***	0.476***	0.347***
	(13.45)	(18.00)	(23.82)	(29.34)	(34.88)	(39.89)	(50.33)	(41.19)	(36.31)	(33.55)
Constant	1191.920***	1209.672***	1228.010***	1244.049***	1254.307***	1259.867***	1207.426***	1066.840***	933.600***	823.232***
	(58.15)	(62.61)	(69.17)	(74.36)	(79.47)	(83.67)	(72.01)	(52.38)	(43.63)	(39.02)
Observations	50	60	70	80	90	100	200	300	400	500
Adjusted R^2	0.929	0.938	0.949	0.955	0.960	0.963	0.939	0.866	0.787	0.715

Notes: The dependent variable is the number of transactions in each bin. *t* statistics in parentheses, * indicates significance at the 10% level, ** indicates significance at the 5% level and *** indicates significance at the 1% level.

4.2.1 Annual Distributions of Distances from Reference Points – Prior Purchase Price

To begin, while examining the results in the aggregate is most informative towards our main research purpose, it may also be useful to know about the mechanics of reference dependence in different market conditions. Intuitively, during heated real estate market conditions in which transaction price is highly likely to exceed the prior purchase price, we may not expect the purchase price to hold as much explanatory power as a reference point, as loss averse homeowners are more willing to incur a gain than a loss. However, during a market downturn, the prior purchase price could be a significant reference point that sellers grasp onto psychologically, in order to avoid incurring a nominal loss on the property.

The Housing Price Index (HPI) for Singapore during our years of analysis is provided in Figure 1 shown earlier. It shows that on the basis of HPI, some quarters of market downturns occurred during the years 1996 to 1998, 2000 to 2004, 2008 to 2009, and 2012 to 2017. In other words, the Singapore housing market has experienced periodic downturns and upswings over the past two decades, with the longest prolonged downturn occurring most recently in the 2012 to 2017 range.

Figure 2 shows the distribution of house sales prices in each year from 1998 to 2017, represented as the difference between the sales price and the prior purchase price of that particular apartment. The sub-figures demonstrate that the distribution of sales prices relative to purchase prices was substantially heterogeneous by year. While the years 1998 to 2006 have relatively more sales activity occurring in the loss domain, years 2007 to 2017 shift to having more sales activity in the gain domain. In the early years (1998 to 2005) and in the later years (2016 to 2017) there is a visible concentration of sales at or very close to the reference point.

To understand how some of the sub-figures in Figure 2 depict loss aversion, it is helpful to discuss some examples. We use as our examples, the years 2004 and 2017, which exhibit our pattern of interest clearly. [26]

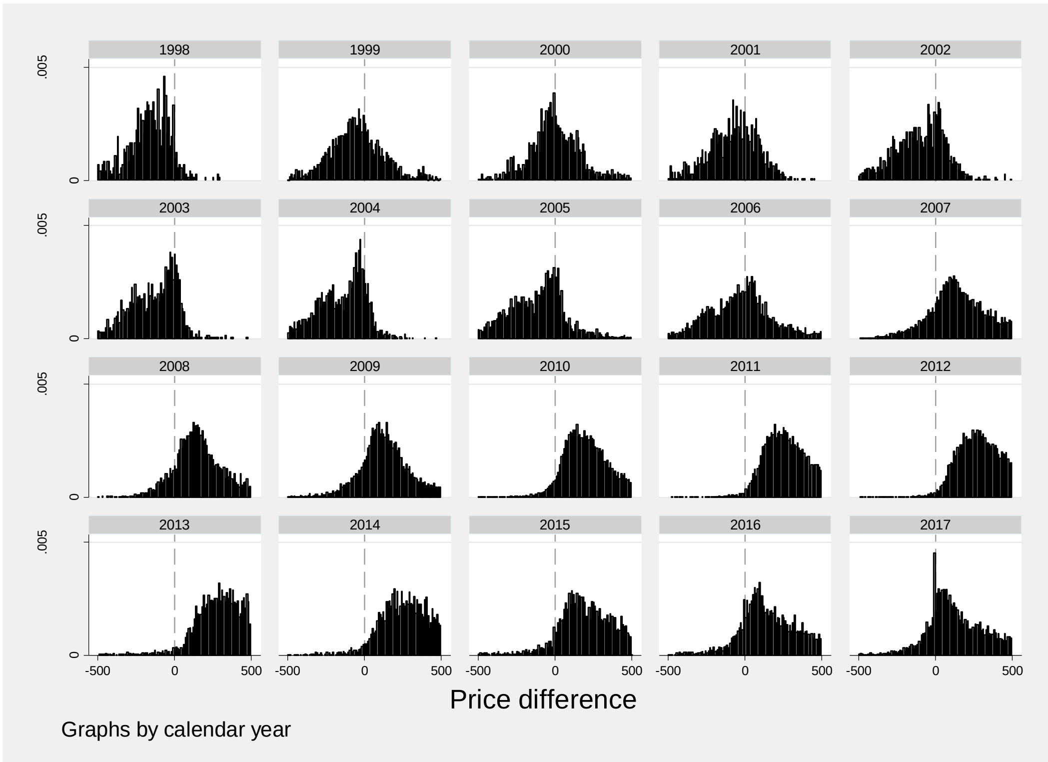
In 2004, relative to original purchase prices, most homeowners sold their house at a nominal loss. The market was at or near its local bottom, as can be seen from Figure 1's HPI plot. For homeowners with a house on the market that year, they would have liked to recover their nominal purchase price if possible, but the market conditions at that time were poor for sellers. Therefore, we observe relatively little sales activity in the gains domain (indeed, even in a downturn, some properties can sell for a gain, noting here that these distributions do not account for any heterogeneous features of the house), and quite a lot of sales activity in the loss domain. Importantly, there exists a spike in the distribution, in other words, disproportionately many houses being sold very close to the prior purchase price. For those properties sold near the purchase price but still not recovering the full loss, one can imagine homeowners trying their best to recoup their loss but with the force of individual preferences running counter to the market trend.

In 2017 on the other hand, most homeowners on the market that year sold their house at a gain relative to the original purchase price. Note that although the market was again in a prolonged downturn, the ability to sell at a gain could be due to various factors. For example, sellers unable to currently recoup their losses may be waiting for the market to turn around before selling. General inflation in the economy outside of the house price domain could be diluting the overall purchasing power of the Singapore dollar, resulting in nominal house price

[26] See also Lien and Zheng (2015) which makes a similar argument for loss aversion in the realization of gambling loss distributions.

increases more generally. While most sellers that year sold in the nominal gains domain, we can observe again, a pileup of house sales near or at the prior nominal sales price. The spike of homes selling within just a couple thousand SGD of the original purchase price is especially noticeable in year 2017. While homeowners would be happier to sell at a greater gain, poor market conditions inhibit most of them from doing so, and they are disproportionately willing to sell at a break-even level or small nominal gain.

Figure 2: Gap between Current Transaction Price and Prior Purchase Price, by Year



Notes: For the purpose of illustration, we report observations from 1998 to 2017. Ranges of X-axis (price differences) are restricted to negative 500,000 to positive 500,000 SGD, with bin size 1,000 SGD.

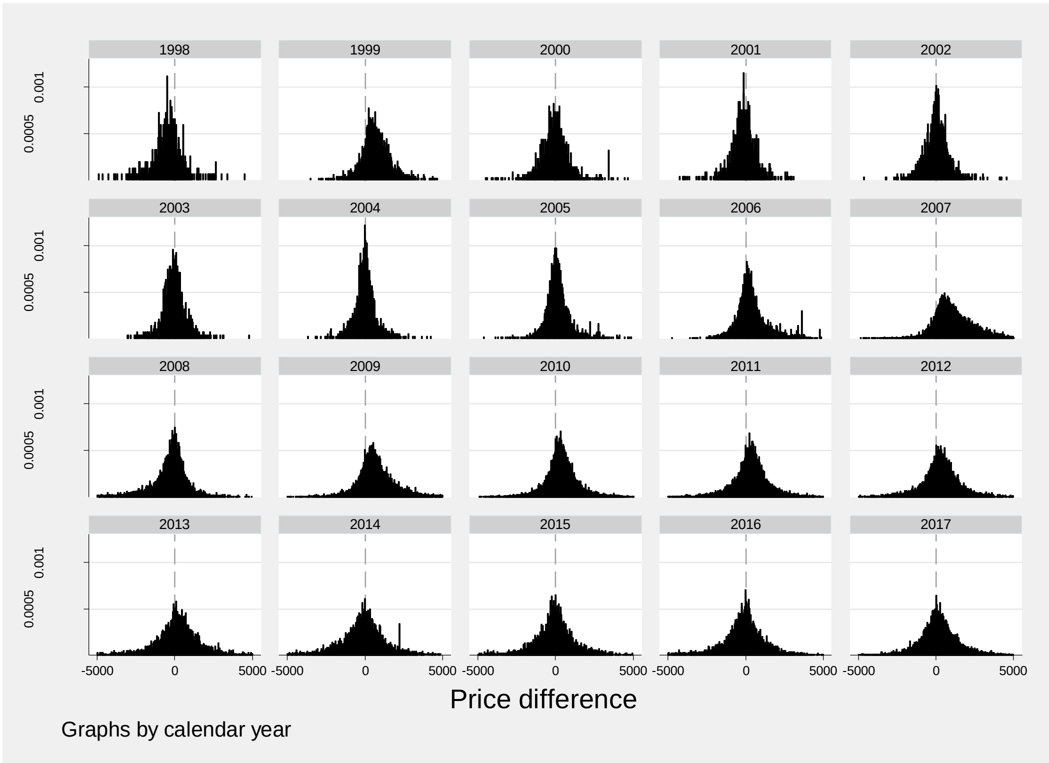
Table B1 in Appendix B shows the linear regression discontinuity estimates similar to in Table 3, disaggregated by year. For the coefficients on price difference and the interaction between loss and price difference, the direction and significance of the coefficients follows the aggregated pattern of Table 3.[27] However, for the loss coefficient, the significant negative coefficient is primarily present for years 2007 onward. This matches the distributions shown in Figure 2 which show very few transactions on the nominal loss side from around 2008 onward. In Figure 2, several years prior to 2007 show a noteworthy concentration of home sales at the prior purchase price or below it in the loss domain, with relatively few transactions in the gain domain (see for example, 1998, 2002, 2003, 2004, 2005). Of these, several do estimate with a positive loss coefficient, indicating a higher intercept to the linear fit on the left of purchase price than on the right (ex, 2000, 2003, 2004, 2005, 2006).

[27] When we report results by calendar year, we do not restrict the sample, so we report results using larger bin width of 5,000 SGD.

4.2.2 Annual Distributions of Distances from Reference Points – Neighborhood Price per Square meter

We now examine the analogous graphs for our other reference point candidate of interest, neighborhood price. For neighborhood price, we focus on the per square meter price measure instead of the nominal price. The reason is that if homeowners are to have a neighborhood price as their reference point, it is reasonable to think that they use the per square meter price, since homes within a neighborhood or even a building can vary considerably by size. For the neighborhood reference point candidate, we use the housing project-specific median price per square meter in the quarter prior to the transaction.

Figure 3: Gap between Transaction Price and Neighborhood Price Adjusted by Area, by Year



Notes: For the purpose of illustration, we report observations from 1998 to 2017. Histograms are restricted to price negative 5,000 to positive 5,000 SGD, with bin size 20 SGD.

Figure 3 shows the annual distributions of transactions based on price per square meter relative to the recent housing project average. Compared to the analogous figures for prior purchase price as a reference point, the distributions of sales prices are relatively more concentrated around the neighborhood price. Note that the great majority of private homes in Singapore are condominium or apartment style, which means that the hedonic features of the homes in each housing complex are relatively uniform.

The figures indicate that the relationship between the annual loss-related coefficients for the case of neighborhood price is less influenced by market conditions compared to the case of prior purchase price. While the discontinuity as exhibited by the loss coefficient is less apparent in this setting, the slope of the loss side of the distribution more often estimates as steeper than the slope of the gains side of the distribution, consistent with loss aversion. The accompanying regression results are reported in Table B2 in Appendix B.

4.3. Length of Ownership – Distribution of Distances from Reference Points

We now focus on the data for our main hypothesis, which is how the length of holding period of the property affects the reference point. Here, we disaggregate the sample by the number of years that the transacted house has been owned by the owner. Since the data time frame runs from 1995 to 2017, an observation held for *n* years in our data must be purchased in either 1995 or later, and sold n years subsequently up to year 2017.

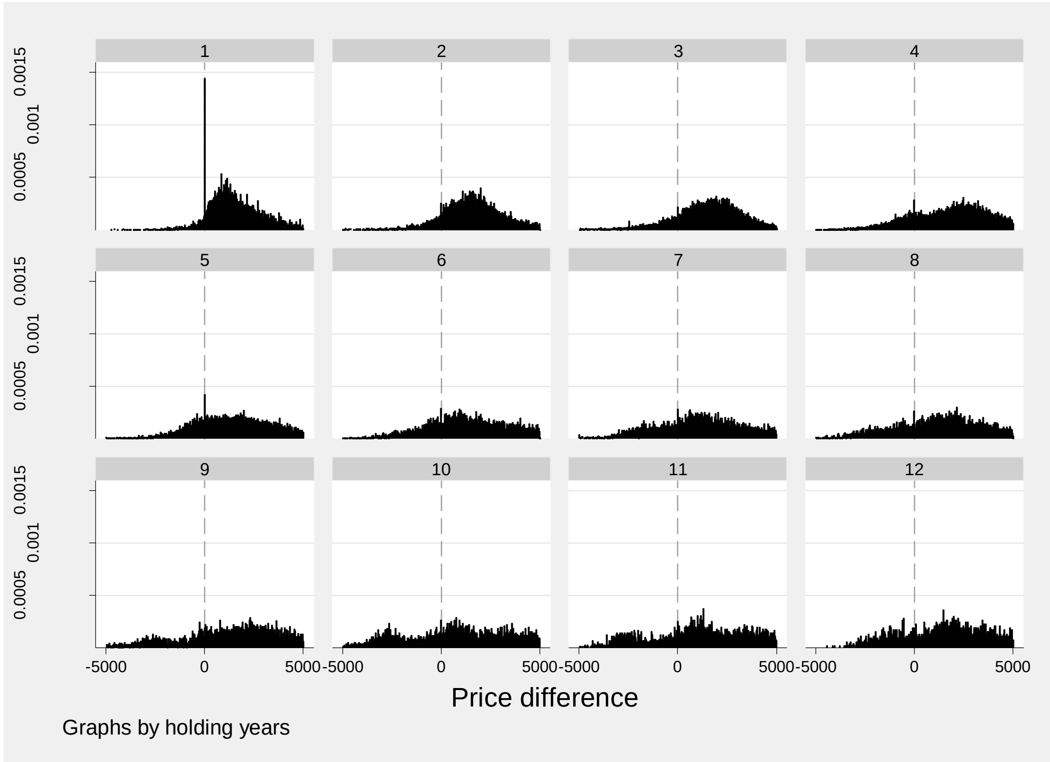
Note that to examine the price gap distributions over holding years, from a practical standpoint, we face a trade-off between number of observations within each bin and the observations within a certain window width. This trade-off is illustrated by Table B3 of the Appendix B which shows the average number of observations within each bin over holding years. Following the local regression discontinuity approach, which focuses on small windows around the potential reference point, we implement a window of SGD [-1000, 1000], as well as a wider window of [-5000, 5000] as a robustness check. We report bin sizes of 20 SGD, while results for other bins (10 SGD and 50 SGD) are in Appendix B.

4.3.1 Years of Ownership – Prior Purchase Price per Square Meter

Figure 4 shows the nominal gap between sales price and original purchase price per square meter, disaggregated by the years of ownership. The subfigures show that sales prices for each number of holding years tend to be distributed more to the right of the original purchase price than to the left. A spike of transactions is apparent for certain numbers of holding years, in particular 1, 4, 5 and 6 year holding periods. A discontinuity in the distribution near the reference point is visible for certain holding periods such as the 1 and 2 year holding periods, while for a number of holding year categories, a mass of distribution centers around a price difference of 0 on the x-axis. For most holding periods, the modal sales price is clearly in the gains domain with respect to prior purchase price, while the distribution becomes noisier around the 9 year holding period onward.

In some cases, reference dependent behavior can be blatantly observed from the phenomenon of transaction price exactly equaling the prior purchase price. For example, for those houses sold within one year after purchase, there are 244 observations in the data with selling price exactly equaling purchase price. The corresponding spike at the prior purchase price can be seen clearly in the top left panel of Figure 4.

Figure 4: Gap between Transaction Price and Prior Purchase Price per Square Meter, by Holding Years



Notes: For the purpose of illustration, we report observations up to 12 holding years. This applies to other figures by holding years. Histograms are restricted to price negative 5000 to positive 5000 SGD, with bin size of 20 SGD.

Table 5 shows the analogous coefficients from the local linear regression discontinuity specification on bins of 20 SGD, using samples in the price difference range of SGD [-1000, 1000]. Tables B4-B9 in Appendix B show results using alternative bin sizes and sample window ranges, and are qualitatively similar to Table 5.

Table 5: Transactions – Prior Purchase Price per Square Meter as Reference Point by Holding Years

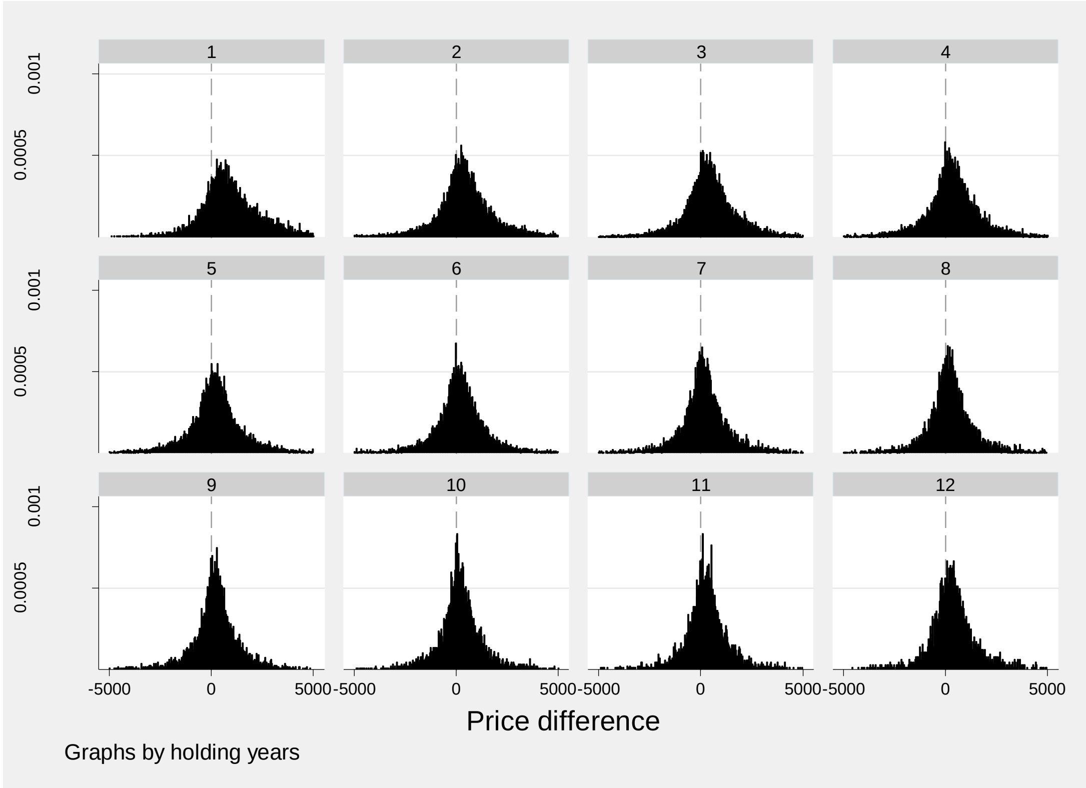
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Hold (n-1,n]	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Loss	-30.451***	-14.129***	-7.997**	-2.339	-1.087	-1.766	-4.274**	-2.045
	(-3.30)	(-5.49)	(-2.45)	(-0.80)	(-0.32)	(-0.75)	(-2.30)	(-1.11)
Price difference	0.020*	0.018***	0.033***	-0.006*	-0.001	0.010***	0.010***	0.003
	(1.74)	(5.75)	(8.19)	(-1.79)	(-0.26)	(3.32)	(4.38)	(1.21)
Loss ×Price diff	-0.004	-0.001	-0.018***	0.016***	0.015**	-0.000	-0.008**	-0.003
	(-0.23)	(-0.19)	(-3.21)	(3.09)	(2.50)	(-0.04)	(-2.58)	(-0.99)
Constant	47.660***	40.711***	42.592***	36.832***	41.072***	30.283***	19.884***	15.834***
	(7.30)	(22.39)	(18.44)	(17.71)	(17.25)	(18.21)	(15.15)	(12.11)
Observations	100	100	100	100	100	100	100	100
Adjusted R^2	0.529	0.872	0.821	0.118	0.213	0.526	0.576	0.096
Hold (n-1,n]	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**
Loss	0.108	-1.586	-1.187	-0.933	-0.058	-1.960**	-2.398**	-0.462
	(0.08)	(-1.03)	(-0.99)	(-0.88)	(-0.06)	(-2.05)	(-2.50)	(-0.94)
Price difference	-0.000	0.003	0.005***	0.002	-0.004***	-0.002*	-0.002*	0.004***
	(-0.02)	(1.44)	(3.72)	(1.40)	(-3.25)	(-1.90)	(-1.85)	(6.77)
Loss ×Price diff	0.008***	0.001	-0.002	-0.004**	0.005***	0.003*	0.008***	-0.004***
	(3.54)	(0.53)	(-1.13)	(-2.29)	(3.01)	(1.68)	(4.72)	(-4.71)
Constant	13.179***	11.025***	9.053***	5.415***	7.230***	8.474***	8.466***	0.754**
	(13.72)	(10.11)	(10.63)	(7.23)	(10.34)	(12.53)	(12.50)	(2.16)
Observations	100	100	100	100	100	100	100	100
Adjusted R^2	0.365	0.317	0.500	0.037	0.135	0.060	0.499	0.601

Notes: The dependent variable is the number of transactions in each bin. *t* statistics in parentheses, * indicates significance at the 10% level, ** indicates significance at the 5% level and *** indicates significance at the 1% level. Bin width is 20 SGD of price per square meter. We use sample of [-1000, 1000] in price difference for each holding year range in this table.

4.3.2 Years of Ownership – Neighborhood Price per Square Meter

Figure 5 shows the analogous distributions by holding years based on the neighborhood reference point measure. Again, compared to the distributions for prior nominal purchase price as the reference point, the distribution is relatively more symmetric. However, subtle differences exist. The distribution is relatively steeper and thinner on the loss side than on the gains side, which can be observed by examining the mass of house sales to the left and to the right of the black dotted lines.

Figure 5: Gap between Transaction Price and Neighborhood Price per Square Meter, by Holding Years



Notes: For the purpose of illustration, we report observations up to 12 holding years. This applies to other figures by holding years. Histograms are restricted to price negative 5000 to positive 5000 SGD, with bin size of 20 SGD.

Running a linear regression discontinuity specification on a restricted window around the reference point Table 6 generally confirms this pattern. The coefficient on the interaction term between loss and price difference compared with the coefficient on price difference most often implies at least a weakly steeper absolute slope on the loss side than the gains side. In addition, the loss coefficient estimates consistently as negative for all levels of holding years, which implies a drop in likelihood below the reference point when a linear functional form is imposed on the gains and loss sides. Again, we have results using various bin sizes and sample ranges, shown in the Tables of Appendix B and they convey the same main message as in Table 6.

Table 6: Transactions – Recent Neighborhood Price per Square Meter as Reference Point by Holding Years

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Hold (n-1,n]	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Loss	-19.262***	-19.222***	-36.468***	-29.804***	-21.265***	-18.217***	-12.920***	-15.148***
	(-5.57)	(-4.63)	(-7.66)	(-7.09)	(-5.55)	(-5.07)	(-3.91)	(-5.00)
Price difference	-0.006	-0.043***	-0.062***	-0.063***	-0.070***	-0.063***	-0.062***	-0.056***
	(-1.51)	(-8.38)	(-10.58)	(-12.31)	(-14.91)	(-14.37)	(-15.29)	(-15.04)
Loss ×Price diff	0.046***	0.117***	0.159***	0.151***	0.146***	0.133***	0.126***	0.114***
	(7.74)	(16.32)	(19.25)	(20.74)	(22.05)	(21.40)	(22.07)	(21.68)
Constant	70.532***	112.009**	161.156**	140.453**	128.188**	109.981**	90.537***	82.361***
	(28.86)	(38.19)	(47.88)	(47.25)	(47.35)	(43.29)	(38.70)	(38.42)
Observations	100	100	100	100	100	100	100	100
Adjusted R^2	0.841	0.853	0.901	0.894	0.867	0.858	0.849	0.855
Hold (n-1,n]	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**
Loss	-17.937***	-13.858***	-15.043***	-10.358***	-5.121***	-6.629***	-4.782***	-3.143**
	(-6.92)	(-5.65)	(-6.10)	(-5.20)	(-2.63)	(-3.61)	(-3.17)	(-2.52)
Price difference	-0.050***	-0.044***	-0.035***	-0.024***	-0.017***	-0.017***	-0.013***	-0.010***
	(-15.89)	(-14.50)	(-11.56)	(-9.65)	(-7.04)	(-7.40)	(-7.15)	(-6.72)
Loss ×Price diff	0.101***	0.085***	0.073***	0.051***	0.038***	0.037***	0.031***	0.021***
	(22.58)	(19.93)	(16.99)	(14.65)	(11.25)	(11.77)	(11.72)	(9.52)
Constant	74.373***	60.881***	57.001***	41.280***	29.954***	29.635***	23.774***	16.531***
	(40.57)	(35.08)	(32.71)	(29.28)	(21.75)	(22.80)	(22.32)	(18.74)
Observations	100	100	100	100	100	100	100	100
Adjusted R^2	0.877	0.835	0.824	0.784	0.647	0.696	0.690	0.534

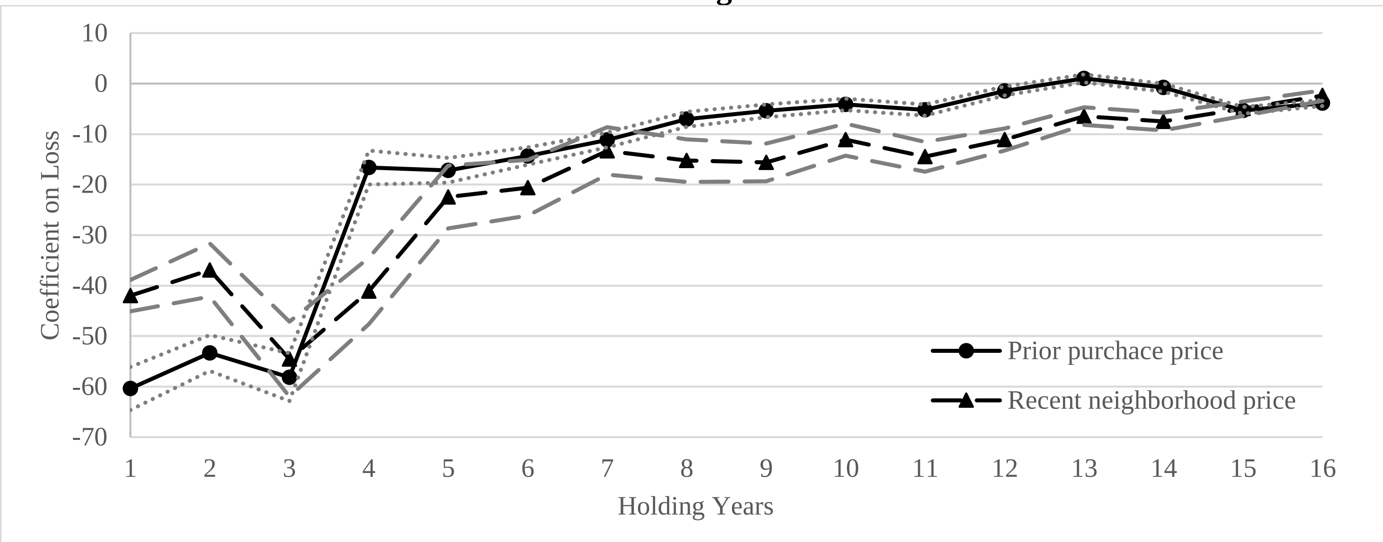
Notes: The dependent variable is the number of transactions in each bin. *t* statistics in parentheses, * indicates significance at the 10% level, ** indicates significance at the 5% level and *** indicates significance at the 1% level. Bin width is 20 SGD of price per square meter. We use sample of [-1000, 1000] in price difference for each holding year range in this table.

4.3.3 Comparison of Two Reference Points based on Years of Ownership

Comparing the loss coefficients across the different reference points obtained in the regressions based on holding years, we can observe the following pattern. The prior purchase price loss coefficient is of greater magnitude in the initial years of ownership, then is quickly exceeded in absolute value by the recent neighborhood price loss coefficient. While Figure 6 below shows the coefficient plot for bin size of 20 SGD and sample range of [-5000 SGD, 5000 SGD], plots for alternative bin sizes and sample ranges are provided in Appendix B, and show similar patterns as in Figure 6. The crossing point between the two loss coefficients occurring at either the 3rd or 4th year of homeownership in Figure 6 and in Appendix using alternative bins, although the crossing point occurring at shorter years of homeownership when using a narrow sample window. This indicates that prior purchase price is more influential as a reference point in the initial time period of ownership, but subsequently loses its influence in favor of the recent neighborhood price.

We note also that the greater number of cumulative years that an individual has owned a house, the less influential either reference point tends to be. By the 7th year of homeownership, the influence of the prior purchase price becomes minimal compared to the recent neighborhood price. Similar patterns hold for the alternative bin sizes and sample ranges, and the corresponding Figures are provided in Appendix B, indicating that this finding is robust.

Figure 6: Loss Coefficients for Prior Purchase Price and Neighborhood Price per Square Meter, by Holding Years



Notes: The coefficients are from regression with bin size of 20SGD and sample [-5000, 5000]; 95% confidence intervals plotted using dashed lines.

4.4 Determinants of Sales Price near Reference Points

Thus far our analysis has focused purely on the distribution of transaction prices, examining how features of the price distribution vary with holding years. In this section, we employ a logit regression approach to testing whether the likelihood of a house being sold within a narrow range of a reference point candidate is robust to various bin widths and sample sizes, as well as housing market conditions.

4.4.1 Prior Purchase Price

Table 7a displays results from the logit model with prior purchase price per square meter as the reference point. The dependent variable is an indicator variable for whether the transaction price falls within a narrow range of the candidate reference point. Panel A considers the window to the left and right of the original purchase price per square meter, while Panel A considers the gains side as the dependent variable. Column (1) uses a window of 10 SGD over the [-30 SGD, 30 SGD] range around the prior price, with increasing bin sizes and windows across the respective columns, where Column (10) uses a window of 100 SGD against the [-300 SGD, 300 SGD] range. In this way, the likelihood effects are proportionally comparable across columns. Table 7b contains the same empirical specifications as in Table 7a but with larger bin sizes and sample windows.

Our explanatory variable of interest is length of homeownership, expressed as years of ownership, with change in market conditions (HPI) over the holding period serving as a control variable. While our previous discussions of market conditions were informal, focusing on calendar years which were known to be part of upward or downward market trends, in the current analysis we control for market conditions more formally by including the trend in HPI as a control variable.

Table 7a, Panel A shows that when considering narrow bin sizes and a relatively small value range around the prior purchase price, an increase in length of ownership consistently implies a reduced likelihood of a transaction price being located in a narrow range around the prior purchase price, even controlling for the current market trend. The effect tends to be stronger when considering narrow bin sizes compared to wider bin sizes, which indicates that the effect is quite precise around the prior purchase price. The marginal effects shown in Panel B, which considers a window of marginal gains, are of similar significance and order of magnitude. Table 7b shows similar results for larger bin widths and range window. Similar to Table 7a, the marginal effect of holding years is significantly negative towards the likelihood of transacting within a narrow range around the prior transaction price (Panel A, except for the largest two bin sizes), and significantly negative in terms of the likelihood of the transaction price occurring within the marginal gains bin (Panel B).

The marginal effects tending to be of comparable or smaller magnitudes in Panels A compared to Panels B of both Table 7a and 7b, , indicates that the main influence of the reference point, at least as driven by holding years, is on the marginal gains side rather than the marginal loss side. This is consistent with the prediction of loss aversion with the prior purchase price as reference point, in that sellers will strongly prefer to be slightly above the prior price than slightly below it. We include the specifications shown in Panel A mainly under the consideration that it may sometimes be difficult for sellers to achieve exactly this objective, but they may rather have to settle for a slightly lower price than desired.

Finally, we note that in the specifications of Tables 7a and 7b, the marginal effect of change in HPI is not always statistically significant. However, when it is significant, the effect is negative. In other words, an increase in overall housing market prices leads to a reduced likelihood of transacting within a narrow range of the prior purchase price. This is consistent with the influence of the prior purchase price as a reference point being greater in market downturns than during market upswings. Intuitively, during poor market conditions for sellers, they are more likely to use their purchase price as a benchmark, while during market booms, they are more likely naturally able to sell at a higher price than their original purchase price.

Table 7a: Logit Regressions – Prior Purchase Price per Square Meter as Reference Point – Fine Bin and Small Sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Bin	10	20	30	40	50	60	70	80	90	100
Panel A: $\text{abs}(\text{price} - \text{reference point}) \leq \text{bin}$										
Holding years	-0.02056***	-0.01346**	-0.01522***	-0.01215***	-0.01004***	-0.00872***	-0.00722**	-0.00618**	-0.00427*	-0.00251
	(-3.76)	(-2.48)	(-3.12)	(-2.87)	(-2.79)	(-2.78)	(-2.53)	(-2.37)	(-1.77)	(-1.16)
Change in HPI	0.00055	-0.00153*	-0.00156**	-0.00147**	-0.00051	-0.00037	-0.00042	0.00012	-0.00014	-0.00067*
	(0.52)	(-1.65)	(-1.99)	(-2.31)	(-0.94)	(-0.76)	(-0.94)	(0.27)	(-0.34)	(-1.73)
Sample	[-30,30]	[-60,60]	[-90,90]	[-120,120]	[-150,150]	[-180,180]	[-210,210]	[-240,240]	[-270,270]	[-300,300]
Obs.	1206	1952	2810	3664	4526	5414	6241	7161	8098	9011
Log Pll.	-772.82249	-1335.4001	-1891.3035	-2419.8284	-2974.8581	-3525.1344	-4065.0285	-4620.3791	-5222.8413	-5792.2278
Panel B: $0 \leq \text{price} - \text{reference point} \leq \text{bin}$										
Holding years	-0.02506***	-0.02196***	-0.02065***	-0.01654***	-0.01456***	-0.01231***	-0.01096***	-0.00917***	-0.00797***	-0.00637**
	(-3.67)	(-3.35)	(-3.49)	(-3.30)	(-3.37)	(-3.21)	(-3.16)	(-2.92)	(-2.84)	(-2.55)
Change in HPI	-0.00016	-0.00121	-0.00101	-0.00082	-0.00013	-0.00003	0.00011	0.00027	0.00028	0.00003
	(-0.15)	(-1.47)	(-1.51)	(-1.45)	(-0.26)	(-0.08)	(0.28)	(0.70)	(0.79)	(0.09)
Sample	[-30,30]	[-60,60]	[-90,90]	[-120,120]	[-150,150]	[-180,180]	[-210,210]	[-240,240]	[-270,270]	[-300,300]
Obs.	1206	1952	2810	3664	4526	5414	6241	7161	8098	9011
Log Pll.	-807.43127	-1282.2189	-1709.562	-2117.2496	-2517.6587	-2924.8153	-3318.176	-3725.1117	-4188.0767	-4612.6837

Notes: Marginal effects reported; t statistics in parentheses using standard errors clustered at the project level. Log Pll. is the Log Pseudo likelihood. * indicates significance at the 10% level, ** indicates significance at the 5% level and *** indicates significance at the 1% level.

Table 7b: Logit Regressions –Prior Purchase Price per Square Meter as Reference Point – Coarse Bin and Large Sample

	(1)	(2)	(3)	(4)
Bin	10	50	100	200
Panel A: $\text{abs}(\text{price} - \text{reference point}) \leq \text{bin}$				
Holding years	-0.00422**	-0.00265*	-0.00091	0.00088
	(-2.46)	(-1.91)	(-0.69)	(0.64)
Change in HPI	-0.00033***	-0.00058***	-0.00080***	-0.00135***
	(-2.66)	(-3.43)	(-3.76)	(-5.08)
Sample	[-600, 600]	[-600, 600]	[-600, 600]	[-600, 600]
Observations	18083	18083	18083	18083
Log Pseudolikelihood	-3130.1073	-5592.0723	-8265.9122	-11451.15
Panel B: $0 \leq \text{price} - \text{reference point} \leq \text{bin}$				
Holding months	-0.00444**	-0.00384**	-0.00292**	-0.00393***
	(-2.41)	(-2.54)	(-2.08)	(-2.70)
Change in HPI	-0.00033***	-0.00036***	-0.00030*	-0.00002
	(-2.93)	(-2.70)	(-1.92)	(-0.09)
Sample	[-600, 600]	[-600, 600]	[-600, 600]	[-600, 600]
Observations	18083	18083	18083	18083
Log Pseudolikelihood	-2765.2712	-4207.2869	-6037.7237	-8874.0923

Notes: Marginal effects are reported; t statistics in parentheses using standard errors clustered at the project level using sample [-600, 600] of difference between selling price and prior purchase price. * indicates significance at the 10% level, ** indicates significance at the 5% level and *** indicates significance at the 1% level.

4.4.2 Neighborhood Price per Square Meter

We now consider the same types of logit regressions as in the previous subsection, but with neighborhood price per square meter as the reference point in question. The tables are structured similarly as in the previous subsection except for larger bins in Table 8a compared to Table 7a. Different from the prior purchase price, researchers cannot observe the exact value of the recent neighborhood price which homeowners use as a reference point when selling their houses. Nevertheless, we show the same bin and sample window in Table 7b and Table 8b.

Table 8a shows that for larger bin sizes and sample ranges (Columns 4 and 5) there is a positive relationship between length of ownership and the likelihood of selling within either a marginal range around (Panel A) or a marginal gain above (Panel B) the neighborhood reference price. Table 8b shows similar results but with a fixed window of [-600 SGD, + 600 SGD] for various bin sizes, as in Table 7b. As in Table 8a, the effect is significant for the larger bin sizes, but tends to not reach significance for the smaller bin sizes. An interpretation is that the relationship between ownership years and likelihood of being within a narrow range of the neighborhood reference point is more robust for more forgiving bin sizes. This may be understandable, particularly due to our approximation of the neighborhood reference point as the most recent quarter's median price within the housing project. For example, the current regression specification does not address hedonic factors such as home size and other features, which are addressed in a later part of the paper. Nevertheless, the regressions which allow for wider marginal gain and loss definitions consistently show a significant positive effect.

Another observation from Tables 8a and 8b is the effect of the trend in HPI, which is often statistically significant, but differing in sign depending on the bin and window sizes. Thus, controlling for holding period of ownership, the direction of effect of change in HPI does not show so much regularity. However, the effect of holding years is positive. Therefore, our interpretation is that controlling for concurrent trends in housing market conditions, length of ownership significantly predicts the likelihood of a home being sold within a fairly narrow range of the neighborhood reference point.

Table 8a: Logit Regressions – Recent Neighborhood Price Per Square Meter as Reference Point

	(1)	(2)	(3)	(4)	(5)
Bin	10	50	100	200	300
Panel A: $\text{abs}(\text{price} - \text{reference point}) \leq \text{bin}$					
Holding years	-0.00086	-0.00008	0.00098	0.00307***	0.00483***
	(-0.39)	(-0.08)	(1.48)	(5.51)	(8.56)
Change in HPI	0.00070**	0.00020	-0.00009	-0.00029***	-0.00056***
	(2.03)	(1.27)	(-0.80)	(-2.95)	(-5.27)
Sample	[-30,30]	[-150,150]	[-300,300]	[-600,600]	[-900,900]
Observations	3431	16035	30637	54950	72033
Log Pseudolikelihood	-2288.0282	-10347.617	-19914.624	-36568.392	-49060.539
Panel B: $0 \leq \text{price} - \text{reference point} \leq \text{bin}$					
Holding years	-0.00176	0.00045	0.00071	0.00134***	0.00192***
	(-0.90)	(0.56)	(1.29)	(2.78)	(4.00)
Change in HPI	0.00076**	0.00020	0.00002	-0.00006	-0.00014
	(2.53)	(1.45)	(0.16)	(-0.73)	(-1.64)
Sample	[-30,30]	[-150,150]	[-300,300]	[-600,600]	[-900,900]
Observations	3431	16035	30637	54950	72033
Log Pseudolikelihood	-1925.7614	-7786.6637	-14994.947	-28168.675	-39372.343

Notes: Marginal effects reported; t statistics in parentheses using standard errors clustered at the project level. * indicates significance at the 10% level, ** indicates significance at the 5% level and *** indicates significance at the 1% level.

Table 8b: Logit Regressions – Recent Neighborhood Price Per Square Meter as Reference Point

	(1)	(2)	(3)	(4)
Bin	10	50	100	200
Panel B: $\text{abs}(\text{price} - \text{reference point}) \leq \text{bin}$				
Holding years	-0.00002	0.00057**	0.00103***	0.00134***
	(-0.16)	(2.28)	(3.00)	(2.78)
Change in HPI	0.00004*	0.00000	-0.00007	-0.00006
	(1.80)	(0.05)	(-1.19)	(-0.73)
Sample	[-600,600]	[-600,600]	[-600,600]	[-600,600]
Observations	54950	54950	54950	54950
Log Pseudolikelihood	-4414.5439	-11753.476	-18710.746	-28168.675
Panel B: $0 \leq \text{price} - \text{reference point} \leq \text{bin}$				
Holding years	0.00008	0.00079**	0.00172***	0.00307***
	(0.45)	(2.41)	(3.96)	(5.51)
Change in HPI	0.00003	-0.00005	-0.00020***	-0.00029***
	(1.11)	(-0.79)	(-2.65)	(-2.95)
Sample	[-600,600]	[-600,600]	[-600,600]	[-600,600]
Observations	54950	54950	54950	54950
Log Pseudolikelihood	-6254.6866	-18000.415	-27298.011	-36568.392

Notes: Marginal effects are reported; t statistics in parentheses using standard errors clustered at the project level, using sample range of [-600, 600] for the difference between selling price and recent neighborhood price. * indicates significance at the 10% level, ** indicates significance at the 5% level and *** indicates significance at the 1% level.

4.5 Relative Influences of Prior Purchase Price and Neighborhood Price

The previous sections separately tested the likelihoods of transaction prices falling into a narrow range of each reference point as a function of length of ownership, controlling for the housing market trend. The results of the previous sections show that transactions are less likely to fall into a narrow range of the prior purchase price, and more likely to fall into a narrow range of the neighborhood price, as the years of ownership increases.

While those results support the notion that ownership time length diminishes the influence of prior purchase price in favor of neighborhood price as a reference point, a natural question is about the potential interactions of these two reference points over the holding period. In other words, in an empirical specification which incorporates both prior purchase price and neighborhood price domains, how do the likelihoods of transaction in the respective gain and loss domains, and their combinations across the two reference point candidates compare? Here, we address this question using the multinomial logit approach described in Section 3.2.3, which allows comparison of the relative likelihoods of a transaction occurring in each of the defined two-dimensional windows.

For convenient reference, the predictions for the multinomial logic model described in Section 3.2.3 are repeated in the Table below. To implement the specification, staying close to the window ranges considered in previous sections, as a baseline specification, we set the range of [-300, +300] SGD per square meter of both the prior purchase price and recent neighborhood price as the comparison group. Transactions price values to the left and the right of this reference point window within 600 SGD serve as the gains and loss regions, respectively.

Table 2 (repeated): Predicted Change in Relative Frequency as a Function of Holding Years

	Prior price loss	***Prior price reference window***	***Prior price gain***
Neighborhood loss	*(2)*	***(3)*** ***(-)***	***(4)*** ***(-)***
Neighborhood reference window	***(5)*** ***(+)***	*(1)* *Comparison group*	*(6)* *(+)*
Neighborhood gain	***(7)*** ***(+)***	*(8)* *(-)*	*(9)*

In Table 9, columns (1) and (2) show the results of the multinomial logit specification with a 300 SGD window around the reference points serving as the reference point range, and a 600 SGD window to the left and right of that range as the losses and gains ranges, respectively. Each window thus corresponds to approximately 5 percent of the average per square meter housing price in the data (10,757 SGD/sqm, see Table 1), which are small increments in the relative price domain, over which we would generally not expect to observe significant difference in the relative sales likelihood. Our main variable of interest is holding years, while the change in HPI over the holding period serves as a control variable. Each row number refers to the box number in Table 2, while columns contain the estimates for differing reference, loss and gain windows, which generally confirm the same empirical patterns.

Recall our hypothesis that recent neighborhood price becomes relatively more influential as a reference point compared to the prior purchase price, as the years of ownership increase. Under such a hypothesis, we expect the likelihoods of transaction prices in the neighborhood reference point range and neighborhood gain domain to experience relative increases, while the likelihood of transactions in the prior purchase price reference point range, and its associated gain domain experience relative decreases as a function of holding years. This may be especially expected to be true in relative likelihood terms, for those situations in which an owner is facing a reference-level or better price in the favored reference point domain, but facing a loss situation in the less favored reference point domain (ie. in particular boxes 5, 7 and 3, 4, highlighted using bold in Table 2 (repeat)).

Table 9: Multinomial Logit: Dependent variables: Price Difference Windows

Reference, loss and gain windows vary by column

	(a) **Loss [-900, -300]; reference [-300,300]; gain [300, 900]**	(b) **Loss [-900, -300]; reference [-300,300]; gain [300, 900]**	(c) **Loss [-1200, -400]; reference [-400,400]; gain [400, 1200]**	(d) **Loss [-1200, -400]; reference [-400,400]; gain [400, 1200]**	(e) **Loss [-600, -200]; reference [-200,200]; gain [200, 600]**	(f) **Loss [-600, -200]; reference [-200,200]; gain [200, 600]**
(2) Nominal loss, neighborhood loss						
Holding years	1.029**	1.078***	1.016	1.076***	1.041***	1.076***
	(2.54)	(6.33)	(1.58)	(6.78)	(2.93)	(5.26)
Change in HPI		0.970***		0.962***		0.980***
		(-9.37)		(-11.51)		(-6.22)
(3) Nominal reference, neighborhood loss						
Holding years	0.985	0.980*	0.980**	0.977**	0.989	0.987
	(-1.49)	(-1.77)	(-2.27)	(-2.39)	(-0.75)	(-0.83)
Change in HPI		1.003		1.002		1.001
		(1.22)		(0.97)		(0.32)
(4) Nominal gain, neighborhood loss						
Holding months	0.997	0.940***	0.997	0.938***	1.005	0.955***
	(-0.20)	(-4.24)	(-0.27)	(-5.13)	(0.31)	(-2.58)
Change in HPI		1.034***		1.037***		1.028***
		(11.05)		(12.03)		(7.29)
(5) Nominal loss, neighborhood reference						
Holding years	1.064***	1.117***	1.064***	1.117***	1.062***	1.097***
	(5.79)	(10.39)	(5.79)	(10.39)	(4.73)	(7.09)
Change in HPI		0.969***		0.969***		0.980***
		(-10.75)		(-10.75)		(-5.42)
(6) Nominal gain, neighborhood reference						
Holding years	1.009	0.948***	0.996	0.931***	1.016	0.959***
	(0.90)	(-5.18)	(-0.47)	(-8.26)	(1.25)	(-3.19)
Change in HPI		1.036***		1.041***		1.031***
		(15.31)		(19.62)		(10.85)
(7) Nominal loss, neighborhood gain						
Holding years	1.085***	1.163***	1.065***	1.160***	1.079***	1.131***
	(7.61)	(12.92)	(6.91)	(14.92)	(5.36)	(8.32)
Change in HPI		0.956***		0.943***		0.971***
		(-13.98)		(-16.46)		(-7.57)
(8) Nominal reference, neighborhood gain						
Holding years	1.037***	1.050***	1.033***	1.050***	1.037***	1.047***
	(3.82)	(4.98)	(4.21)	(6.15)	(3.16)	(3.96)
Change in HPI		0.992***		0.989***		0.994*
		(-3.14)		(-5.47)		(-1.70)
(9) Nominal gain, neighborhood gain						
Holding years	0.978**	0.929***	0.948***	0.901***	0.994	0.947***
	(-2.24)	(-7.13)	(-5.85)	(-11.27)	(-0.49)	(-4.20)
Change in HPI		1.030***		1.032***		1.026***
		(13.67)		(16.09)		(8.62)
Observations	18716	18716	27806	27806	10079	10079
Log Pseudolikelihood	-39457.53	-38230.71	-57226.609	-54652.209	-21673.937	-21289.577

Notes: Exponentiated coefficients (odds ratios) are reported; *t* statistics in parentheses; * indicates significance at the 10% level, ** indicates significance at the 5% level and *** indicates significance at the 1% level.

As predicted, a significantly negative odds ratio (less than 1.0, corresponding to lower relative likelihood than the comparison group) is present in the full sample for the cases of prior purchase price reference, neighborhood loss (3), and nominal gain, neighborhood loss (4). In addition, a significantly positive odds ratio is present for the cases of nominal loss, neighborhood reference (5) and nominal loss, neighborhood gain (7), consistently with the main predictions.

Categories (6) and (8) represent scenarios in which the transaction price is directly in the reference point range for one reference point, but is in the gains domain for the other reference point. Understandably, relative shifting of likelihood into and away from these boxes over the holding period may be weaker than the effects in categories (5), (7), (3) and (4), because neither category falls into the loss domain of either reference point candidate, which is the driving force of the prediction in the reference-dependent model. Indeed, in the multinomial logit, the relative likelihoods of a transaction occurring in these categories is reversed compared to our prediction in Table 2. However, note that when we incorporate the possibility of transaction costs by shifting the loss, reference and gain domains upward by the specified range intervals, the odds ratios move to the predicted directions for categories (6) and (8), at least for the basic specification on holding years.[28] These results are provided in Table B10 of Appendix B.

Our framework does not hold any special prediction for the categories of nominal loss, neighborhood loss (2) or nominal gain, neighborhood gain (9). However, the data generally show a higher likelihood of selling in the dual loss domain than the dual gain domain over the holding period.

4.6 The Average Effect of Loss on Transaction Price

Thus far, our analysis has focused on examining the distribution of sale prices, ie. the likelihood that transaction prices occur in specific price range relative to a reference point. However, much of the literature addressing reference-dependence in real estate markets has focused directly on loss as a determinant of listing prices and transactions prices themselves. This approach focuses on recovering the average treatment effect on prices, of a house being in the loss domain.

To add such analysis to our existing evidence, we implement least squares regressions similar to those in Genesove and Mayer (2001) and subsequent literature such as Anenberg (2011), Bokhar and Geltner (2011), Bucchianeri and Minson (2013), and Liu and van der Vlist (2019). Although our data differs from most of these previous studies by being at the transaction level rather than at the listing level, we implement a regression similar to that implemented for the transactions price specification in Genesove and Mayer (2001).

That is, in order to estimate the loss that the homeowner is facing at the time of the transactions, we estimate a hedonic regression on the market value of the home as a first stage regression. The estimated home value is then used to compute the loss level that the homeowner faces for each reference point candidate. Table C1 in Appendix C shows the summary statistics of the sample used for the hedonic regression that predicts price at the time of transaction in the first stage. The hedonic regression sample includes houses that are transacted only once in the data, whereas in the second stage, since we need to compare purchase price and selling price, we use those houses that have been transacted at least twice.[29] Table C2 shows the results of the hedonic regression. Column (1) uses price per square meter as the dependent variable, while column (2) uses the log of price per

[28] An alternative possible approach is to measure transactions costs directly. However, our data do not contain information on the exact transaction costs faced by each buyer/seller, therefore we use the alternative specification with shifted relative price ranges as an approximation for what we might expect to obtain.

[29] To predict the housing price using all samples in the first stage, we control for a variable "construction status," which represents whether a house is transacted before the construction is completed, as a house is allowed to sell before being constructed in Singapore and in many other Asian countries. However, in the second stage, we do not include this variable since very few houses transacted at least twice before the completion of construction.

square meter. In the following analysis, we use log of price per square meter, following the practice in the literature.

As noted earlier, there are a few differences regarding our OLS specification compared to that in Genesove and Mayer (2001). First, they have unobservable quality v_i in their hedonic regression for property value. In the Singapore data, we are much less likely to encounter this problem since the housing market is quite homogeneous within the same housing project. After including project fixed effects and controlling for other observable features such as floor level and area, the housing units are nearly identical. Thus, the expected price estimate using the predicted price from the hedonic model are much less likely to suffer from an unobservable quality variable v_i.[30]

Secondly, since the method follows a two-stage estimation procedure, Genesove and Mayer (2001) calculate standard errors via the method described in Newey and McFadden (1994). Theoretically, the estimator is the sum of the White (1980) covariance matrix for the least squares and a correction term for the first-stage estimation, which are essentially heteroscedasticity-consistent standard errors for two-step estimators. Here, we follow Annenberg (2011) by using bootstrap to calculate the standard errors for the generated regressors in the second stage with replications of 500, clustering the standard errors at the housing project level.

Finally, we interact the loss term with our main variable of interest, holding years, in order to test our main hypothesis. We also interact loss with changes in market performance to control for the interaction of loss with market factors.

Table 10 provides the regression results for prior purchase price (per square meter) as the reference point. The regression includes as control variables: the housing features such as floor level and area, holding period, as well as loss variables, namely loss, loss squared and the interaction between loss and holding period. Housing project fixed effects, time fixed effects, and planning area-specific year fixed effects are also included. As argued in previous studies (Huang, Li, and Ross, 2018), once these factors are controlled for, the transaction price of the house should be largely determined.

In this framework, a positive and significant estimated coefficient on loss implies that the homeowner is loss averse and that he/she raises his or her willingness to accept price in response to being in the loss domain. We find such a robust, positive and significant coefficient on loss in Table 10, whose specifications vary based on the loss-related terms included. All else equal, the impact of the prior purchase price on current transactions price diminishes with holding years, as a house depreciates over time. The coefficients on the floor level and area variables show that other relevant factors constant, higher floors yield higher transactions prices, and larger areas yield lower per square meter prices, which is consistent with intuition.

The interaction term between loss and holding years is also important for our main question. While the coefficient on the loss variable alone has been used to demonstrate the influence of loss aversion in prior studies, the interaction term with holding years tests our hypothesis about the trend of influence of the reference point in question over the holding period. The significant and negative coefficients indicate that the impact of being in the

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[30] As we see in Table A15, the adjusted R-squared is more than 0.95 in our hedonic regression after controlling these effects as well as year-quarter fixed effects and area specific year fixed effects.

loss domain on current transaction price decreases with holding years, consistently with our hypothesis, while the net effect of loss remains positive, in specifications (3) to (5).

As suggested by the coefficients on loss squared in specifications (2) and (4), current price is generally concave in loss magnitude, which is consistent with diminishing sensitivity to losses. The coefficient on the interaction between loss and change in HPI suggests that the positive effect of loss on transaction price tends to be magnified in a rising market. This is intuitive since in a rising market, the forces of supply and demand are also amenable to higher transaction prices.

Table 10: Price – Prior Purchase Price per Square Meter as Reference Point

(Bootstrap estimation with replications of 500; z statistics are reported in parentheses)

	(1)	(2)	(3)	(4)	(5)
Loss	0.18073***	0.39711***	0.64286***	0.72034***	0.66661***
	(29.46)	(25.16)	(41.45)	(42.48)	(37.78)
Holding years	-0.00351***	-0.00349***	-0.00236***	-0.00241***	-0.00237***
	(-35.01)	(-34.27)	(-23.29)	(-23.62)	(-24.53)
Floor	0.00453***	0.00452***	0.00452***	0.00452***	0.00451***
	(66.93)	(71.33)	(73.10)	(70.85)	(71.19)
Area	-0.00122***	-0.00121***	-0.00124***	-0.00123***	-0.00125***
	(-68.42)	(-71.47)	(-75.03)	(-74.20)	(-85.14)
Loss squared		-0.50510***		-0.23595***	0.14329***
		(-13.98)		(-7.32)	(2.99)
Loss × Holding years			-0.06584***	-0.06248***	-0.05984***
			(-36.22)	(-30.49)	(-31.54)
Loss × Change in Log(HPI)					0.61468***
					(14.50)
Project FE	YES	YES	YES	YES	YES
Year × Quarter FE	YES	YES	YES	YES	YES
Planning Area × Year FE	YES	YES	YES	YES	YES
Observations	120230	120230	120230	120230	120230
R-squared	0.949	0.950	0.951	0.951	0.951

Notes: The dependent variable is the log of price per square meter. Change in Log(HPI) between selling time and purchase time has been fully accounted for by Year × Quarter FE, hence Log(HPI) is omitted from specification (5). Standard errors are derived via bootstrap estimation with 500 replications, z statistics reported in parentheses; * indicates significance at the 10% level, ** indicates significance at the 5% level and *** indicates significance at the 1% level.

Table 11 shows the analogous results for neighborhood price as the reference point. Across specifications, houses sold in the loss domain with respect to the previous quarter's median price in the project are transacted for significantly higher prices, controlling for other factors. The overall impact of holding years on a housing pricing above the neighborhood reference point is negative, similarly to that in Table 10. However, in contrast to Table 10, the coefficient on the interaction term between loss and holding years is positive, which shows that the influence of the neighborhood reference point increases over the holding period.

In comparison with Table 10, the intuitive coefficients on floor level and area remain, while the lack of a significant coefficient on loss squared indicates that the relationship between loss magnitude and current transaction price is largely linear.

Table 11: Price – Recent Neighborhood Price per Square Meter as Reference Point

(Bootstrap estimation with replications of 500; z statistics are reported in parentheses)

	(1)	(2)	(3)	(4)	(5)
Loss	0.55202***	0.58790***	0.50913***	0.54479***	0.54213***
	(58.89)	(25.59)	(33.34)	(20.80)	(20.16)
Holding years	-0.00277***	-0.00277***	-0.00299***	-0.00298***	-0.00298***
	(-31.07)	(-31.01)	(-27.94)	(-29.47)	(-29.89)
Floor	0.00570***	0.00572***	0.00569***	0.00572***	0.00572***
	(81.81)	(84.02)	(86.96)	(80.86)	(83.81)
Area	-0.00154***	-0.00153***	-0.00154***	-0.00153***	-0.00153***
	(-89.37)	(-91.69)	(-91.92)	(-93.81)	(-95.37)
Loss squared		-0.15255		-0.14969	-0.14725
		(-1.44)		(-1.44)	(-1.33)
Loss × Holding years			0.00779***	0.00771***	0.00692***
			(3.61)	(3.60)	(3.13)
Loss × Change in Log(HPI)					0.04256
					(1.18)
Project FE	YES	YES	YES	YES	YES
Year × Quarter FE	YES	YES	YES	YES	YES
Planning Area × Year FE	YES	YES	YES	YES	YES
Observations	115824	115824	115824	115824	115824
R-squared	0.953	0.953	0.953	0.953	0.953

Notes: The dependent variable is the log of price per square meter. Change in Log(HPI) between selling time and purchase time has been fully accounted for by Year × Quarter FE, hence Log(HPI) is omitted from specification (5). Standard errors are derived via bootstrap estimation with 500 replications, z statistics reported in parentheses; * indicates significance at the 10% level, ** indicates significance at the 5% level and *** indicates significance at the 1% level

Table 12 shows the specifications with both prior purchase price and neighborhood price as reference points included. The coefficients on the losses are again positive for each reference point and are of similar order of magnitude as in Tables 11 and 10. Once again, other factors controlled for, holding years figure negatively into the current transactions price, while the coefficients on the floor and area variables retain their intuitive signs.

Our key variables of interest are the interaction terms between loss and holding period, now incorporated simultaneously into specifications (3) to (5). Compared to the previous regressions in Tables 10 and 11 which test the interaction terms separately, the signs and significance of the coefficients are similar to those in the regressions that consider each reference point separately. That is, when considered simultaneously, the reference-dependent effect for prior purchase price decreases over the holding period, while the reference-dependent effect for neighborhood price increases over the holding period. This precisely illustrates the phenomenon, demonstrating that the effects found in the analysis of the transactions price distributions also holds in terms of average pricing effects.

Table 12: Price – Prior Purchase Price and Recent Neighborhood Price Per Square Meter as Reference Points

(Bootstrap estimation with replications of 500; z statistics are reported in parentheses)

	(1)	(2)	(3)	(4)	(5)
Loss – prior	0.15177***	0.33480***	0.53996***	0.60943***	0.56990***
	(24.92)	(24.72)	(35.66)	(35.35)	(34.13)
Loss – neighbor	0.53689***	0.56908***	0.43631***	0.47357***	0.46301***
	(57.52)	(25.49)	(29.04)	(19.37)	(19.23)
Holding years	-0.00318***	-0.00317***	-0.00262***	-0.00268***	-0.00268***
	(-34.14)	(-32.82)	(-26.30)	(-26.64)	(-27.12)
Floor	0.00565***	0.00566***	0.00558***	0.00560***	0.00560***
	(85.75)	(83.67)	(83.63)	(81.19)	(81.00)
Area	-0.00154***	-0.00153***	-0.00154***	-0.00153***	-0.00154***
	(-98.41)	(-96.73)	(-99.30)	(-101.40)	(-103.27)
Loss squared – prior		-0.42707***		-0.21062***	0.15574***
		(-14.00)		(-6.46)	(3.37)
Loss squared – neighbor		-0.16039		-0.17552*	-0.23015**
		(-1.55)		(-1.76)	(-2.52)
Loss × Holding years – prior			-0.05461***	-0.05160***	-0.05043***
			(-30.43)	(-27.09)	(-28.34)
Loss × Holding years – neighbor			0.01282***	0.01334***	0.01097***
			(5.85)	(6.04)	(4.65)
Loss × Log of HPI – prior					0.57030***
					(13.74)
Loss × Log of HPI – neighbor					0.20137***
					(5.44)
Project FE	YES	YES	YES	YES	YES
Year × Quarter FE	YES	YES	YES	YES	YES
Planning Area × Year FE	YES	YES	YES	YES	YES
Observations	115824	115824	115824	115824	115824
R-squared	0.953	0.954	0.954	0.954	0.955

Notes: The dependent variable is the log of price per square meter. Change in Log(HPI) between selling time and purchase time has been fully accounted for by Year × Quarter FE, hence Log(HPI) is omitted from specification (5). Standard errors are derived via bootstrap estimation with 500 replications, z statistics reported in parentheses; * indicates significance at the 10% level, ** indicates significance at the 5% level and *** indicates significance at the 1% level

5. Theoretical Interpretation

Finally, we provide a behavioral model that can qualitatively account for the empirical findings we have presented. Since most models of reference dependent preferences only incorporate a single reference point, it is useful to provide a model of homeowner utility that can explain our evidence on dual reference points with time-dependent importance, as found in our empirical results.

Our model, by proposing memory as the channel to achieve time-dependence for weights across multiple reference points, bears similarity to that of Bhatia and Golman (2019), which proposes attention as a driver for reference point selection in reference-dependent models. Although memory and attention are both related to cognitive load, a key difference between our model and Bhatia and Golman (2019) is that we focus on the time dynamics of memory while they consider cross-sectional allocation of attention. Bordalo, Gennaioli and Shleifer (2020) also studies the dynamic updating process of reference points but does not specifically consider the co-existence of multiple reference points.

The typical homeowner's utility function for selling a house at price p can be described as follows:

$$U(p;r_{pp},r_{rp},t)=v(p)+\alpha_{pp}(t)\cdot u_{pp}(p;r_{pp})+\alpha_{rp}(t)\cdot u_{rp}(p;r_{rp}) \ ,$$

where $v(p)$ is the absolute term of utility, and $u_i(p;r_i)$ ($i\in\{pp,rp\}$) are the relative terms of utility. r_{pp} refers to the purchase price of the house as a reference point candidate, while r_{rp} refers to the recent price for neighboring houses as the other reference point candidate. The parameter $\alpha_{pp}(t)$ ($\alpha_{rp}(t)$) represents the relative holding-period-dependent weight or likelihood to use r_{pp} (r_{rp}) as the reference point, while t is the holding period of the house. We assume that functions $\alpha_{pp}(\cdot)$ and $\alpha_{rp}(\cdot)$ as a function of holding time, are continuously differentiable.

First, the absolute term in the utility function comes directly from classical theory, and the following assumption on curvature is well-accepted in classical utility functions.

Assumption 1: $v'>0$, $v''<0$.

Following the reference-dependence literature, we make the following assumption regarding the relative terms in the utility function.

Assumption 2: For $i\in\{pp,rp\}$, $u_i(p;r_i)\equiv\begin{cases}\lambda_{i,g}w_i(p-r_i) & if \quad p\geq r_i\\ -\lambda_{i,l}w_i(r_i-p) & if \quad p<r_i\end{cases}$, where

$\lambda_{i,l}\geq\lambda_{i,g}>0, w_i'>0, w_i'>0$ for any $p,r_i\in R_+$.

The presence of $u_i(p;r_i)$ (that is, $\alpha_{pp}(t)\cdot\alpha_{pp}(t)>0$ and $u_i(p;r_i)>0$) implies that the homeowner's utility is reference-dependent, and the asymmetric intensity weighting between the gains domain and the loss domain (that is, $\lambda_{i,l}\geq\lambda_{i,g}>0$) implies that such reference-dependence takes the form of loss aversion.

With the existence of multiple candidates as the reference point, a key question that naturally arises is which reference point candidate is more likely to be chosen as the reference point itself, or in a more general sense, which reference point candidate will be given more weight. For a given candidate reference point r_i with $i\in\{pp,rp\}$, α_i depends on how salient r_i is. Among the many factors which may influence the salience level of a reference point, time is our main focus in this paper.

It is understandable that as time goes by, an individual's memory fades and the salience level of events that have occurred in the past decrease. This directly implies that the purchase price r_{pp} as a candidate reference point, will be given successively less weight as the holding period t increases, as described in the following assumption.

Assumption 3: $\frac{\partial \alpha_{pp}(t)}{\partial t} < 0$.

It is also reasonable to assume that the memory depreciation of a fairly current event (ie. recent neighborhood price) is slower than the memory depreciation of an event farther in the past (ie. original purchase price). This implies that the decrease in weight for purchase price r_{pp} as a candidate reference point is faster than the weighting decrease for recent price r_{rp} as a candidate reference point, as the holding period t becomes longer. This is summarized in Assumption 4, and reflected in the relative magnitudes of coefficients on loss from our empirical analysis, exemplified in Figure 6.

Assumption 4: $\frac{\partial(\alpha_{pp}(t) - \alpha_{rp}(t))}{\partial t} < 0$.

Comparing the salience levels of an event that is current and an event that has occurred in the past, due to limited attention (which is also consistent with limited cognitive resources more generally), via the substitution effect, the relative likelihood depends on the length of holding period t. We can show that as t increases, the purchase price r_{pp} will first serve as the dominant reference point, followed by a switch to the recent price level for neighborhood houses r_{rp} as the dominant reference point. This main result is summarized in the following proposition.

Proposition 1: There exists a unique $t^* > 0$ such that $\forall t < t^*$, $\alpha_{pp}(t) > \alpha_{rp}(t)$ and $\forall t > t^*$, $\alpha_{pp}(t) < \alpha_{rp}(t)$.

Proposition 1 can be derived by combining Assumption 4 with the fact that $\alpha_{pp}(\cdot)$ and $\alpha_{rp}(\cdot)$ are both continuous, along with the following two key observations: First, notice that when the holding period is sufficiently long (considering the lifetime of the homeowner as an extreme case), the weight on r_{pp} will be less than the weight on r_{rp} due to depreciating memory, indicating $\alpha_{pp}(t) - \alpha_{rp}(t) < 0$ for large t. Second, when the holding period is close to zero, meaning directly after the house was bought, it is clear that the weight on r_{pp} will be greater than the weight on r_{rp}, implying that $\alpha_{pp}(t) - \alpha_{rp}(t) > 0$ for small t. Defining $f(t) \equiv \alpha_{pp}(t) - \alpha_{rp}(t)$, and since $f(\cdot)$ is decreasing in t, the above two observations immediately lead to Proposition 1, by continuity of $f(\cdot)$.

Such a utility function as described above, can be responsible for homeowners' prior purchase price being the reference point in initial years of ownership, while recent neighborhood price is the dominant reference point during later years. This property is supported by the empirical results throughout the paper, best summarized by Figure 6.

6. Conclusion and Discussion

While the behavioral and experimental literature has made some progress in examining how reference points shift over time in a controlled setting, relatively less knowledge has been established about how reference points shift in different real-world contexts. In this paper, we have proposed and empirically verified an intuitive pattern in how reference-dependent behavior in the housing market changes over time. Specifically, in the early years of homeownership, individuals generally hold their original purchase price as the reference point, while as the number of holding years increase, the emphasis instead gravitates to recently sold neighborhood homes.

Using both a distributional analysis on sales prices along the lines of Lien and Zheng (2015), Allen, Dechow, Pope and Wu (2016), Rees-Jones (2018) and Gao, Lien and Zheng (2020), and a two-stage hedonic method for estimating the average treatment effect of loss, following Genesove and Mayer (2001) and subsequent studies, we find that over time homeowners shift their reference-point from their own prior purchase price, to a price level that is more representative of the current localized situation in their neighborhood.

Our analysis contributes to the literature on determinants of the reference point in individual utility functions. In particular, some discussions have arisen about the relative explanatory power of lagged status quo, versus more forward-looking reference points such as proposed in Koszegi and Rabin (2006). While lagged status quo is an influential reference point, our analysis shows that its relative influence diminishes over time in favor of more recent and local benchmarks. In some senses this is intuitive and reasonable, since one would not expect homeowners to hold their prior purchase price as the reference point forever. Our findings suggest that decision-makers may gravitate towards a more present-oriented reference point over time.

We believe there are several avenues for future research. While our study focuses on the real estate market, it may be worthwhile to test whether other assets display similar gravitation from a lagged status quo reference point to a more recent cross-sectional reference point over time. In addition, while our study detects movement from a reference point in the past to one focusing more on the present, we have not explored the potential role of forward-looking reference points here. In particular, forward-looking reference points such as expectations, may be more difficult to detect in field settings, due to the reliance on identifying decision-makers' expectations, which can be quite heterogeneous or uncertain, even in the mind of the decision-maker. Finally, our study has focused on detecting reference-dependence in the housing market, and testing the relative influence of lagged status quo and neighborhood reference points, however, we do not attempt to quantify the effect of such preferences on the market as a whole. Future work may consider simulating the effect on market conditions and drawing policy implications for housing markets.

References

Allen, E.J., Dechow, P.M., Pope, D.G. and Wu, G., 2016. Reference-dependent preferences: Evidence from marathon runners. *Management Science*, *63*(6), pp.1657-1672.

Andersen, S., Badarinza, C., Liu, L., Marx, J., and Ramadorai, T., 2021. Reference Dependence in the Housing Market. *Working Paper* (January 26, 2021 SSRN).

Anenberg, E., 2011. Loss Aversion, Equity Constraints and Seller Behavior in the Real Estate Market. *Regional Science and Urban Economics*, 41(1), pp.67-76.

Baltagi, B.H. and Li, J., 2015. Cointegration of matched home purchase and rental price indexes – Evidence from Singapore. *Regional Science and Urban Economics*, 55, pp. 80-88.

Berger, J. and Pope, D., 2011. Can losing lead to winning? *Management Science*, *57*(5), pp.817-827.

Best, M.C. and Kleven, H.J., 2017. Housing market responses to transaction taxes: Evidence from notches and stimulus in the UK. *The Review of Economic Studies*, *85*(1), pp.157-193.

Bhatia, S. and Golman, R., 2019. Attention and reference dependence. *Decision*, 6(2), p.145–170.

Bokhari, S. and Geltner, D., 2011. Loss aversion and anchoring in commercial real estate pricing: Empirical evidence and price index implications. *Real Estate Economics*, *39*(4), pp.635-670.

Bordalo, P., Gennaioli, N., and Shleifer A., 2020. Memory, Attention, and Choice. *Quarterly Journal of Economics*, 135(3), pp. 1399-1442

Bucchianeri, G.W. and Minson, J.A., 2013. A homeowner's dilemma: Anchoring in residential real estate transactions. *Journal of Economic Behavior & Organization*, *89*, pp.76-92.

Eil, D. and Lien, J.W., "Staying Ahead and Getting Even: Risk Attitudes of Experienced Poker Players", *Games and Economic Behavior*, Vol. 87 (2014), p. 50 – 69.

Gao, F., Lien, J.W., and Zheng J., 2020. Exaggerating to break-even: Reference-dependent moral hazard in auto insurance claims, *Working Paper*.

Genesove, D. and Mayer, C., 2001. Loss aversion and seller behavior: Evidence from the housing market. *The Quarterly Journal of Economics*, *116*(4), pp.1233-1260.

Giglio, S., Maggiori, M. and Stroebel, J., 2015. Very long-run discount rates. *The Quarterly Journal of Economics*, *130*(1), pp.1-53.

Huang, N., Li, J. and Ross, A., 2018. The impact of the cost of car ownership on the house price gradient in Singapore. *Regional Science and Urban Economics*, *68*, pp.160-171.

Imbens, G.W. and Lemieux, T., 2008. Regression discontinuity designs: A guide to practice. *Journal of econometrics*, *142*(2), pp.615-635.

Jiang, L., Phillips, P.C. and Yu, J., 2015. New methodology for constructing real estate price indices applied to the Singapore residential market. *Journal of Banking & Finance*, *61*, pp.S121-S131.

Kőszegi, B. and Rabin, M., 2006. A model of reference-dependent preferences. *The Quarterly Journal of Economics*, *121*(4), pp.1133-1165.

Lien, J.W. and Zheng, J. 2015. Deciding when to quit: Reference-dependence over slot machine outcomes, *American Economic Review, Papers and Proceedings*, Vol. 105, p. 366 – 370.

Lien, J.W., Xu, M., and Zheng, J, 2018. What brings consumers bank for more? Evidence from quantifiable gain and loss experiences in penny auctions", *Working Paper*.

List, J.A., "Does Market Experience Eliminate Market Anomalies?" *Quarterly Journal of Economics*, Vol. 118 (2003), No. 1, p. 41 – 71.

List, J.A., "Neoclassical Theory versus Prospect Theory: Evidence from the Marketplace", *Econometrica*, Vol 72 (2004), No. 2, p. 615 – 625.

Liu, X., & van der Vlist, A. J. (2019). Listing strategies and housing busts: cutting loss or cutting listprice?. *Journal of Housing Economics*, 43, 102-117.

McCrary, 2008. Manipulation of the Running Variable in the Regression Discontinuity Design: A Density Test. *Journal of Econometrics*, 142(2), pp.698-716.

Newey, Whitney K., and Daniel McFadden, "Large Sample Estimation and Hypothesis Testing," in Robert F. Engle and Daniel L. McFadden, eds., *The Handbook of Econometrics* (Amsterdam: North-Holland, 1994).

Pope, D.G. and Schweitzer, M.E. "Is Tiger Woods loss averse? Persistent bias in the face of experience, competition, and high stakes," *The American Economic Review*, Vol. 101 (2011), No, 1, p. 129-157.

Rees-Jones, A., 2018. Quantifying loss-averse tax manipulation. *The Review of Economic Studies*, *85*(2), pp.1251-1278.

Slemrod, J., Weber, C., and Shan, H., 2017. The behavioral response to housing transfer taxes: Evidence from a notched change in D.C. policy, *Journal of Urban Economics*, Vol. 100, p. 137 – 153.

Tong, L.C.P., Ye, K.J., Asai, K., Ertac, S., List,J.A., Nusbaum, H.C., and Hortacsu, A., "Trading Experience Modulates Anterior Insula to Reduce the Endowment Effect", *Proceedings of the National Academy of Sciences*, Vol. 113 (2016), No. 33, p. 9238 – 9243.

Appendix A:

Derivation of Multinomial Logit Predictions:

Table 2 (repeat): Predicted Change in Relative Frequency as a Function of Holding Years

	Prior price loss	***Prior price reference window***	***Prior price gain***
Neighborhood loss	*(2)*	***(3)*** ***(-)***	***(4)*** ***(-)***
Neighborhood reference window	***(5)*** ***(+)***	*(1)* *Comparison group*	*(6)* *(+)*
Neighborhood gain	***(7)*** ***(+)***	*(8)* *(-)*	*(9)*

The prediction above regarding the expected direction of relative likelihood as holding years on a house increases is derived under the following reasoning: First, we assume that house price transactions are distributed along the dominant reference point domain in the ordering of 1. Reference window; 2. Gains; 3. Losses (see also Lien and Zheng, 2015 and other reference-dependence studies for argument). The second assumption is that within each of these three categories of the dominant reference point domain, transactions are distributed within each category according to the weaker reference point domain, also in the ordering of 1. Reference window; 2. Gains; 3. Losses.

Under the above mentioned two assumptions, the rank ordering (left to right) of the numbered boxes depicted in Table 2 for a low holding period (prior purchase price is the dominant reference point) are:

1	8	3	6	9	4	5	7	2

For longer holding periods (neighborhood price as the dominant reference point), the rank ordering is (left to right):

1	6	5	8	9	7	3	4	2

A comparison of the rank ordering of numbered boxes between the two rows indicates that the following numbered boxes are decreasing in rank as a function of holding years: 8, 3, 4; while the following boxes are increasing in rank as a function of holding years: 6, 5, 7. The dual reference window of box 1 serves as the comparison group in the multinomial logit, and is fixed in predicted rank. Thus, neither box 1, 2, or 9 are expected to exhibit any significant change based on the holding period hypothesis.

It can also be intuitively understood as *relative* likelihood shifting on net from the reference-dependent house seller's prior price reference window (box 3) and prior price gain domain (box 4) under the neighborhood loss domain, to the corresponding neighborhood reference window (box 5) and neighborhood gain domain (box 7) under the prior purchase price loss domain. These changes are highlighted in bold font in Table 2.

The relative changes in boxes 6 and 8 as a function of holding years are weaker in their prediction, largely because the aforementioned box in the dominant reference window range competes with it for the transaction likelihood, but is circumstantial in the sense of being able to actually attain a gain in the relevant domain. Thus, the direction of shift predicted in boxes 6 and 8 may be viewed as a potential weaker prediction about the likelihood shift compared to the boxes highlighted in bold.

Appendix B:

Table B1: Transactions – Prior Purchase Price as Reference Point, by Year

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Sample	**1998**	**1999**	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**
P_dif	0.724	2.201	3.661***	-0.957	-1.052	3.720***	2.505*	4.345***	7.707***	-8.783***
	(0.81)	(1.61)	(3.77)	(-1.09)	(-0.94)	(2.71)	(1.84)	(3.01)	(4.14)	(-2.74)
Loss × P_dif	-0.000	-0.000***	-0.000**	-0.000**	-0.000***	-0.000	-0.000	-0.000**	-0.000***	-0.000***
	(-1.01)	(-3.54)	(-2.12)	(-2.44)	(-3.07)	(-0.79)	(-1.37)	(-2.54)	(-3.75)	(-7.19)
Loss×Price diff	0.000	0.000***	0.000***	0.000***	0.000***	0.000*	0.000**	0.000***	0.000***	0.000**
	(1.35)	(5.99)	(4.82)	(2.74)	(3.82)	(1.67)	(2.39)	(5.15)	(8.07)	(2.22)
Observations	186	315	250	218	234	216	242	302	437	631
Adjusted R^2	0.038	0.112	0.099	0.033	0.074	0.129	0.096	0.124	0.138	0.075
Sample	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**
Loss	-3.672	-18.369***	-19.637***	-19.568***	-22.304***	-9.860***	-8.060***	-8.221***	-7.356***	-14.652***
	(-1.43)	(-4.95)	(-4.31)	(-4.84)	(-5.77)	(-5.73)	(-5.59)	(-6.50)	(-5.07)	(-6.06)
P_dif	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(-5.69)	(-6.91)	(-6.41)	(-7.00)	(-7.11)	(-6.38)	(-6.48)	(-6.75)	(-6.54)	(-7.40)
Loss × P_dif	0.000**	0.000***	0.000	0.000	0.000**	0.000**	0.000***	0.000***	0.000***	0.000***
	(2.37)	(4.72)	(1.63)	(1.40)	(2.12)	(2.18)	(2.83)	(4.43)	(5.84)	(5.54)
Observations	423	523	553	515	477	475	414	458	470	566
Adjusted R^2	0.073	0.094	0.080	0.101	0.119	0.111	0.115	0.128	0.107	0.110

Notes: The dependent variable is the number of transactions in each bin. *t* statistics in parentheses, * indicates significance at the 10% level, ** indicates significance at the 5% level and *** indicates significance at the 1% level. Bin width is 5,000 dollars of price. The regression contains a constant term but we do not report it.

Table B2: Transactions – Recent Neighborhood Price Per Square Meter as Reference Point, by Year

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Sample	**1998**	**1999**	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**
Loss	5.990***	-30.594***	7.943**	4.367	3.251	7.581*	1.917	-7.821	-8.490	-88.499***
	(3.52)	(-7.26)	(2.30)	(1.53)	(0.85)	(1.97)	(0.34)	(-1.14)	(-0.83)	(-7.27)
P_dif	-0.003***	-0.010***	-0.003***	-0.007***	-0.008***	-0.013***	-0.017***	-0.017***	-0.019***	-0.016***
	(-3.97)	(-13.03)	(-4.87)	(-5.92)	(-6.91)	(-8.21)	(-7.71)	(-8.28)	(-10.37)	(-16.55)
Loss × P_dif	0.006***	0.017***	0.010***	0.014***	0.020***	0.030***	0.036***	0.032***	0.049***	0.031***
	(7.08)	(8.15)	(8.48)	(9.72)	(9.76)	(12.52)	(10.86)	(10.64)	(10.59)	(8.62)
Observations	117	141	138	111	109	103	106	138	165	295
Adjusted R^2	0.459	0.601	0.336	0.486	0.466	0.603	0.524	0.451	0.486	0.520
Sample	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**
Loss	6.980	-93.295***	-77.674***	-46.329***	-74.663***	-16.566***	3.282	6.984	2.258	-15.670*
	(0.97)	(-8.50)	(-4.49)	(-3.96)	(-7.42)	(-3.72)	(0.99)	(1.61)	(0.43)	(-1.96)
P_dif	-0.009***	-0.023***	-0.025***	-0.017***	-0.025***	-0.008***	-0.006***	-0.006***	-0.010***	-0.016***
	(-6.77)	(-15.80)	(-11.31)	(-11.78)	(-13.93)	(-11.95)	(-10.06)	(-8.52)	(-10.56)	(-12.16)
Loss × P_dif	0.018***	0.035***	0.043***	0.031***	0.035***	0.013***	0.012***	0.013***	0.021***	0.030***
	(10.60)	(13.32)	(10.81)	(12.31)	(15.10)	(14.39)	(15.02)	(13.18)	(15.24)	(15.21)
Observations	241	264	264	283	262	290	246	255	241	257
Adjusted R^2	0.327	0.535	0.385	0.406	0.491	0.427	0.479	0.402	0.490	0.482

Notes: The dependent variable is the number of transactions in each bin. *t* statistics in parentheses, * indicates significance at the 10% level, ** indicates significance at the 5% level and *** indicates significance at the 1% level. Bin width is 50 dollars of price. The regression contains a constant term.

Table B3: Average Number of Observations within Each Bin, by Holding Years

Bin size	10	10	20	20	50	50
Sample window	±1000	±5000	±1000	±5000	±1000	±5000
Panel A: Prior purchase price psm as RP						
1 year or less	16.68	9.30	33.37	18.59	83.42	46.48
1 to 2 years	16.93	11.35	33.86	22.69	84.65	56.73
2 to 3 years	21.57	15.82	43.14	31.63	107.85	79.08
3 to 4 years	15.87	12.74	31.73	25.49	79.33	63.73
4 to 5 years	18.44	11.30	36.88	22.59	92.20	56.48
5 to 6 years	14.72	8.94	29.44	17.88	73.60	44.70
6 to 7 years	9.91	6.67	19.82	13.34	49.55	33.34
7 to 8 years	7.80	5.88	15.45	11.76	39.00	29.40
8 to 9 years	5.58	4.69	11.15	9.38	27.88	23.46
9 to 10 years	4.94	3.81	9.88	7.63	24.70	19.07
10 to 11 years	4.53	3.60	9.05	7.21	22.63	18.02
11 to 12 years	3.00	2.65	6.00	5.29	15.00	13.23
12 to 13 years	2.96	1.99	5.91	3.97	14.78	9.93
13 to 14 years	3.40	1.84	6.80	3.68	17.00	9.20
14 to 15 years	2.65	1.49	5.31	2.97	13.28	7.43
15 to 16 years	0.77	1.09	1.53	2.17	3.83	5.42
Panel B: Recent neighborhood price psm as RP						
1 year or less	24.66	9.42	49.32	18.84	123.30	47.10
1 to 2 years	36.54	11.80	73.08	23.60	182.70	59.01
2 to 3 years	51.63	16.19	103.25	32.38	258.13	80.94
3 to 4 years	43.90	13.69	87.79	27.38	219.47	68.44
4 to 5 years	40.50	12.16	81.00	24.31	202.50	60.78
5 to 6 years	33.78	9.92	67.57	19.84	168.93	49.61
6 to 7 years	26.23	7.45	52.46	14.89	131.15	37.23
7 to 8 years	23.16	6.52	46.33	13.04	115.83	32.60
8 to 9 years	20.03	5.49	40.06	10.99	100.15	27.47
9 to 10 years	16.39	4.43	32.77	8.87	81.92	22.16
10 to 11 years	15.68	4.26	31.35	8.52	78.38	21.31
11 to 12 years	11.73	3.21	23.45	6.43	58.63	16.07
12 to 13 years	8.95	2.38	17.90	4.76	44.75	11.90
13 to 14 years	8.47	2.18	16.95	4.36	42.38	10.90
14 to 15 years	6.87	1.73	13.74	3.45	34.35	8.63
15 to 16 years	4.91	1.26	9.82	2.52	24.55	6.30
Number of bins	200	1000	100	500	40	200

Table B4: Transactions – Prior Purchase Price Per Square Meter as Reference Point by Holding Years

(Bin width is 20 SGD; sample is [-5000, 5000], Corresponds to Figure 6 in text)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Hold (n-1,n] years	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Loss	-60.377***	-53.367***	-58.143***	-16.612***	-17.169***	-14.339***	-11.167***	-7.065***
	(-27.86)	(-29.53)	(-24.25)	(-9.72)	(-13.75)	(-16.24)	(-15.17)	(-9.38)
Price difference	-0.014***	-0.012***	-0.012***	-0.001***	-0.006***	-0.005***	-0.004***	-0.002***
	(-25.49)	(-26.38)	(-20.55)	(-3.23)	(-18.50)	(-21.02)	(-21.27)	(-11.52)
Loss ×Price diff	0.016***	0.016***	0.018***	0.008***	0.013***	0.010***	0.008***	0.005***
	(20.87)	(25.03)	(21.95)	(13.98)	(30.97)	(33.02)	(29.52)	(20.12)
Constant	68.371***	68.967***	83.487***	44.142***	47.928***	37.672***	28.327***	21.857***
	(44.61)	(53.96)	(49.25)	(36.52)	(54.27)	(60.35)	(54.44)	(41.02)
Observations	500	500	500	500	500	500	500	500
Adjusted R^2	0.754	0.815	0.787	0.757	0.819	0.837	0.776	0.680
Hold (n-1,n] years	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**
Loss	-5.422***	-4.134***	-5.228***	-1.484***	1.024**	-0.778*	-5.312***	-3.872***
	(-8.44)	(-7.28)	(-9.30)	(-3.27)	(2.54)	(-1.91)	(-15.83)	(-12.64)
Price difference	-0.001***	-0.001***	-0.001***	-0.000**	0.000***	-0.000***	-0.001***	0.000
	(-3.28)	(-7.13)	(-7.71)	(-2.39)	(2.64)	(-3.20)	(-12.90)	(0.96)
Loss ×Price diff	0.002***	0.002***	0.002***	0.002***	0.001***	0.002***	0.002***	-0.000
	(9.63)	(11.18)	(11.87)	(11.77)	(9.69)	(12.80)	(15.23)	(-0.17)
Constant	14.774***	12.448***	12.709***	8.344***	5.146***	6.322***	7.843***	4.084***
	(32.52)	(30.98)	(31.98)	(26.01)	(18.09)	(21.97)	(33.06)	(18.86)
Observations	500	500	500	500	500	500	500	500
Adjusted R^2	0.606	0.441	0.524	0.566	0.546	0.528	0.653	0.599

Notes: The dependent variable is the number of transactions in each bin. *t* statistics in parentheses, * indicates significance at the 10% level, ** indicates significance at the 5% level and *** indicates significance at the 1% level. Bin width is 20 dollars of price per square meter. We use sample of [-5000, 5000] of price difference each holding years in this table.

Table B5: Transactions – Recent Neighborhood Price Per Square Meter as Reference Point by Holding Years

(Bin width is 20 SGD; sample is [-5000, 5000], Corresponds to Figure 6 in text)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Hold (n-1,n] years	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Loss	-42.017***	-36.920***	-54.560***	-41.081***	-22.468***	-20.632***	-13.321***	-15.252***
	(-26.60)	(-13.78)	(-14.44)	(-12.33)	(-7.09)	(-7.36)	(-5.57)	(-7.09)
Price difference	-0.016***	-0.021***	-0.030***	-0.025***	-0.021***	-0.018***	-0.013***	-0.012***
	(-40.33)	(-31.99)	(-32.47)	(-30.93)	(-27.08)	(-26.02)	(-23.04)	(-23.40)
Loss ×Price diff	0.023***	0.033***	0.047***	0.040***	0.036***	0.030***	0.024***	0.021***
	(41.40)	(36.05)	(36.01)	(34.95)	(33.23)	(31.40)	(28.51)	(27.96)
Constant	68.164***	83.875***	118.569***	98.334***	81.153***	68.255***	51.070***	46.708***
	(61.03)	(44.29)	(44.38)	(41.75)	(36.21)	(34.45)	(30.20)	(30.71)
Observations	500	500	500	500	500	500	500	500
Adjusted R^2	0.841	0.753	0.754	0.735	0.698	0.676	0.628	0.625
Hold (n-1,n] years	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**
Loss	-15.589***	-11.117***	-14.490***	-11.084***	-6.456***	-7.501***	-4.983***	-2.380***
	(-8.16)	(-6.89)	(-9.66)	(-9.92)	(-7.23)	(-8.47)	(-6.75)	(-4.49)
Price difference	-0.011***	-0.009***	-0.009***	-0.007***	-0.005***	-0.005***	-0.004***	-0.002***
	(-23.77)	(-22.23)	(-24.37)	(-24.19)	(-22.31)	(-21.96)	(-20.51)	(-19.18)
Loss ×Price diff	0.018***	0.015***	0.014***	0.010***	0.008***	0.008***	0.006***	0.004***
	(27.39)	(26.26)	(27.20)	(27.00)	(26.10)	(24.61)	(23.61)	(23.53)
Constant	41.429***	32.780***	33.441***	25.030***	18.077***	17.544***	13.490***	9.115***
	(30.68)	(28.72)	(31.52)	(31.69)	(28.64)	(28.02)	(25.84)	(24.30)
Observations	500	500	500	500	500	500	500	500
Adjusted R^2	0.621	0.596	0.626	0.625	0.595	0.576	0.546	0.534

Notes: The dependent variable is the number of transactions in each bin. *t* statistics in parentheses, * indicates significance at the 10% level, ** indicates significance at the 5% level and *** indicates significance at the 1% level. Bin width is 20 dollars of price per square meter. We use sample of [-5000, 5000] of price difference each holding years in this table.

Table B6: Transactions – Prior Purchase Price Per Square Meter as Reference Point by Holding Years

(Bin width is 10 SGD; sample is [-5000, 5000])

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Hold (n-1,n] years	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Loss	-30.192***	-26.683***	-29.075***	-8.305***	-8.584***	-7.170***	-5.582***	-3.531***
	(-28.12)	(-36.51)	(-31.19)	(-11.72)	(-15.02)	(-16.56)	(-15.52)	(-10.27)
Price difference	-0.007***	-0.006***	-0.006***	-0.001***	-0.003***	-0.002***	-0.002***	-0.001***
	(-25.74)	(-32.62)	(-26.42)	(-3.89)	(-20.21)	(-21.43)	(-21.75)	(-12.61)
Loss ×Price diff	0.008***	0.008***	0.009***	0.004***	0.007***	0.005***	0.004***	0.003***
	(21.08)	(30.95)	(28.22)	(16.86)	(33.84)	(33.67)	(30.19)	(22.04)
Constant	34.189***	34.483***	41.746***	22.069***	23.964***	18.836***	14.162***	10.926***
	(45.04)	(66.73)	(63.33)	(44.05)	(59.29)	(61.53)	(55.68)	(44.93)
Observations	1000	1000	1000	1000	1000	1000	1000	1000
Adjusted R^2	0.609	0.771	0.753	0.694	0.730	0.727	0.645	0.560
Hold (n-1,n] years	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**
Loss	-2.710***	-2.067***	-2.614***	-0.742***	0.512***	-0.389**	-2.655***	-1.936***
	(-8.97)	(-7.77)	(-9.75)	(-3.34)	(2.71)	(-2.03)	(-16.21)	(-13.18)
Price difference	-0.000***	-0.000***	-0.001***	-0.000**	0.000***	-0.000***	-0.001***	0.000
	(-3.48)	(-7.61)	(-8.08)	(-2.44)	(2.82)	(-3.41)	(-13.21)	(1.01)
Loss ×Price diff	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	-0.000
	(10.24)	(11.94)	(12.44)	(12.03)	(10.33)	(13.62)	(15.60)	(-0.18)
Constant	7.386***	6.224***	6.354***	4.172***	2.573***	3.161***	3.921***	2.042***
	(34.59)	(33.10)	(33.53)	(26.60)	(19.29)	(23.38)	(33.85)	(19.65)
Observations	1000	1000	1000	1000	1000	1000	1000	1000
Adjusted R^2	0.465	0.311	0.377	0.405	0.406	0.388	0.496	0.448

Notes: The dependent variable is the number of transactions in each bin. *t* statistics in parentheses, * indicates significance at the 10% level, ** indicates significance at the 5% level and *** indicates significance at the 1% level. Bin width is 10 SGD of price per square meter. We use sample of [-5000, 5000] of price difference each holding years in this table.

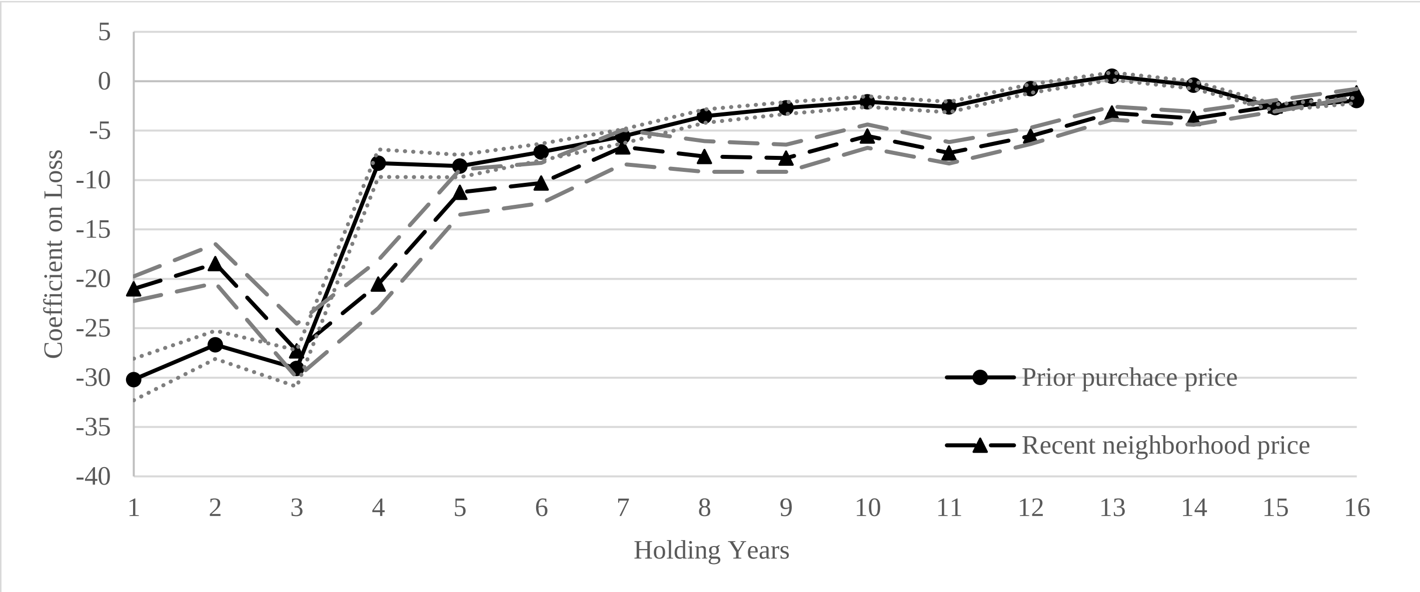
Table B7: Transactions – Recent Neighborhood Price Per Square Meter as Reference Point by Holding Years

(Bin width is 10 SGD; sample is [-5000, 5000])

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Hold (n-1,n] years	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Loss	-21.010***	-18.459***	-27.280***	-20.536***	-11.234***	-10.316***	-6.660***	-7.624***
	(-33.01)	(-18.41)	(-19.55)	(-16.66)	(-9.65)	(-9.94)	(-7.59)	(-9.61)
Price difference	-0.008***	-0.010***	-0.015***	-0.013***	-0.011***	-0.009***	-0.007***	-0.006***
	(-50.05)	(-42.73)	(-43.97)	(-41.78)	(-36.85)	(-35.11)	(-31.37)	(-31.73)
Loss ×Price diff	0.011***	0.017***	0.024***	0.020***	0.018***	0.015***	0.012***	0.010***
	(51.37)	(48.16)	(48.76)	(47.22)	(45.22)	(42.37)	(38.82)	(37.92)
Constant	34.083***	41.938***	59.285***	49.165***	40.577***	34.128***	25.536***	23.353***
	(75.73)	(59.16)	(60.10)	(56.40)	(49.27)	(46.48)	(41.13)	(41.65)
Observations	1000	1000	1000	1000	1000	1000	1000	1000
Adjusted R^2	0.803	0.731	0.738	0.717	0.682	0.655	0.610	0.606
Hold (n-1,n] years	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**
Loss	-7.794***	-5.558***	-7.245***	-5.541***	-3.229***	-3.750***	-2.492***	-1.190***
	(-11.03)	(-9.29)	(-13.02)	(-13.18)	(-9.35)	(-11.05)	(-8.67)	(-5.62)
Price difference	-0.006***	-0.004***	-0.004***	-0.003***	-0.002***	-0.002***	-0.002***	-0.001***
	(-32.10)	(-29.99)	(-32.86)	(-32.14)	(-28.82)	(-28.66)	(-26.37)	(-24.01)
Loss ×Price diff	0.009***	0.007***	0.007***	0.005***	0.004***	0.004***	0.003***	0.002***
	(36.99)	(35.42)	(36.68)	(35.87)	(33.72)	(32.11)	(30.34)	(29.45)
Constant	20.715***	16.390***	16.721***	12.515***	9.039***	8.771***	6.745***	4.558***
	(41.44)	(38.73)	(42.49)	(42.10)	(37.00)	(36.57)	(33.21)	(30.42)
Observations	1000	1000	1000	1000	1000	1000	1000	1000
Adjusted R^2	0.599	0.573	0.603	0.596	0.551	0.536	0.499	0.473

Notes: The dependent variable is the number of transactions in each bin. *t* statistics in parentheses, * indicates significance at the 10% level, ** indicates significance at the 5% level and *** indicates significance at the 1% level. Bin width is 10 dollars of price per square meter. We use sample of [-5000, 5000] of price difference each holding years in this table.

Figure B1: Loss Coefficients for Prior Purchase Price and Neighborhood Price per Square Meter, by Holding Years



Notes: The coefficients are from regression with bin size of 10 SGD and sample [-5000, 5000].

Table B8: Transactions – Prior Purchase Price Per Square Meter as Reference Point by Holding Years

(Bin width is 50 SGD; sample is [-5000, 5000])

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Hold (n-1,n] years	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Loss	-150.927***	-133.432***	-145.389***	-41.523***	-42.933***	-35.842***	-27.933***	-17.674***
	(-26.87)	(-20.42)	(-16.45)	(-6.83)	(-10.72)	(-13.99)	(-13.01)	(-8.35)
Price difference	-0.034***	-0.029***	-0.030***	-0.003**	-0.014***	-0.011***	-0.010***	-0.005***
	(-24.59)	(-18.25)	(-13.94)	(-2.27)	(-14.43)	(-18.11)	(-18.24)	(-10.26)
Loss ×Price diff	0.039***	0.039***	0.046***	0.021***	0.034***	0.025***	0.019***	0.013***
	(20.14)	(17.32)	(14.89)	(9.82)	(24.14)	(28.45)	(25.30)	(17.92)
Constant	170.908***	172.441***	208.745***	110.357***	119.828***	94.178***	70.835***	54.649***
	(43.04)	(37.33)	(33.41)	(25.66)	(42.30)	(51.99)	(46.66)	(36.53)
Observations	200	200	200	200	200	200	200	200
Adjusted R^2	0.877	0.841	0.809	0.794	0.873	0.905	0.865	0.809
Hold (n-1,n] years	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**
Loss	-13.557***	-10.335***	-13.059***	-3.711***	2.550**	-1.956	-13.278***	-9.685***
	(-7.18)	(-6.82)	(-8.13)	(-2.87)	(2.19)	(-1.57)	(-14.16)	(-10.53)
Price difference	-0.001***	-0.002***	-0.003***	-0.001**	0.001**	-0.001***	-0.003***	0.000
	(-2.79)	(-6.68)	(-6.74)	(-2.10)	(2.27)	(-2.64)	(-11.54)	(0.79)
Loss ×Price diff	0.005***	0.006***	0.006***	0.005***	0.003***	0.005***	0.004***	-0.000
	(8.19)	(10.49)	(10.39)	(10.33)	(8.39)	(10.49)	(13.63)	(-0.14)
Constant	36.933***	31.120***	31.766***	20.864***	12.873***	15.818***	19.608***	10.213***
	(27.68)	(29.06)	(27.99)	(22.82)	(15.66)	(18.01)	(29.57)	(15.71)
Observations	200	200	200	200	200	200	200	200
Adjusted R^2	0.736	0.635	0.679	0.715	0.693	0.653	0.790	0.722

Notes: The dependent variable is the number of transactions in each bin. *t* statistics in parentheses, * indicates significance at the 10% level, ** indicates significance at the 5% level and *** indicates significance at the 1% level. Bin width is 50 SGD of price per square meter. We use sample of [-5000, 5000] of price difference each holding years in this table.

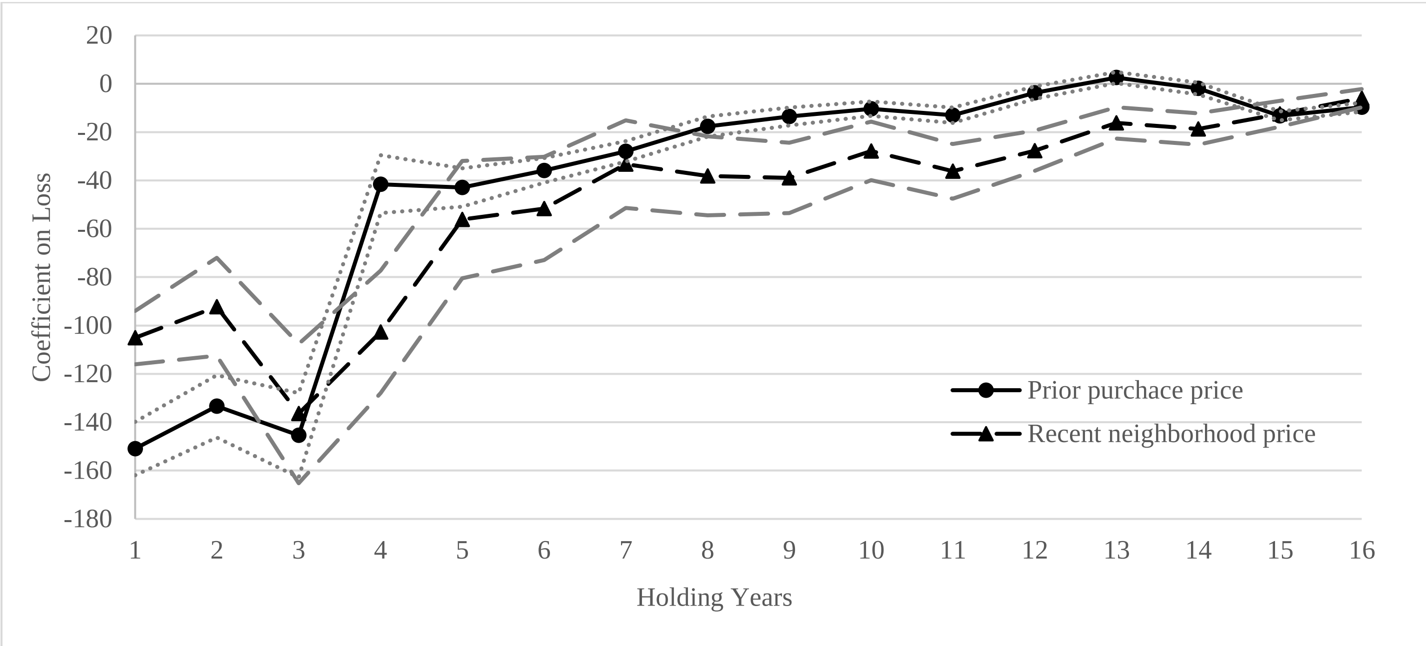
Table B9: Transactions – Recent Neighborhood Price Per Square Meter as Reference Point by Holding Years

(Bin width is 50 SGD; sample is [-5000, 5000])

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Hold (n-1,n] years	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Loss	-105.025***	-92.300***	-136.422***	-102.677***	-56.175***	-51.574***	-33.285***	-38.091***
	(-18.80)	(-9.00)	(-9.34)	(-8.00)	(-4.57)	(-4.75)	(-3.62)	(-4.60)
Price difference	-0.039***	-0.052***	-0.075***	-0.063***	-0.053***	-0.045***	-0.034***	-0.031***
	(-28.51)	(-20.87)	(-20.99)	(-20.07)	(-17.44)	(-16.78)	(-14.97)	(-15.20)
Loss ×Price diff	0.057***	0.084***	0.118***	0.101***	0.091***	0.076***	0.059***	0.052***
	(29.27)	(23.53)	(23.28)	(22.68)	(21.40)	(20.25)	(18.53)	(18.17)
Constant	170.398***	209.684***	296.432***	245.828***	202.896***	170.643***	127.665***	116.747***
	(43.14)	(28.90)	(28.69)	(27.08)	(23.32)	(22.22)	(19.63)	(19.95)
Observations	200	200	200	200	200	200	200	200
Adjusted R^2	0.869	0.764	0.762	0.745	0.706	0.684	0.640	0.637
Hold (n-1,n] years	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**
Loss	-38.956***	-27.794***	-36.209***	-27.714***	-16.159***	-18.745***	-12.462***	-5.967***
	(-5.27)	(-4.52)	(-6.32)	(-6.55)	(-4.93)	(-5.72)	(-4.57)	(-3.12)
Price difference	-0.028***	-0.022***	-0.022***	-0.017***	-0.012***	-0.012***	-0.009***	-0.006***
	(-15.34)	(-14.59)	(-15.95)	(-15.97)	(-15.20)	(-14.83)	(-13.88)	(-13.31)
Loss ×Price diff	0.045***	0.037***	0.035***	0.026***	0.020***	0.019***	0.015***	0.011***
	(17.68)	(17.24)	(17.81)	(17.82)	(17.78)	(16.62)	(15.97)	(16.32)
Constant	103.563***	81.954***	83.598***	62.588***	45.197***	43.848***	33.727***	22.799***
	(19.80)	(18.85)	(20.63)	(20.92)	(19.51)	(18.93)	(17.49)	(16.86)
Observations	200	200	200	200	200	200	200	200
Adjusted R^2	0.630	0.613	0.642	0.645	0.630	0.607	0.579	0.579

Notes: The dependent variable is the number of transactions in each bin. *t* statistics in parentheses, * indicates significance at the 10% level, ** indicates significance at the 5% level and *** indicates significance at the 1% level. Bin width is 50 dollars of price per square meter. We use sample of [-5000, 5000] of price difference each holding years in this table.

Figure B2: Loss Coefficients for Prior Purchase Price and Neighborhood Price per Square Meter, by Holding Years



Notes: The coefficients are from regression with bin size of 50 SGD and sample [-5000, 5000].

Table B10: Multinomial Logit: Dependent variables: Price Difference Windows (allowing for transaction costs)

	(a)	(b)	(c)	(d)	(e)	(f)
Prior purchase price	**Loss [-600, 0]; reference [0,600]; gain [600, 1200]**		**Loss [-800, 0]; reference 0,800]; gain [800, 1600]**		**Loss [-1000, 0]; reference [0, 1000]; gain [1000, 2000]**	
Neighborhood price	**Loss [-900, -300]; reference [-300, 300]; gain [300, 900]**		**Loss [-1200, -400]; reference [-400, 400]; gain [400, 1200]**		**Loss [-1500, -500]; reference [-500, 500]; gain [500, 1500]**	
(2) Nominal loss, neighborhood loss						
Holding years	1.014	1.062***	1.014	1.071***	1.015*	1.082***
	(1.43)	(6.04)	(1.47)	(7.30)	(1.76)	(9.14)
Change in HPI		0.970***		0.962***		0.953***
		(-12.20)		(-15.98)		(-19.63)
(3) Nominal reference, neighborhood loss						
Holding years	0.985	0.979*	0.992	0.991	0.993	0.993
	(-1.38)	(-1.88)	(-0.82)	(-0.93)	(-0.86)	(-0.85)
Change in HPI		1.004		1.001		1.000
		(1.36)		(0.43)		(0.06)
(4) Nominal gain, neighborhood loss						
Holding months	1.012	0.965***	1.019*	0.969***	1.021**	0.965***
	(1.09)	(-2.84)	(1.95)	(-2.93)	(2.52)	(-3.84)
Change in HPI		1.028***		1.031***		1.037***
		(8.20)		(9.60)		(12.28)
(5) Nominal loss, neighborhood reference						
Holding years	1.038***	1.086***	1.047***	1.107***	1.050***	1.120***
	(4.00)	(9.00)	(5.86)	(13.05)	(6.90)	(15.94)
Change in HPI		0.970***		0.961***		0.953***
		(-12.14)		(-17.55)		(-22.93)
(6) Nominal gain, neighborhood reference						
Holding years	1.013	0.958***	1.014*	0.955***	1.023***	0.958***
	(1.43)	(-4.73)	(1.88)	(-5.59)	(3.53)	(-6.07)
Change in HPI		1.032***		1.037***		1.042***
		(13.05)		(14.75)		(18.19)
(7) Nominal loss, neighborhood gain						
Holding years	1.072***	1.139***	1.072***	1.157***	1.072***	1.174***
	(7.07)	(12.64)	(9.17)	(17.29)	(9.89)	(20.25)
Change in HPI		0.959***		0.946***		0.934***
		(-13.73)		(-18.68)		(-23.17)
(8) Nominal reference, neighborhood gain						
Holding years	0.998	1.006	0.996	1.009	0.988*	1.006
	(-0.26)	(0.69)	(-0.59)	(1.33)	(-1.94)	(0.93)
Change in HPI		0.995**		0.991***		0.988***
		(-2.41)		(-5.01)		(-7.84)
(9) Nominal gain, neighborhood gain						
Holding years	0.974***	0.934***	0.960***	0.922***	0.952***	0.917***
	(-2.86)	(-7.14)	(-4.94)	(-9.50)	(-6.61)	(-11.34)
Change in HPI		1.024***		1.025***		1.025***
		(10.26)		(11.97)		(13.14)

Observations	20894	20894	31923	31923	43021	43021
Log	-44312.422	-43156.546	-66438.657	-63849.537	-87530.639	-82883.78

Notes: Exponentiated coefficients (odds ratios) are reported; *t* statistics in parentheses; * indicates significance at the 10% level, ** indicates significance at the 5% level and *** indicates significance at the 1% level.

Appendix C:

Table C1: Summary Statistics - Data used to get predicted price

	Observations	Mean	Std. Dev.	Min	Max
Transaction Price Per Square Meter	375,485	10,817.94	5,94.41	1,009	73,629
Floor	375,485	9.03	7.71	-2.00	71.00
Area	375,485	116.10	54.08	24.00	1,261.00
Sale before completion of construction	375,485	0.60	0.49	0	1

Table C2: Regression to Get Predicted Housing Price (Standard errors are clustered at the project level)

Dependent variable	Price per square meter	Log of price per square meter
Floor	71.9181***	0.0056***
	(21.94)	(21.41)
Area	-11.2670***	-0.0012***
	(-15.27)	(-20.77)
Sale before completion of construction	191.7828***	0.0630***
	(3.96)	(13.29)
Project Fixed effects	YES	YES
Year × Quarter Fixed Effects	YES	YES
Planning Area × Year Fixed Effects	YES	YES
Observations	375,485	375,485
R-squared	0.9515	0.9546