Anchoring in the Housing Market: Evidence from Sydney

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Abstract

This paper investigates the behavior of 'buyers' in the Sydney housing market when they purchase homes. The literature suggests that when individuals evaluate their utilities in an uncertain situation, they may use a reference point as an anchor. We suggest that asking prices in the housing market could act as reference points or anchors and affect the utility buyers receive from buying properties. We note that the other role of the asking price is to signal unobserved characteristics of properties to buyers. In this study, we separate these two effects and empirically investigate the implications on the final price of properties with data on the Sydney housing market. We found strong evidence of anchoring behavior by buyers in this market.

Keywords: Reference dependence; anchoring; asking price; housing market.

JEL Classification: D80; R30; D12

1 Introduction

The behavior of individuals in the housing market has drawn several attentions in the literature during the past three decades (Horowitz, 1992; Chen and Rosenthal, 1996). There are many ways to look at this issue from economics perspective. However, one consideration that has attracted less attention is the reference-dependent

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behavior of 'buyers' in this particular market.[1] Many buyers in the housing market are not experts and face significant uncertainties during their search time and when they want to make the purchase decision. One could argue that this is a classic situation for reference-dependent behavior and in fact, buyers may evaluate their utilities based on a reference point. To further clarify such behavior, we provide an illustrative example.

Imagine a case where there are two identical houses with different asking prices. For instance, house number one has an asking price equal to \$700,000 and house number 2's asking price is \$750,000. A buyer has similar values for both of these houses equal to \$800,000. The buyer would negotiate with both sellers because she knows the asking price is not the final price of a house. Suppose after negotiation seller one suggests that there is another interested buyer and an offer equal to \$725,000 will be accepted by her. Seller two however, does not have any other interested buyers and is willing to sell her house with a discount equal to \$25,000. So essentially the buyer pays the same price equal to \$725,000 for both houses. But the question is would this buyer evaluate her utility from purchasing both of these houses the same? Or in other words would she get the same utility from purchasing any of these two houses? Of course, one major variable which accounts for a significant part of her utility is the difference between her value and the price she pays. However, the amount of discount she receives relative to the original asking price could also be an important factor. The buyer's initial expectation was that since the second seller posted a higher price, on average, she would accept higher offers than seller one. Therefore, the fact that the second seller is willing to accept the same offer as the first seller is a satisfying outcome for the buyer. This kind of behavior is shaped due to reference-dependent preferences. In this particular example, the buyer evaluates the outcome based on a reference point, that is, the asking price.

Prospect theory, which was first introduced by Kahneman and Tversky (1979), is one of the first attempts to model individual behaviour with reference-dependent utility, in which individuals assess their utility based on a reference point. The difference between this approach and the standard expected utility theory is that people are risk averse towards the gains from a reference point and risk seeking towards losses from that reference point. The result of prospect theory is a S-shaped utility curve, which becomes less steep beyond the reference point. As Beggs (2015) suggests, there are three main ways to determine a reference point: arbitrary, past

[1] The loss aversion and reference-dependent behavior of sellers have been studied before. For instance, see Genesove and Mayer (2001) and Bucchianeri and Minson (2013). Also some papers considered the loss aversion of buyers in the housing market transactions. See Khezr (2018) as an example.

experience and expectation.[2]

Reference-dependent decision making has been applied to many real-world markets, such as the market for arts, the labor market, financial markets and the housing market (Beggs and Graddy, 2009; Farber, 2008; Shefrin and Statman, 1985; Genesove and Mayer, 2001). One of the features of the reference-dependence is the anchoring heuristic, first introduced by Tversky and Kahneman (1974). Anchoring happens when people adjust their values with some disjointed messages they receive. However, in empirical works, it is usually difficult to distinguish between relevant and irrelevant messages. Graddy *et al.* (2014), Bucchianeri and Minson (2013) and Leung and Tsang (2013) are some examples of the anchoring evidence.

The current study empirically investigates the evidence of reference-dependent decisions by buyers in the housing market. The biggest challenge of any empirical test is the data on the reference points, which are not usually observable. Depending on the market, some reference points have been suggested and tested in the literature. For instance, Rosenkranz and Schmitz (2007) suggest that the reserve price in auctions can act as a reference point, and they show a small effect of a reference point can indicate some of the features of real-world auctions, such as secret reserve prices. Beggs and Graddy (2009) suggested the previous sale price or the pre-sale estimates as possible anchors for art auctions.

Many similar studies in the housing market literature define lagged status quo, such as previous sale prices, as anchors or reference points for sellers. For instance, Genesove and Mayer (2001) suggest that the previous purchase prices act as reference points for sellers. They show evidence of loss aversion for sellers in Boston housing market during 1990s. They suggest condominium home owners, on average, set higher asking prices compared to other sellers and this results in the higher selling prices for their properties. Bokhari and Geltner (2011) extend the Genesove and Mayer (2001) results to a case in which the sellers are professional investors in commercial real estate. They suggest that loss aversion has a significant role in determining prices, even larger than what Genesove and Mayer (2001) show for residential real estate. Bucchianeri and Minson (2013) is another empirical study on the anchoring effect in the housing market. Their findings are similar to the one in Genesove and Mayer (2001) and suggest that, on average, higher asking prices would result in higher selling prices.

In this paper, unlike many other similar papers in the literature, our focus is to determine a reference point for buyers. We suggest that the asking price is a

[2]There are several efforts to model the expectation-based reference points, (Bell, 1985; Loomes and Sugden, 1986; Shalev, 2000; Kőszegi and Rabin, 2006, 2007)

good candidate for the reference point since it affects buyers' expectations for the transaction price and the seller's reservation value. This is mainly due to the fact that there is no other credible information available to buyers in this market. The current study is based on the Sydney housing market, in which past prices are subject to significant changes over time. For instance, the housing price index in Sydney showed a dramatic increase of 21.4% between June 2009 and June 2010.[3] In this volatile market, neither sellers nor buyers can trust the previous sale price of a property as a sign of its current value. Sellers also never reveal their reservation prices[4] for their properties. Thus, choosing an optimal asking price becomes more critical for sellers and the only piece of information for buyers regarding the seller's reservation price. In fact, we suggest asking prices include two valuable pieces of information for buyers. First, they can act as a reference point to adjust buyers' expectations of the current value of the property. Second, they include information regarding unobserved characteristics of the property and the reservation value of the seller. In this study, we separate these two effects of the asking price and examine the evidence of both effects on the price of the property. To capture the effects of unobservable characteristics and reference-dependence factors, we use the regional attributes (e.g., location) as instruments in our estimation strategy.

2 A basic model of the housing market

Buyers in the housing market usually observe the advertised asking price of a property and its characteristics. Then, based on this information, they make offers to sellers. If a buyer makes an offer that is acceptable by the seller, then she will buy the property and pay the offered price. The housing market data show that the transaction price can be below the asking price, equal to the asking price, or sometimes even above the asking price. In section 4 we provide detailed information on the data.

Behavior of this kind might increase the possibility of reference-dependent decisions of buyers. As mentioned before, buyers usually do not know the seller's reservation price, and their only indication of the property's value is the asking price. There is also a possibility of competition between interested buyers when an offer is made. All these scenarios together make the housing market a very special market with a very complicated selling mechanism. In the bargaining environment, if the seller's reservation price is directly observable by buyers, then the seller could

[3]According to the Australian Bureau of Statistics price index report; www.abs.gov.au.
[4]Reservation price is the lowest price at which a seller is willing to sell her property.

potentially lose his entire surplus, especially if only one interested buyer arrives at a time. This may explain why sellers do not reveal the lowest price they would be willing to accept for their properties. In this section, we will explain a simple model of reference-dependent utility for buyers to use the argument for our empirical analysis.

Suppose the asking price is l; this is a reference point for buyers in the following way. A buyer who pays a price p receives utility based on l. In the simplest linear setup, suppose the buyers' utility function is given by

$$U(v, p, l) = v - p + \gamma(l - p), \tag{1}$$

where v is the buyer's private value for the property, p is the price he pays, and γ is a positive real number less than 1. This set-up suggests that a buyer who pays more than the asking price receives some negative utility, whereas a buyer who pays a price below the asking price receives additional utility. Although we have not made any restriction for v, it is clear that v needs to be high enough for a buyer to offer a price above the asking price.

Sellers must consider two important facts. First, if the asking price is a reference point for buyers, then higher asking prices increase the utility of buyers if all other variables are kept constant. Thus, there is a marginal benefit for a seller to increase the asking price. Second, the asking price is also an indication of the seller's reservation price, and a higher asking price signals that the seller has a higher reserve price. Since visual inspection of properties when making an offer is a costly activity for buyers, they may avoid inspecting those properties if they believe there is a less chance to complete a successful trade. Thus, if the asking price is a positive function of the seller's reservation price, then a higher asking price indicates a higher value *ceteris paribus*. In this case, the asking price might decrease the possibility that a buyer will visit a given property. For instance, given two identical properties, the one with a higher asking price will have fewer visits and therefore less possibility of receiving an offer. This would result in a marginal cost for a seller to increase the asking price of her property. These two features suggest that a seller maximizes her revenue by choosing an asking price in which the marginal cost is equal to the marginal benefit. Moreover, there is also some level of competition between sellers in the housing market. Therefore, the decreasing arrival rate of buyers with higher asking prices could also indicate that alternatives are available to buyers.

Given the two main effects of the asking price we mentioned above, there could remain an ambiguity regarding the difference between the value of buyers and the seller. The seller's value may reflect some idiosyncratic factors that are not important to buyers. But if the seller has some bargaining power this could influence the selling price. From our observation it is difficult to distinguish between these effects and the seller's private information regarding the quality. However, this issue is addressed in our identification strategy by adding a variable that can capture any unobserved characteristics that can affect the price of a property. These include any idiosyncratic factors that may not be important to buyers.

To gain a better understanding of the situation, let us divide the game into two stages as follows. First, the seller advertises the asking price with the characteristics of the property. Buyers then update their information regarding the seller's reservation price and decide whether to inspect the property. Second, the buyer, after inspecting the property, decides to make an offer or not based on their utility. According to our setup for the buyer's utility, a buyer i with value v_i would receive zero utility by offering a price equal to

$$p_i = \frac{v_i + \gamma l}{1 + \gamma} \tag{2}$$

Therefore, p_i is the upper bound of buyer i's offer. Because γ is positive and exogenously and independently defined, then a seller can increase the upper bound of offers by increasing the asking price. However, as explained before, because there is competition between sellers, a given seller cannot set the asking price too high. If she does so, she will reduce the number of arriving potential buyers.

3 Empirical analysis

Suppose the ideal model for the value of a property is as follows.

$$p_{it} = \tilde{p}_{it} + s_i + \psi_t \tag{3}$$

The price of property i at time t is determined by the expected price $\tilde{p}_{it}$ of the property plus unobserved characteristics s_i and the market status during that particular time ψ_t. $\tilde{p}$ is determined by the physical characteristics of the property as well as its location and ψ_t is i.i.d. (also independent of other variables) and normally distributed. It is important to mention that s_i includes any unobserved characteristics that can affect the price, including any idiosyncratic factors that are important for the seller but not important to buyers. Buyers receive a partially informative signal v_i, which has a joint normal distribution with s_i. Thus, buyers do not directly observe the unobserved characteristics, such as the reservation price, but receive a signal about it. Therefore, the buyer's estimate for the value of the property is,

$$p_{it}^b = \tilde{p}_{it} + E(s_i | l_{it}, \hat{l}_{it}, v_i).$$

l_{it} is the asking price, which is observable to buyers, and $\hat{l}_{it}$ is the predicted asking price for that particular property. Again, it is possible to estimate $\hat{l}_{it}$ with a hedonic regression of the property characteristics. Thus, the expectation for unobserved characteristics can be written as,[5]

$$E(s_i | l_{it}, \hat{l}_{it}) = \theta(l_{it} - \hat{l}_{it}), \tag{4}$$

with

$$\theta = \frac{\sigma_s^2}{\sigma_s^2 + \sigma_\psi^2}.$$

This expectation is true with the consideration of joint and normal distribution of the unobserved characteristics, s_i, and the partially informative signal that buyers receive, v_i. Therefore, given the assumption of our theoretical model for the reference-based utility, we would estimate the following equation.

$$p_{it} = \beta_0 + \beta_1 \hat{p}_{it} + \delta(l_{it} - \hat{l}_{it}) + \gamma(l_{it} - \hat{p}_{it}) + \Theta_{it} \tag{5}$$

Here, p_{it} is the transaction price of property i in neighborhood j at quarter t. The term $(l_{it} - \hat{p}_{it})$ captures the reference-dependent effects and the term $(l_{it} - \hat{l}_{it})$ captures unobserved characteristics of the property. Therefore, we are able to separate these two effects in our model.

To obtain prediction for the asking price and the transaction price, one standard approach is to use a log-linear hedonic regression with the logarithm of either prices as the dependent variable over a fair range of property and neighborhood characteristics, as well as time-of-sale dummies. In particular, we estimate the following equations.

$$P_{it} = X_i \beta + Y_i \alpha + \epsilon_{it}, \tag{6}$$

where P_{it} is the natural logarithm of the price of property i at time t, X is the set of property characteristics, and Y is some fairly chosen neighborhood characteristics. Finally, ϵ_{it} is the error term. We have another regression for the asking price as

$$L_{it} = X_i \lambda + Y_i \rho + \varepsilon_{it} \tag{7}$$

[5]For further details of this derivation see Appendix.

where L is the log of the asking price of property i. To test for reference dependence, we use the outcomes of the hedonic regression to build the predicted value of the transaction price and the asking price of a particular property.

A straight forward estimation of the reference price can be performed by using the two steps estimation method. In the first step, the log linear hedonic regressions can be performed for equations (6) and (7). In hedonic models, one would be interested to determine how the price of a property changes with the attributes attached to it. However, coefficients obtained in the second stage will not be efficient due to error (Pagan, 1984; Epple, 1987).

In other words, the predicted price included on the right hand side of equation (5) will be correlated with the error term added to the equation. Thus, OLS estimation will produce inconsistent estimates. Moreover, the inclusion of predicted sale and asking prices as a right hand side variable in the equation also raises the concern of endogeneity issue. To address this issue, we follow an instrumental variable (IV) approach to identify the equation. Let Z_i be an instrumental variable that is correlated with P_i but uncorrelated with ϵ_i. This variable can be used as an instrument such that $P_i = Z_i'\alpha + \upsilon_i$, where Z_i is a vector of exogenous variables of order $m \times 1$, α is a vector of parameters and υ_i is a vector of error term. To ensure the identification of the casual effects of β, δ and γ respectively, we assume (i) $\mathbb{E}(Z_i\epsilon_i) = 0$ and (ii) $\mathbb{E}(Z_i\hat{p}_{it}) \neq 0$ and $\mathbb{E}(Z_i l_{it}) \neq 0$. Our identification assumption is that, in addition to property, household and neighborhood characteristics, different property locations also affect the both asking and sale prices (Kendall and Tulip, 2018). Therefore, we exclude this regional classification while estimating the regional classification and use this variable as an instrument. Similarly, we also use quarter dummies, which represent the quarter in which the property was sold, as instruments. To overcome these issue we apply the two stage least square (2SLS) method to obtain the corrected standard errors and deal with the simultaneity problem.

4 Data

The data for this study include 33,828 properties that were advertised between the first quarter of 2010 and the last quarter of 2011 in the greater Sydney region in Australia.[6] Each observation includes the exact location of the property plus important observable characteristics. We also observed the asking price of each property and the advertisement date, plus the selling price or the transaction price

[6]The data for the current study is collected and provided by Australian Property Monitors. The main source of this data is the government of New South Wales and real estate agents.

and the transaction date.[7]

As Table 1 shows for both of the transaction price and the asking price, means are larger than medians. Thus, the distributions of both prices are skewed to the left. The average number of bedrooms is 2.72 with a median equal to 3. Also most of the properties have at most one bathroom. Overall, 18,258 properties are in the category of houses and the rest are apartments. Table 1 also shows descriptive statistics of the neighborhood characteristics based on the postcodes.

Table 1: Descriptive statistics

	Mean	Median	Maximum	Minimum	Std. Dev.
Transaction price†	658	535	107	9,700	453044
Asking price†	667	540	100	10,000	463198
Property type*	0.53	1	1	0	0.49
Bedrooms	2.72	3	8	1	1.06
Bathrooms	1.59	1	5	1	0.69
Parking	1.36	1	5	0	0.78
Pool	0.09	0	1	0	0.28
Media age	35.6	35	53	27	3.42
Median weekly rent (AU$)	407	406	780	175	93.04
Population	28,036	22,760	95,041	1,545	20,052
Mean income (AU$)	67,058	61,618	176,396	40,726	22,898
Number of houses	18,258				
Observations	33,828				

*Takes the value 1 for houses and 0 for apartments.
†Numbers are in thousand Australian dollars.

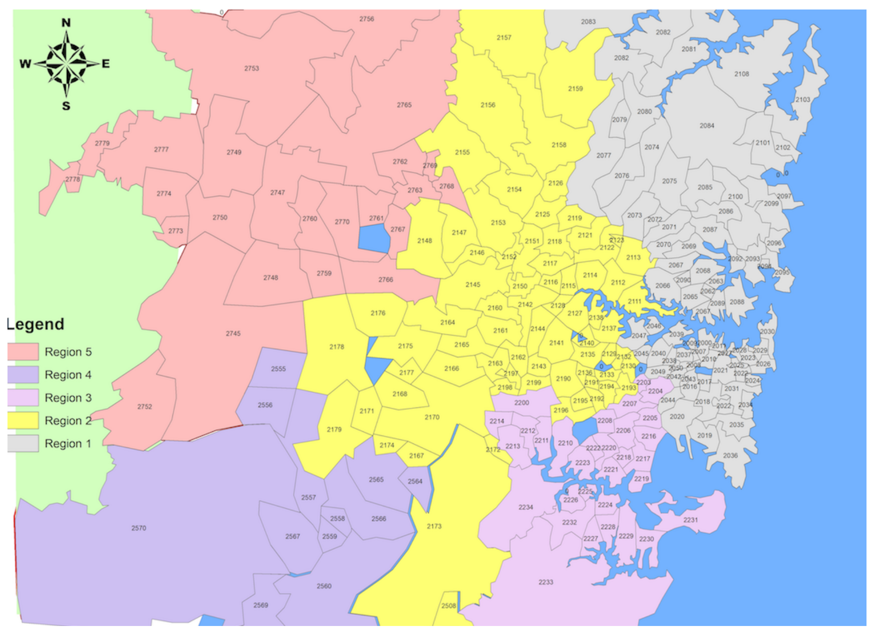
Properties were divided into two types: houses and apartments. There are four major characteristics for each property; these include the number of bedrooms, number of bathrooms, the parking situation, and whether a pool is present. Neighborhood characteristics were based on the postcode, which usually included one suburb. There are four major characteristics for each neighborhood: median age, median

[7] In the data used for currents study, we do not observe the accurate construction size of each property. However, in the Australian housing market experts believe that the price per square meter does not significantly impact the value of a property. See http://www.therealestateconversation.com.au/blog/chris-wilkins/price-square-meter-the-property-equation as an example of a quote from experts.

weekly rent, population, and mean income. Mean income represents household income, not individual income, and is provided in Australian dollars.

In addition to the above information, we also know the exact location of each property. We use this information and divide the data into five major regions (see Figure 1). This data is used for the instrumental variables in our estimation. Finally, we also know the exact time of sale and we use this information to construct quarter dummies which represent the quarter in which the property was sold. These dummy variables were also used in our estimation as instrumental variables to control for heterogeneity of properties.

Figure 1: The map of Sydney based on five regions



5 Estimation

In this section we present the estimation results of the model. First, we estimated two log linear hedonic ordinary least squares models to construct the predictions for the transaction price and the asking price. Tables 2 and 3 show the estimates for the hedonic regressions with robust standard errors. The robust standard errors for hedonic regressions (Table 2 and 3) are obtained using Huber-White Sandwich estimators. The results suggest that the coefficients are highly significant and all of them have the expected signs. For instance, houses were, on average, more expensive than apartments, and the presence of a pool had a positive effect on the final price of a property. The analysis of neighborhood characteristics suggests that, on average, the older the individuals in one neighborhood, the cheaper the properties. Population also showed a negative coefficient, and both median rent and mean income had positive coefficients, as expected. The significance of all coefficients and relatively high R-squared would result in better performance for predicted values of the asking price and the transaction price. The predicted transaction price has a median of \$542,000 compared to the actual median of \$535,000 and a mean equal to \$627,000 compared to the actual mean of \$658,000 and both distributions are skewed to the left. Also for the predicted asking price we have a median of \$551,000 while the actual median is \$540,000 and a mean equal to \$635,000 with the actual mean equal to \$667,000.

Table 2: Hedonic regression of the transaction price (p)

Dependent Variable: $Log(p)$			
Variable	Coefficient	Robust Std. Err.	p-value
Constant	-2.81	0.088	0.000
Property type	0.192	0.004	0.000
Bedrooms	0.122	0.002	0.000
Bathrooms	0.133	0.003	0.000
Parking	0.044	0.002	0.000
Pool	0.049	0.006	0.000
Log(Duration)	0.004	0.001	0.000
Log(Median age)	-0.286	0.023	0.000
Log(Median weekly rent)	0.348	0.011	0.000
Log(Population)	-0.090	0.002	0.000
Log(Mean income)	0.747	0.011	0.000
R-squared	0.71		
Observations	33,828		

*Quarter dummies are included in this regression but not in the table.

Using the results from the first two hedonic regressions, we constructed the pre-

Table 3: Hedonic regression of the asking price (l)

Dependent Variable: $Log(l)$			
Variable	Coefficient	Robust Std. Err.	p-value
Constant	-2.63	0.090	0.000
Property type	0.193	0.004	0.000
Bedrooms	0.125	0.002	0.000
Bathrooms	0.134	0.003	0.000
Parking	0.045	0.002	0.000
Pool	0.052	0.006	0.000
Log(Duration)	0.012	0.001	0.000
Log(Median age)	-0.300	0.023	0.000
Log(Median weekly rent)	0.321	0.011	0.000
Log(Population)	-0.087	0.002	0.000
Log(Mean income)	0.745	0.011	0.000
R-squared	0.70		
Observations	33,828		

*Quarter dummies are included in this regression but not in the table.

dicted values for the transaction price and the asking price. At this stage we estimate equation (5) using two stage least square (2SLS) method to obtain corrected standard errors for the coefficient of the right hand side variables. We test for the endogeneity and reject the null hypothesis in all models as F-test turns out significant. The test statistics are reported in Table 4 and 5. Similarly, we also performed the over-identification test to confirm whether instruments are uncorrelated with the error term. The Woodridge test-statistics for over-identifying restrictions are also reported in Table 4 and 5, which indicate that instruments are valid. Further to our robust estimation, we also obtain bootstrap confidence intervals for the accurate statistical inference of estimates. Estimates reported in the paper are based on 10,000 sub-samples.[8]

The variables of interest are $(l_{it} - \hat{l}_{it})$ and $(l_{it} - \hat{p}_{it})$. $(l_{it} - \hat{l}_{it})$ is the variable that captures the unobserved characteristics of properties. It is the difference between the

[8]Any further increase in replications had no significant change in standard errors.

actual asking price and the predicted asking price based on observed characteristics. The coefficient suggests that this effect was positive, and on average, sellers were able to signal the unobserved characteristics of their properties with asking prices. The more important variable for the current analysis is $(l_{it} - \hat{p}_{it})$ which captures the reference-dependence effect. It is the difference between the asking price and the predicted price of the property. If the asking price is the reference point, then this difference construct the reference-dependent component of the utility the buyer receives.[9] As shown in Table 4, the reference-dependence coefficient has a value of 0.73 with a high level of significance. This indicates that buyers are willing to pay more if the asking price of a property is larger with respect to its predicted price.[10] Therefore, our results provide evidence for both roles of the asking price we suggested earlier.

Table 4: 2SLS estimation of the transaction price (Bootstrapping)

Dependent Variable: p					
Variable	Coefficient	Robust Std. Error	Bootstrap Std. Error	z	p-value
Constant	7.89	1.043	1.030	7.57	0.000
$\hat{p}_{it}$	0.98	0.002	0.002	420	0.000
$(l_{it} - \hat{l}_{it})$	0.10	0.064	0.063	1.67	0.092
$(l_{it} - \hat{p}_{it})$	0.92	0.059	0.059	15.4	0.000
Over-identification (χ^2)	2.18				0.701
Endogeneity (Robust F-test)	63.4				0.000
Observations	33,828				

Although our identification strategy assumes that there is a linear relation between the transaction price and the reference-dependent variable, but it is possible that the reference-dependent effect are about the logarithm of the price rather than the price. This suspicion could raise since we used log-price as the dependent variable to estimate predicted transaction price and the asking price. However, we should

[9]Note that the coefficient of this variable acts as an estimate of γ in our theoretical model.

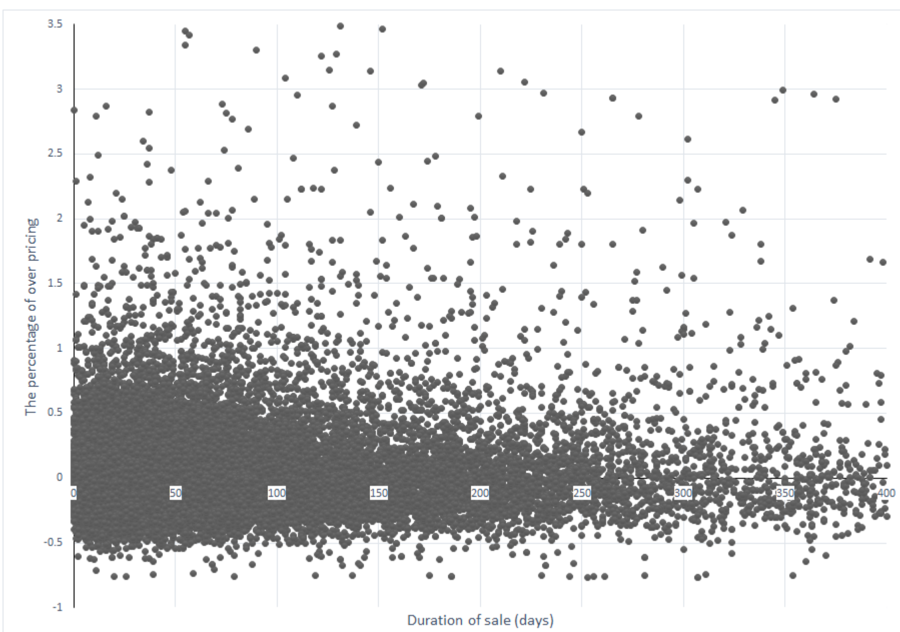
[10]We should note that this observation is in line with the prediction of those theoretical models which suggest the asking price is the ceiling price. See Chen and Rosenthal (1996) and Horowitz (1992) as two examples.

distinguish between these two models, since the nature of the hedonic regressions are quite different than the main model. In hedonic regressions, log-linear models provide better estimates because the characteristics of a property could have non-linear effects on its price, while for the estimation of reference-dependence this is not necessarily the case. In fact, as our estimates show, linear models provide more significant results compared to log-linear models. Also since two of the key variables $(l_{it} - \hat{l}_{it})$ and $(l_{it} - \hat{p}_{it})$ can have negative values, we have to use them in non-logarithmic form.

5.1 Robustness checks

To further check the robustness of our estimates, an alternative method is to use the generalized method of moment (GMM). GMM estimation allows us to test the validity of moment conditions (e.g., over-identifying restrictions). Moreover, in the presence of heteroscedasticity, the GMM estimator is more efficient than simple IV estimator. The result of these estimates are reported in Table 6 and 7 in the Appendix. As it is shown the results are similar to those obtained from 2SLS estimation.

Figure 2: The effect of overpricing on the duration of sale



Yet we have strong evidence that, on average, higher asking prices have positive effects on the final price of properties because of the reference-based preference of buyers. However, there is another important factor in the housing market, which is the time that sellers spend on the market to sell their properties. This can also be estimated as the probability of sale. Thus, we should determine whether high asking prices reduced the probability of sale significantly. Figure 2 shows the dispersion of duration versus the percentage of overpricing. Percentage of overpricing was calculated based on the difference between the actual asking price and the predicted asking price divided by the actual asking price.

Table 5: 2SLS estimation of the transaction price, with duration (Bootstrapping)

Dependent Variable: p					
Variable	Coefficient	Robust Std. Error	Bootstrap Std. Error	z	p-value
Constant	7.83	1.039	1.043	7,54	0.000
$\hat{p}_{it}$	0.98	0.002	0.002	424	0.000
$(l_{it} - \hat{l}_{it})$	0.10	0.063	0.063	1.69	0.090
$(l_{it} - \hat{p}_{it})$	0.91	0.059	0.059	15.4	0.000
$(D - \hat{D})$	-0.01	0.006	0.006	-2.88	0.000
Over-identification (χ^2)	3.88				0.867
Endogeneity (Robust F-test)	106				0.000
Observations	33,828				

*D represents duration and $\hat{D}$ represent its predicted value.

There is no evidence that overpricing was positively related to the duration of sale. Figure 2 suggests that most properties were sold in fewer than 100 days. There are also properties with a lower asking price than their prediction that nevertheless took a very long time to sell.

To have a better understanding of the effect of overpricing we are going to run another model to specifically test for the duration of sale. We first run another regression with the duration as a dependent variable over property characteristics, neighborhood characteristics and time dummies. Second, we construct prediction for the duration of sale based on the results of this regression. Finally, we run a second stage regression like the one in 4 but with one more variable, that is, the difference between the predicted duration and the actual duration. Table 5 represents the results for this estimation. Since variable $(D - \hat{D})$ has a very small coefficient, we can conclude that there is no evidence to suggest that properties with higher prices took longer than expected in the market. In fact, since the coefficient is negative the contrary is suggested by this result, however, with negligible effect. There are also very small marginal effect on coefficients of other variables.

The other robustness check is to separate fixed effects from time-dependent effects. The only time-dependent variable in our model is quarter dummies. When these effects were separated in the model, the coefficients did not change significantly and the results remained similar.

6 Conclusion

Many theoretical studies discuss reference-dependent preferences as an alternative to classic expected utility theory. There is also strong experimental evidence for such behaviour. However, there are few empirical studies in this area because of the difficulties with observations on reference points. In this article, unlike other papers in the literature, we focus on the reference dependent behaviour of buyers in the housing market. We suggest that, in the housing market, in which sellers do not reveal their reservation values and buyers face uncertainty regarding the value of properties, buyers adjust their values based on a reference point. Since one way to determine the reference point is through the expectation, the asking price could affect the expectation of buyers for the value of a property. Therefore, buyers would adjust their values after observing the asking price. Another important role of the asking price is to signal unobservable characteristics of a property. We separate these two effects and estimate a model based on instrumental variable (IV) method to verify them. We applied the two stage least square (2SLS) and generalized method of moment (GMM) estimations to obtain consistent and robust estimates by using bootstrapping methods. Our results suggest that the asking price acts as a reference point to buyers. The major implication of these results is that the asking price of a house is an important factor for deriving the final transaction price. It is not only a signal of unobservable characteristics of a property but also adjusts the expectation of buyers for the value of a property.

7 Appendix

7.1 GMM estimation results

Table 6: GMM estimation of the transaction price (Bootstrapping)

Dependent Variable: p				
Variable	Coefficient	Std. Error	z	p-value
Constant	7.33	1.026	7.15	0.000
$\hat{p}_{it}$	0.98	0.002	434	0.000
$(l_{it} - \hat{l}_{it})$	0.13	0.060	2.31	0.021
$(l_{it} - \hat{p}_{it})$	0.89	0.056	15.6	0.000
Hansen's J-test (Over identification)	8.37			0.397
GMM C statistic chi2	203.9			0.000
Observations	33,828			

Table 7: GMM estimation of the transaction price, with duration (Bootstrapping)

Dependent Variable: p				
Variable	Coefficient	Std. Error	z	p-value
Constant	7.26	1.020	7.12	0.000
$\hat{p}_{it}$	0.98	0.002	439	0.000
$(l_{it} - \hat{l}_{it})$	0.13	0.059	2.32	0.020
$(l_{it} - \hat{p}_{it})$	0.89	0.056	15.7	0.000
$(D - \hat{D})$	-0.019	0.002	-3.09	0.002
Hansen's J-test (Over identification)	8.13			0.420
GMM C statistic chi2	229.3			0.000
Observations	33,828			

7.2 Derivation of Equation (4)

First, denote ω_i as,

$$\omega_i = E(s_i | l_{it}, \hat{l}_{it}, v_i).$$

It follows that ω_i depends on the list price and the estimated list price as well as the signal received. Therefore, the expectation of ω_i equates the conditional expectation of the unobserved characteristics and we have,

$$E(\omega_i | l_{it}, \hat{l}_{it}) = E(s_i | l_{it}, \hat{l}_{it}).$$

From the joint normality of of s_i and v_i we have,

$$E(s_i | l_{it}, \hat{l}_{it}) = \frac{\sigma_s^2}{\sigma_s^2 + \sigma_\psi^2}(l_{it} - \hat{l}_{it}),$$

which is equivalent to equation (4).

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