Prospect Theory, Reverse Disposition Effect and the Housing Market

Zhaohui Li, Michael J. Seiler and Hua Sun*

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Abstract

We model a house seller's pricing decision under a prospect value function. Our model shows that reference dependence generates a disposition effect, which is magnified by loss aversion. Surprisingly, diminishing sensitivity will lead to a local reverse disposition effect in which a seller's asking price can be decreasing with increasing potential loss. Our model also predicts a larger price dispersion in a cold market and reaffirms the price-volume relation. We find consistent evidence using multiple listing service data in Virginia. Finally, the empirical pricing curve suggests the extent of diminishing sensitivity can vary with the loss/gain position of the agent.

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*Zhaohui Li: Strome College of Business, Old Dominion University, 5115 Hampton Blvd, Norfolk, VA 23529 (email: z1li@odu.edu); Michael J. Seiler: Raymond A. Mason School of Business, The College of William & Mary, P.O. Box 8795, Williamsburg, VA 23187, USA (email: Michael.Seiler@mason.wm.edu) and London School of Economics, London WC2A 2AE, UK (email: m.seiler@lse.ac.uk); Hua Sun: Corresponding author, Ivy College of Business, Iowa State University, Ames, IA 50011 (email: hsun@iastate.edu)

The seminal work on prospect theory by Kahneman and Tversky [1979] and Tversky and Kahneman [1991, 1992] proposes three major components to help explain the decision-making process of individuals under uncertainty. The first component is reference-dependence, in which people draw utility over gains and losses relative to a reference value such as a prior acquisition price or an initial endowment.[1] In the second component, the loss aversion effect, people treat losses and gains asymmetrically in their value functions. In particular, an equal-sized loss looms larger than an equal-sized gain.[2] In the third component, diminishing sensitivity, the marginal value for both gains and losses declines with size. Barberis [2013] offers a comprehensive review of the wide applications of the prospect theory in economics.

Although conceptually intuitive, much evidence that supports prospect theory comes from experimental studies (e.g., Kahneman, Knetsch and Thaler [1991]; Tversky and Kahneman [1991]; Knetsch, Tang and Thaler [2001]; Imas[2016], etc.). Not surprisingly, finding non-experimental evidence of loss aversion becomes an active research topic. Primary field evidence supporting prospect theory is documented within the finance literature. Many studies support the disposition effect, in that relative to the purchasing price, investors have a greater propensity to sell stocks that have risen in value rather than those that have fallen (Shefrin and Statman [1985], Odean [1998], Grinblatt and Keloharju [2001], Feng and Seasholes [2005], Linnainmaa [2010], Chang, Solomon, and Westerfield [2016], etc.). There is an active debate concerning which component of the prospect theory that drives the observed disposition effect in the stock market (Barberis [2013]). Barberis and Xiong [2012] show that reference dependence alone can generate the disposition effect if the discount rate is sufficiently positive. Bodnaruk and Simonov [2016] provide evidence that mutual fund managers with higher degree of loss aversion tend to exhibit a stronger disposition effect. Some researchers, however, argue that it is diminishing sensitivity that generates the disposition effect (Shefrin and Statman [1985], Li and Yang [2013], etc). Contrary to Bodnaruk

[1]As discussed by Benartzi and Thaler [1995], this is opposite to the classical expected utility theory in which the thing that matters is wealth itself.

[2]That is, $W(x) < -W(-x)$. See Loewenstein and Prelec [1992] for a discussion.

and Simonov [2016], the simulation results from Li and Yang [2013] suggest that, in general, loss aversion tends to mitigate the disposition effect.

As one of the classic tests on prospect theory beyond stock market, Genesove and Mayer [2001] examine house sellers' behavior and find a similar disposition effect. That is, compared to potential gainers, a seller subject to a larger potential loss sets a higher asking price, exhibits lower sales hazard and obtains a higher transaction price if the house is sold (*finding one*). They further find that the marginal mark-up declines with the size of a seller's potential loss exposure (*finding two*). Genesove and Mayer interpret finding one, henceforth the disposition effect, as a test of the loss aversion effect and finding two as a test of diminishing sensitivity. Their proposed connection between the prospect theory and seller behavior has quickly grown in popularity in the literature. Follow up studies using either house listing or transaction prices to test loss aversion include Bokhari and Geltner [2011] and Anenberg [2011]. Both find similar results as in Genesove and Mayer [2001] and view them as evidence of loss aversion. Neo, Ong and Somerville [2006] test the loss aversion effect using housing auction data by finding an increasing relation between transaction prices and sellers' loss exposures. Chan [2001] and Engelhardt [2003] test the loss aversion effect by examining factors that influence household mobility. Both find that potential losses have a negative relation with a household's mobility, which is consistent with the behavior that a seller subject to a larger potential loss will set a higher price when selling a house. Beggs and Graddy [2009] test the loss aversion effect using painting auction data and fail to find significance in a regression of auction price on seller's loss exposure suggesting there is no loss aversion.

Motivated by split views in the literature on the relation between the prospect theory components and empirical trade patterns, this paper aims to examine and clarify exactly how the components within prospect theory affect a seller's pricing behavior. We illustrate this by building a simple search model in an asset (housing) market, which incorporates Tversky and Kahneman's prospect utility as a special case. Our model provides a clear correspondence between each component of the prospect theory and its unique empirical implication.

In particular, we show that both findings from Genesove and Mayer [2001] offer evidence supporting a reference-dependent value function. Therefore, they are valid tests of the first component in prospect theory. However, unlike the argument made in Genesove and Mayer [2001], neither does finding one have a direct relation with loss aversion, nor does finding two have a direct relation with diminishing sensitivity. In fact, we show that an increasing and concave relation between a seller's asking price and her potential loss exposure is fully consistent with a value function that is loss neutral and has a marginally increasing sensitivity in both gain/loss dimensions. As a result, there is a conceptual mismatch between the two empirical findings and their theoretical counterparts. This finding has important implications when testing loss aversion since many studies interpret evidence of loss aversion in the same way as in Genesove and Mayer [2001], as shown above.

With the notable exception of the reference-dependence effect, empirical tests confirming findings one and two are of very limited testing power. Accordingly, we show that in order to test loss aversion and diminishing sensitivity, we must examine the behavior of both potential gainers and losers. We show that a value function that is fully consistent with prospect theory implies a non-linear, non-monotonic pricing curve with changing curvature. In particular, in our model, loss aversion implies significant slope run-up among sellers who are near their perceived break-even positions. This finding echoes Ray, Shum and Camerer [2015], which examines asymmetric demand elasticity around a reference price. Although merely a discussion, the authors argue that it is the reference dependence effect that causes asymmetric demand elasticity, while loss aversion simply magnifies this asymmetry. Another striking prediction from our model is that diminishing sensitivity may lead to a locally reversed disposition effect. That is, when a prospect-utility seller is subject to a range of moderately sized losses, her asking price can be decreasing when the potential loss is increasing. Finally, our model predicts that the price dispersion in a cold market is greater than in a hot one, and also helps to explain the positive price-volume relation observed in housing markets. Using multiple listing service data in Virginia, we find evidence that is consistent with the predications made by prospect theory.

The remainder of the paper is structured as follows. Section 1 provides an exposition of the model for a seller's decision problem which incorporates prospect utility as a special case, and discusses its implications. The empirical predictions are tested in section 2, while section 3 concludes the paper.

1 Model Setup and Results

1.1 General Setup

Our search model set up is similar to Williams [1998][3].Consider a large housing market with a countably infinite number of potential sellers. Each seller has an ex-ante identical house for sale. To sell it, she must commit effort to search for a potential buyer, who arrives via an independent Poisson process. For seller i, we define the proportional time spent on searching as t_i, which ranges from 0 to 1. During time window, Δt, a buyer arrives with the probability of $B(t_i)\Delta t$. As a result, no buyer arrives with the probability of $1 - B(t_i)\Delta t$, and more than one buyer arrives with a probability that is smaller than the order of Δt. The time not spent searching is consumed as leisure. During time window, Δt, the working time incurs at a cost of $H(t_i)\Delta t$. Later, we will study two cases: a costless search case and a costly search case. Although less realistic, we still want to study the first case since it will significantly simplify our model in order to obtain an analytical relation between a seller's asking price and her reference value, which parallels empirical finding one in Genesove and Mayer [2001]. In that case, we simply assume $B(t) = 1$ and $H(t) = 0$ for all t. In the model with costly search, we assume that arrival function B has the following properties. First, it is twice continuously differentiable everywhere. Second, B is increasing and strictly concave in t_i. This assumption implies a marginal decreasing productivity on a seller's searching ability. To prevent corner solutions, we also assume $B(0) = 0, B'(0) = \infty$. Consistent with the literature, we further assume the search cost function H to be twice differentiable, increasing and strictly convex in t_i. Finally, we assume $H'(0) = 0$ and $H'(1) = \infty$ to prevent

[3] In Williams [1998], one difference is that households delegate this selling procedure to a broker, who can have multiple houses for sale.

any corner solutions.

When a potential buyer arrives due to seller i's search effort, the buyer inspects i's house and decides if the quality matches his own preference. Depending on the matching quality, the buyer decides the highest possible price p_i that he is willing to pay. We assume p_i is a random draw from distribution G. If there is no match, $p_i = 0$. If there is a perfect match, $p_i = 1$, which is only a normalization. Therefore, G has a finite support [0,1]. Furthermore, we assume p_i is independent across buyers, houses and time. The distribution G could be very general in this regard. One typical assumption is that, in all cases the hazard function, $g/(1-G)$ is non-decreasing. The seller chooses an asking price r_i for her house. If $p_i \geq r_i$, the transaction is closed and the seller pays r_i.

Collectively, seller i's objective is to solve the following maximization problem:

$$\begin{aligned} U^{v_i,c_i} = \underbrace{max}_{t_i,r_i} \quad & e^{-\beta\Delta t}\{B(t_i)(1-G(r_i))\Delta t W(r_i,v_i) - H(t_i)\Delta t \\ & +[1-B(t_i)(1-G(r_i))\Delta t](U^{v_i,c_i} - c_i\Delta t)\} + o(\Delta t) \end{aligned} \tag{1}$$

subject to $0 \leq t_i \leq 1$ and $o \leq r_i \leq 1$, for $i = 1, 2......$

In equation (1), β is the discount rate, and c_i reflects the per-period net cost of staying in the current house, possibly due to the disutility of not being able to sell the house at the current period. A positive value of c_i means the seller has an incentive to move sooner due to some attractive outside option. However, we acknowledge the possibility that for some sellers c_i could be negative, which implies that remaining in the current house is more attractive than moving. This idea generates the positive effect of spatial lock-in. In this case, fishing by asking a higher than expected market price is a natural response for sellers, since they must ask potential buyers to compensate for giving up the benefit from superior matching. To rule out this trivial case, henceforth, we only consider the case that c_i is non-negative.

Conditional on a successful sale, seller i receives a utility gain, as measured by value function $W(r_i, v_i)$. Particularly, we assume $W(r_i, v_i)$ has the following form:

$$W(r_i, v_i) = \begin{cases} (r_i - v_i)^\alpha & \text{if } r_i - v_i \geq 0, \\ -\lambda(v_i - r_i)^\alpha & \text{if } r_i - v_i < 0 \end{cases} \tag{2}$$

where $\lambda, \alpha > 0$. Our specification of $W(r_i, v_i)$ is very general. On the one hand, when $v_i = 0$ for all i and $\alpha = \lambda = 1$, equation (1) reduces to the traditional search model in which risk neutral sellers attempt to maximize the expected selling proceeds. On the other hand, $W(r_i, v_i)$ also incorporates Kahneman and Tversky's prospect utility as a special case when $v_i \neq 0, \lambda > 1$ and $0 < \alpha < 1$. The component of reference-dependence corresponds to the existence of a non-zero v_i. Instead of drawing utility directly from selling proceeds, people will evaluate it relative to an inherited reference value. Therefore, v_i is explicitly treated as an un-sunk cost, opposing the classical model, in which all prior costs are sunk and are therefore irrelevant to the current decision. We also assume v_i is drawn from distribution V. In our model, we do not allow v_i to change over time. It has been found in several studies, including Genesove and Mayer [2001], that people tend to have nominal reference values.

Since loss aversion refers to a behavior where a loss looms larger than an equal-sized gain, it is clear that $\lambda > 1$ measures this asymmetric response. This is the reason why Kahneman and Tversky [1979] and Tversky and Kahneman [1992] define λ as the coefficient of loss aversion. Finally, the diminishing sensitivity is measured by α. These authors propose that λ should be approximately 2.25 and α near 0.88.

We now discuss the implication as outlined in equation (1). Over the time interval Δt, the seller maximizes the discounted expected payoff from the following decision problem. First, it is possible that one buyer will arrive who is willing to pay r_i. The first term in the bracket of equation (1) measures this effect. Likewise, the second term measures the total search cost expended by seller i. In the third term, $1 - B(t_i)(1 - G(r_i))\Delta t$ refers to the probability of the remaining current state. In this case, the seller incurs a waiting cost, $c_i \Delta t$, and will repeat the current decision problem U^{v_i, c_i}. It should be noted that the terms in brackets correctly consider all possible and non-trivial events that could happen during period Δt. The other events can only occur with the probability of a smaller order than Δt. Those terms are collected as $o(\Delta t)$.

By Taylor expansion on $e^{-\beta \Delta t}$, equation (1) can be rewritten as:

$$
\begin{aligned}
0 = \underbrace{max}_{t_i, r_i} \quad & \{B(t_i)(1 - G(r_i))\Delta t[W(r_i, v_i) + c_i \Delta t - U^{*v_i, c_i}] \\
& -H(t_i)\Delta t - c_i \Delta t\} - \beta U^{*v_i, c_i} \Delta t
\end{aligned} \tag{3}
$$

Dividing the above equation by Δt, taking the limit as $\Delta t \to 0$ and re-organizing the terms gives us

$$
U^{*v_i, c_i} = \frac{B(t_i^*)(1 - G(r_i^*))W(r_i^*, v_i) - H(t_i^*) - c_i}{B(t_i^*)(1 - G(r_i^*)) + \beta} \tag{4}
$$

Taking the first-order condition with respect to t_i and r_i, yields:

$$
B'(t_i^*)(1 - G(r_i^*))[W(r_i^*, v_i) - U^{*v_i, c_i}] - H'(t_i^*) = 0 \tag{5}
$$

$$
(1 - G(r_i^*))W_{r_i}(r_i^*, v_i) - g(r_i^*)[W(r_i^*, v_i) - U^{*v_i, c_i}] = 0 \tag{6}
$$

where the subscript directs us to take the partial derivative with respect to the corresponding variable. Equations (5) to (6) fully characterize equilibrium solutions, since we have two equations to solve for three unknowns: t_i^* and r_i^*. A proof of the existence and a unique solution for this type of searching problem can be found in Williams [1998].

1.2 Results

Although the solving process is straightforward, equations (5) and (6) are too general to provide any clear implications on the relation between a seller's asking price and the reference value, in particular, the slope, $\frac{dr^*}{dv_i}$. To get more concrete results, in the next subsection we first consider the case of a costless search. By doing so, we greatly simplify our model to get the analytical expression, $\frac{dr^*}{dv_i}$.

1.2.1 The Case of Costless Search

As previously mentioned, in this case, we assume $B(t) = 1$ and $H(t) = 0$ for t. As a result, equation (5) goes away. We can rewrite equation (4) as:

$$U^{*v_i,c_i} = \frac{(1 - G(r_i^*))W(r_i^*, v_i) - c_i}{1 - G(r_i^*) + \beta} \tag{7}$$

Substituting equation (7) into equation (5) gives us:

$$[1 - G(r_i^*)]W'_{r_i}(r_i^*, v_i) - g(r_i^*)\left[W(r_i^*, v_i) - \frac{[1 - G(r_i^*)]W(r_i^*, v_i) - c_i}{[1 - G(r_i^*)] + \beta}\right] = 0 \tag{8}$$

Knowing W'_r is a function of $v - r$, we simplify it and separate $v - r$ and r into different sides of the equation resulting in:

$$v_i - r^* - \frac{\alpha c}{\beta W'_{r^*}} = -\frac{\alpha(1 - G + \beta)(1 - G)}{\beta g}{}_4 \tag{9}$$

Conditional on a common c, we can differentiate equation (9) towards r:

$$\frac{dv_i}{dr^*} - 1 - \frac{\alpha c}{\beta}\frac{d\frac{1}{W'_{r^*}}}{dr} = \frac{\alpha}{\beta}(1 - G) - \frac{\alpha}{\beta}(1 - G + \beta)\frac{d(\frac{1-G}{g})}{dr} \tag{10}$$

First, it can be seen that as $g/(1 - G)$ is non-decreasing against r, $(1 - G)/g$ should be non-increasing with r. Therefore, the right-hand side term is strictly positive. To evaluate the validity of finding one in Genesove and Mayer [2001] as a test of the loss aversion effect, we further assume that a potential buyer's value function is linear, i.e., $\alpha = 1$, which yields the following result:

Lemma 1.1 *With a costless search, a linear value function, and conditional on a common* c_i,

$$\frac{dr^*}{dv_i} = \frac{1}{1 + \frac{1}{\beta}(1 - G) - \frac{1}{\beta}(1 - G + \beta)\frac{d(\frac{1-G}{g})}{dr}} > 0 \tag{11}$$

The proof comes directly from equation (10) in that $\alpha = 1$ gives $W'_r = 1$. One implication from Lemma 1 is that loss aversion plays no necessary role in determining the sign of $\frac{dr^*}{dv_i}$. In other words, a positive association between a seller's asking price and the reference value,

[4] $G(r^*)$ and $g(r^*)$ are henceforth written simply as G and g.

which is essentially finding one in Genesove and Mayer [2001][5], does not imply $\lambda > 1$. Later, we will show that this finding still holds in a more general context with costly search and for a broad range of bidding distributions. A paper related to this finding is Barberis and Xiong [2012], who show that with a sufficiently positive discount rate, a linear reference-dependent realization utility can generate the disposition effect. Lemma 1 shows that, in our model, the reference-dependence effect alone can generate the same disposition effect. Nevertheless, finding one is a valid test for reference dependence (i.e., $v_i \neq 0$). If this was not the case and v_i is always zero, then from equation (4), we know U^{*v_i,c_i} is no longer a function of v_i. Therefore, it must be the case that $\frac{dr^*}{dv_i} = 0$ for all v_i. The link between finding one and reference dependence is intuitive. If reference value plays no role in affecting seller utility, it should not have any predictive power on the optimal asking price which a seller chooses.

Although Lemma 1 provides direct insight into the potential disconnection between the empirical test on loss aversion by Genesove and Mayer [2001] and its theoretical counterpart, its assumption of a costless search is unrealistic. We now consider the general case with costly search.

1.2.2 The Case of Costly Search: Comparative Statics

With costly search, equation (10) can now be written as:

$$v_i = r^* + \frac{\alpha[c + H(t^*)]}{\beta W'_{r^*}} - \frac{\alpha[B(t^*)(1-G) + \beta](1-G)}{\beta g} \tag{12}$$

Taking the derivative of $W(r, v)$, the equation above is now transformed as:

$$\begin{aligned} v_i &= r^* + \frac{(c+H)}{\beta}(r^* - v_i)^{(1-\alpha)} - F(r^*) \qquad \text{if } v_i - r^* < 0 \\ v_i &= r^* + \frac{(c+H)}{\beta}\frac{(v_i - r^*)^{(1-\alpha)}}{\lambda} - F(r^*) \qquad \text{if } v_i - r^* > 0 \end{aligned} \tag{13}$$

where $F(r^*) = \frac{\alpha}{\beta}[B(t)(1-G) + \beta]\frac{(1-G)}{g}$. As $B(t)$ and $G(r)$ are positive, $[B(t)(1-G) + \beta]$ is decreasing with r. Coupled with the fact that $(1-G)/g$ is non-increasing with r, it can

[5] More precisely, Genesove and Mayer [2001] find a positive relation between the asking price and a seller's potential loss exposure, $v_i - \overline{P}$, where $\overline{P}$ means the expected market price. However, as $\overline{P}$ is ex-post fixed in our theory, this finding is equivalent to a positive relation between r_i^* and v_i.

be shown that $dF(r^*)/dr^* < 0$. Proposition 1 below characterizes how the optimal pricing strategy responds to the key parameters of α, λ, v and c.

Proposition 1: The relation between the optimal asking price and other key parameters can be summarized in the following table:

	$\alpha > 1$ and for all $\lambda > 0$		$\alpha = 1$ and for all $\lambda > 0$	$\alpha < 1$ and for all $\lambda > 0$	
	$v_i - r^* < 0$	$v_i - r^* > 0$	$v_i - r^* \neq 0$	$v_i - r^* < 0$	$v_i - r^* > 0$
$\frac{\partial r^*}{\partial c}$	< 0[6]	< 0	< 0	< 0	< 0[7]
$\frac{\partial r^*}{\partial v}$	Non-monotonic: positive first, then negative and positive again	> 0	> 0	> 0	Non-monotonic: positive first, then negative and positive again
$\frac{\partial r^*}{\partial \lambda}$	> 0		> 0	> 0[7]	

Details on the proof of Proposition 1 are in the appendix. There are several major take-aways from this proposition. Firstly, the optimal asking price r^* is negatively associated with waiting cost c for most circumstances. Secondly, the optimal asking price depends on loss/gain exposure (hence v), and thus it is a valid test of reference dependence, the first key component of the prospect theory. Thirdly, $\frac{\partial r^*}{\partial \lambda} > 0$ on all positive α and λ suggests that a valid test of the loss aversion effect is not the degree of slope of the pricing curve, but the run-up of the slope level when compared to a reference-dependent but loss-neutral seller. Fourthly, the fact that $\frac{\partial r^*}{\partial v}$ is non-monotonic when a seller is in a loss position (i.e., when $v_i - r^* > 0$) only when $\alpha < 1$ suggests that it is a valid test of the diminishing sensitivity. We will defer additional discussion on the test of loss aversion (i.e., $\lambda > 1$) and diminishing sensitivity (i.e., $\alpha < 1$) until the next section as it is more intuitive when we visualize the Proposition 1 results via simulation.

[6]Technically, this holds only if $(r^* - v_i)^{-\alpha} < [1 - \frac{dF(r^*)}{dr^*}]/[\frac{(c+H)(\alpha-1)}{\beta}]$. Given the parameter ranges, this condition is loose and unlikely to be violated. See the appendix for a more detailed discussion. Our simulation results in section 1.2.3 also confirm this.

[7]Technically, both hold only if $(v_i - r^*)^{-\alpha} < [1 - \frac{dF(r^*)}{dr^*}]/[\frac{(c+H)(1-\alpha)}{\lambda\beta}]$. Given the parameter ranges, this condition is loose and unlikely to be violated. See the appendix for a more detailed discussion. They are also confirmed in our simulation results found in section 1.2.3

1.2.3 The Case of Costly Search: Simulation

In this section we conduct a series of simulations to help visualize and better understand Proposition 1. We first need to specify the functional form of search productivity $B(t)$, cost $H(t)$, the distribution of potential buyers' valuation $G(r)$, and the joint distribution of sellers' reference values and net waiting costs $F(v, c)$. Hereafter, we will assume:

$$B(t) = \sqrt{2t - t^2} \tag{14}$$

$$H(t) = 1 - \sqrt{1 - t^2} \tag{15}$$

Both $B(t)$ and $H(t)$ are quarter portions from unit circles. A convenient feature of this specification is that it satisfies all the assumptions we make concerning the productivity and cost functions. The terms are both monotonically increasing and twice continuously differentiable. Continuing, we can easily verify that they also satisfy the curvature assumptions made. Furthermore, we assume v_i and c_i are independent variables. In other words, the reference value and net waiting cost for individual sellers are uncorrelated.

A more realistic assumption concerning potential buyers' bidding distribution should have a greater central tendency than the uniform distribution. Since G has a finite support of [0,1], we cannot assume the usual normal distribution for G. Specifically, we use the $Beta(2, 2)$ (quasi-triangular) distribution:

$$\begin{cases} G(r) = 3r^2 - 2r^3 \\ g(r) = 6r - 6r^2 \qquad for \quad 0 \leq r \leq 1 \end{cases} \tag{16}$$

The density of this distribution is shown in Figure 1.

Similar to a normal distribution, a $Beta(2, 2)$ distribution is also symmetric and peaked at its center. The simulation results presented below are based on this distribution. Meanwhile, when conducting parallel studies on a uniform distribution, we obtain very similar results.

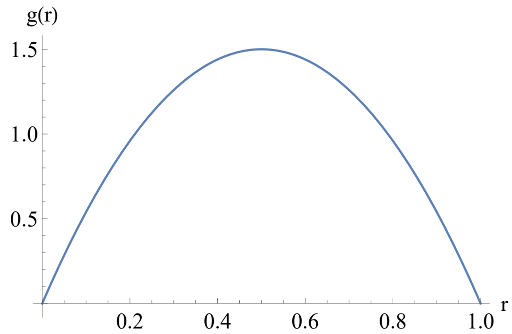

Figure 1: THE DENSITY FUNCTION OF BETA(2,2)

Equipped with specifications for $G(r), B(t)$, and $H(t)$, we can substitute them into equations (5) and (6). For a given set of v_i, c_i and β, we can solve the system numerically to get t_i^* and r_i^*. In particular, we assume that β is 5 percent and c_i is 0.05[8]. Hereafter, we maintain these parameter values unless stated otherwise. To show that finding one from Genesove and Mayer [2001] has no necessary relation with the loss aversion effect, we set $\lambda = 1$. We also assume $\alpha = 1$ to rule out any potential effects from diminishing sensitivity in the value function. Hence, $W(r_i, v_i) = r_i - v_i$.

First, we examine the relations among a seller's asking price, searching effort and reference value. The results are presented in Figure 2.

In both cases, a seller's asking price is increasing with the reference value, which is consistent with finding one. Since we set $\lambda = 1$, we can confirm the prior conclusion that finding one has very limited power when testing the loss aversion effect. The impact attained from reference dependence is intuitive. Because the reference value is regarded as an un-sunk cost by sellers, the higher the reference value, the more compensation the seller will ask for because the higher the reference value, the more likely the seller is to realize a loss when selling. Another finding is that with more heterogeneous valuations from potential buyers (uniform case), a seller tends to increase her asking price, ceteris paribus. This is true for all possible

[8]We also tried other cases in which c_i is random, and found very similar results. The advantage of using a constant c_i is that, conditional to it, we can examine the relation between a seller's asking price, her reference value and the expected market price.

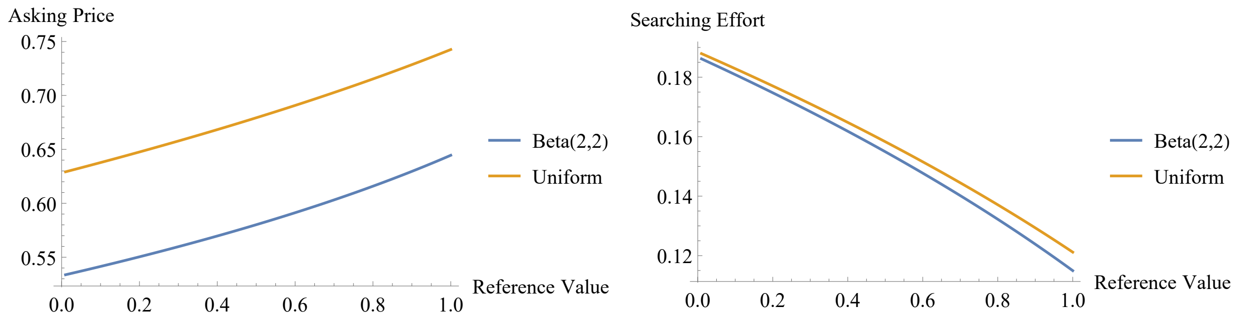

Figure 2: Seller's Asking Price, Searching Effort and Reference Value ($\lambda = 1$)

reference values. The intuition is that because potential buyers are more heterogeneous in terms of their preferences, the probability of meeting a buyer who is willing to pay a higher matching premium becomes larger. As a result, it is more attractive for a seller to ask a higher price in the market. Finally, we find that the search effort decreases with the asking price. This implies that on the one hand, a seller may want to fish in the market by asking for a higher price. On the other hand, she may also choose to spend less effort in searching for potential buyers. One obvious force that helps to generate this finding is the role of the reference value. The higher the reference value, the higher the asking price, because they are conditional to a given holding cost. Since the reference value is also a cost component in addition to searching, an increase in reference value may depress the seller's searching incentive.

In Genesove and Mayer [2001], and many other studies, a seller's asking price is examined with respect to her potential loss exposure, which is the difference between a seller's reference value and the expected market price. To make a more direct comparison, we need to define the expected market price.

It can be seen from equations (5) and (6) that equilibrium are functions of v_i and c_i. Supposing the C.D.F of its joint distribution is $F(v, c)$, and conditional on $F(v, c)$, the expected market price can be defined as the average of all transaction prices, weighted by the probability of realizing such sales. As a result,

$$\overline{P} = \frac{\iint r^*(v,c)[B(t_i^*(r_i^*))(1-G(r_i^*))f_{v,c}(v,c)dvdc]}{[B(t_i^*(r_i^*))(1-G(r_i^*))f_{v,c}(v,c)dvdc]} \tag{17}$$

In the simulation, we assume the seller's reference values are distributed uniformly in [0,1]. Each time we randomly draw 1,000 sellers from this distribution and calculate the expected market price following equation (17). We then define $Loss_i = v_i - \overline{P}$, consistent with extant empirical studies.

To isolate the unique predictions from the prospect theory, we consider two kinds of value functions in our simulation. We first set $\alpha = 1.2$, implying an increasing sensitivity and in opposition to the prospect theory. We then set $\alpha = 0.88$, as proposed by Kahneman and Tversky in the prospect theory. Within each α setting, we compare cases both with and without loss aversion. Based on equations (5) and (6), by introducing the distribution function $G(r)$ and assigning the parameters the same values, we can identify the relation between r and loss exposure in different values of λ. Figure 3 shows the results.

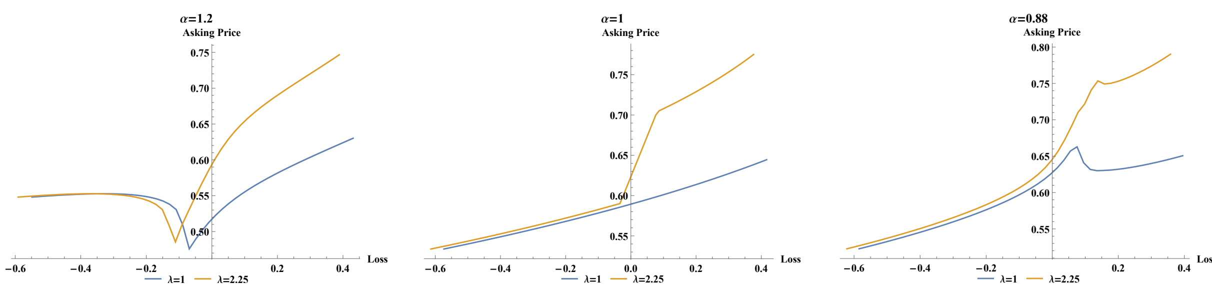

Figure 3: Asking Price with Different Value Functions ($Loss = v_i - \overline{P}$)

Genesove and Mayer [2001] conclude that sellers subject to a greater potential loss ask for a higher price, and find that the marginal mark up declines as the size of the potential loss increases. They interpret the first finding as evidence of loss aversion (i.e., $\lambda > 1$), and the second finding as evidence of a marginal diminishing effect (i.e., $\alpha < 1$). It is now clear why Genesove and Mayer [2001] lack testing power on both claims. From the left panel of Figure 3 we can see that for losers (i.e., $v_i - r^* > 0$), $\frac{\partial r^*}{\partial v} > 0$ and $\frac{\partial^2 r^*}{\partial v^2} < 0$ both hold for house sellers with $\lambda = 1$ and $\alpha > 1$. Therefore, these findings serve neither as evidence that loss aversion exists, nor as evidence that there is a marginal diminishing effect.

So what is the appropriate test to consider? It is clear from Proposition 1 and Figure 3 that $\frac{\partial r^*}{\partial v} > 0$ alone cannot be used as a test for loss aversion. Furthermore, as $\frac{\partial r^*}{\partial \lambda} > 0$ for all positive α, if the loss aversion effect holds (i.e., $\lambda > 1$ if $v - r^* > 0$), we anticipate that the pricing curve along v is higher than if $\lambda = 1$. Thus, it is the slope run-up, not the (positive) slope itself that reflects the loss aversion effect. Our simulation further shows that the slope run-up starts when the seller is subject to a small perceived gain, which is the difference between the $\overline{P}$ and v. To test the diminishing sensitivity (i.e., $\alpha < 1$), we first notice from Proposition 1 and Figure 3 that the non-monotonicity of the pricing curve only holds when $\alpha \neq 1$. Furthermore, if $\alpha < 1$, $\frac{\partial r^*}{\partial v}$ becomes non-monotonic only for losers (i.e., $v_i - r^* > 0$). The prediction reverses when the agent exhibits marginally increasing sensitivity, in which case non-monotonicity will arise only for gainers. Therefore, diminishing sensitivity uniquely predicts a local reverse disposition effect among potential losers, due to the non-monotonic pricing strategy.

The distinct non-monotonic behaviors depend on whether α is above or below 1 is not as controversial as it may appear. On the one hand, for sellers with a large potential loss (hence, high reference values), asking a higher price could increase the prospective gain if successfully sold. On the other hand, a higher asking price could significantly reduce the probability of realizing a sale and increase the time on the market, which is a cost to the seller. It is not surprising that the second effect could dominate the first in the presence of non-trivial waiting costs and marginally diminishing sensitivity to loss. Remember buyers' biddings are centered on the middle point, which is often below the optimal asking price for sellers who are subject to a large potential loss. Because of the high asking price, selling hazard rates for these sellers are lower. As a result, the effective benefit from asking more is relatively trivial since it is very unlikely to result in a sale. The opposite is true for sellers with small reference values but marginally increasing sensitivity. Due to the lower asking price, their asking prices are actually close to the central point of the bidding distribution. In this range, a small increase in the asking price will have a smaller impact on reducing selling hazard rate. Due to the increasing sensitivity from prospective gains, the first effect may tend to dominate the second. This is why we find that big gainers may increase their asking prices compared with small gainers in the left panel of Figure 3.

Another factor that influences a seller's pricing behavior is the waiting cost. Clearly, a higher waiting cost makes price mark up less attractive, since fishing on market will decrease the hazard rate of selling a house. Eventually, if the waiting cost is large enough, the stress of selling a house will quickly dominate the incentive to fish and earn greater conditional proceeds. Therefore, the asking price should decrease with the waiting cost. To verify this intuition, we apply several waiting costs and plot the results in Figure 4. To isolate the waiting cost effect from the loss aversion (λ) effect, we present the findings with a $Beta(2, 2)$ bidding distribution by holding $\lambda = 1$.

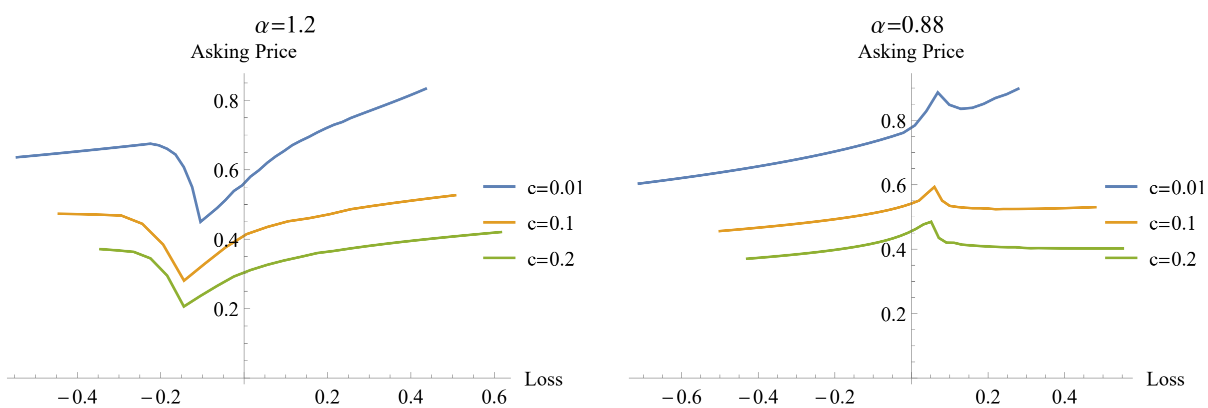

Figure 4: Asking Prices When Waiting Costs Are Different

Consistent with our intuition and from Proposition 1, we find that the asking price tends to decrease when the waiting cost increases. Moreover, the slope becomes flatter when the cost is higher, which indicates the weakening effect from reference value, as sellers will want to ask a price that facilitates a sale as soon as possible.

1.2.4 Implication on the Price-volume Relation and Dispersion Effect

One puzzling finding in the housing market is the strong positive correlation between house prices and transaction volume. For example, using national level data, Stein [1995] finds that a 10 percent decline in prices is associated with a reduction in transaction volume by over 1.6 million units in the United States. Another study by Ortalo-Magne and Rady [2006] shows a similar relation in the U.K. In this section, we demonstrate that, with prospect utility, the decision problem as outlined in equation (1) can help explain this phenomenon. As reflected in the right panel of Figure 3, with prospect utility, although house sellers tend to mark up their asking price along with reference values, the positive slope of the asking price curve is much flatter for sellers who have low reference values than for sellers who have high reference values. This is due to the loss aversion effect. Compared to the expected market price, for sellers who have high reference values, it is more likely that they will encounter a loss, which yields a greater disutility due to the asymmetric response in the value function. As a result, they have a greater incentive to inflate the asking price so as to mitigate this disutility.

The heterogeneity of pricing behavior between sellers with low versus high reference values naturally leads to a positive price-volume relation. The intuition is simple. Conditional on a given distribution of reference values, when the market becomes hot, the willingness to pay from potential sellers will increase. As a result, in a hot market, the proportion of sellers who have low reference values relative to market price becomes larger. Because these sellers are not subject to potential equity loss, the incentive for them to mark up the price is relatively low. As increasingly more sellers in the market choose to sell at a moderate price, as reflected by the lower and flatter asking price curve, it is clear that the probability of a successful sale will increase, which in turn generates a higher transaction volume.

Furthermore, a flatter asking price curve for sellers with low reference values may shed light on the extent of price dispersion under different market conditions. As previously mentioned, when a market becomes hot, the proportion of sellers who have low reference values relative to market price becomes larger. With a high market price, as more and more sellers cluster to the range of low reference values, differences among their asking prices becomes smaller. In aggregate, we should expect that, ceteris paribus, in a hot market, the observed transaction prices will be less dispersed with respect to the expected market price than in a cold market.

To confirm the implication of the price-volume relation and dispersion effect from our model, we simulate different market conditions and then compare the corresponding transaction volume and variance in asking prices within these markets. In particular, we define the market fundamental as the mean of the buyer's bidding distribution. Therefore, in the last section, the market fundamental for a $Beta(2,2)$ distribution with support of [0,1] is 0.5. In the following simulation, we expand the $Beta(2,2)$ distribution by gradually increasing the market fundamental from 0.3 to 0.9. Here, we use the set of Beta distributions to change the mean of the market fundamental. For example, beta distribution $Beta(2,2)$ is the exact quasi-triangular distribution we have used before. $Beta(2,3)$ has a mean of 0.4 and $Beta(3,2)$ has a mean of 0.6.

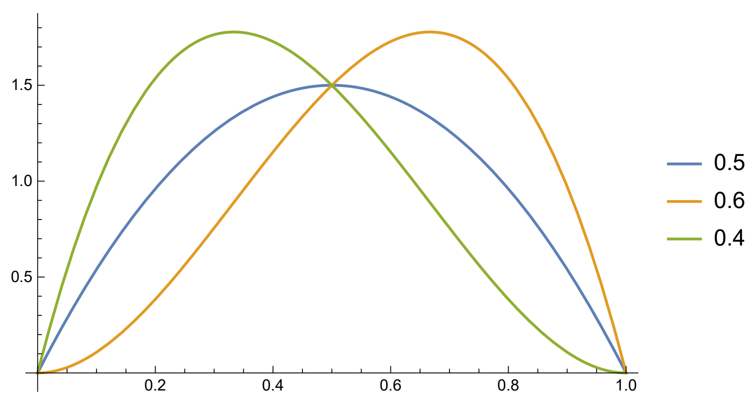

Figure 5: Beta distributions in Different Means

The simulation process remains the same as before. That is, we assume the seller's reference values distribute uniformly within [0,1]. Each time we randomly draw 1,000 sellers from this distribution. Again, we set $\beta = 5$ percent, $c_i = 0.05$, $\alpha = 0.88$ and $\lambda = 2.25$. We normalize the transaction volume per unit period as 100 when the market fundamental equals 0.5. In doing so, it is easier to infer the percentage change in transaction volume with expected market price. When calculating the variance of asking prices under each expected market price, we weight every seller's asking price by the corresponding selling probability. The simulation results are presented in Figure 6.

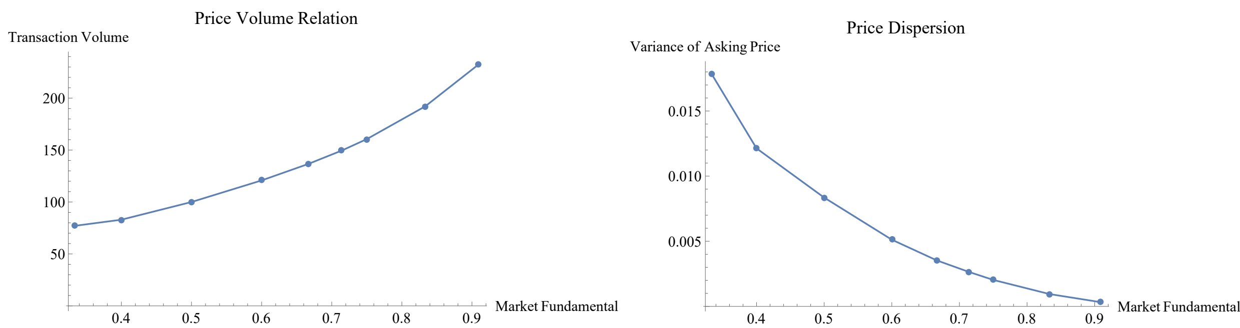

Figure 6: PRICE-VOLUME RELATION AND DISPERSION EFFECT

As expected, the left panel of Figure 6 reveals a positive price-volume relation. Conditional on a given pool of potential sellers in the marketplace, when the market fundamental increases from approximately 0.5 to 0.72, the transaction volume also increases by roughly 15 percent. Likewise, the right panel of Figure 6 also follows our expectation. When the market fundamental increases from approximately 0.5 to 0.72, the variance of the asking price drops from 0.08 to 0.03.

1.2.5 The Impact of Bidding Heterogeneity on Asking Price

In the previous section, our primary focus is the changing mean of the bidding distribution. Another interesting perspective is the spread of the bidding distribution. In particular, what is its impact on a seller's optimal asking price when we hold mean of the bidding distribution constant, but vary the bidding heterogeneity among buyers? To answer this question, we now introduce a series of Beta functions with equal mean, but difference variances. Specifically, we use Beta functions from $Beta(1, 1)$ (a uniform distribution) to $Beta(7, 7)$ as plotted in Figure 7.

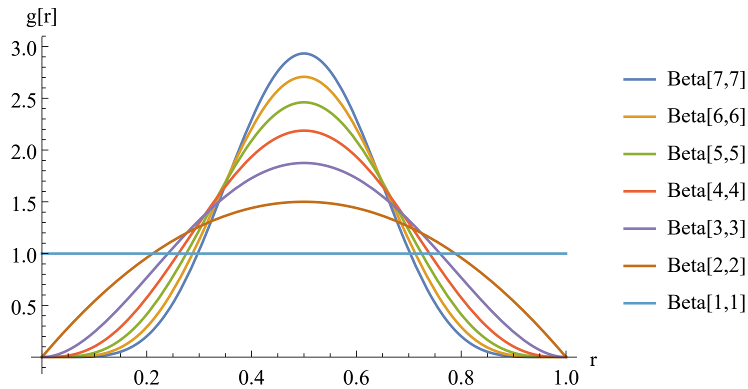

Figure 7: Beta Functions with the Same Mean, but Different Variances

We observe that as the parameters of Beta distribution increase, its tail becomes thinner, which means that buyers tend of have less heterogeneous house valuations, and hence a smaller likelihood of receiving an offer that is significantly above the mean.

We then plug in different Beta functions and solve for optimal asking prices. The parameter setting is the same as in the previous section. We next compute the average asking price, r, out of 1,000 randomly selected reference values, v_i, and plot the results in Figure 8.

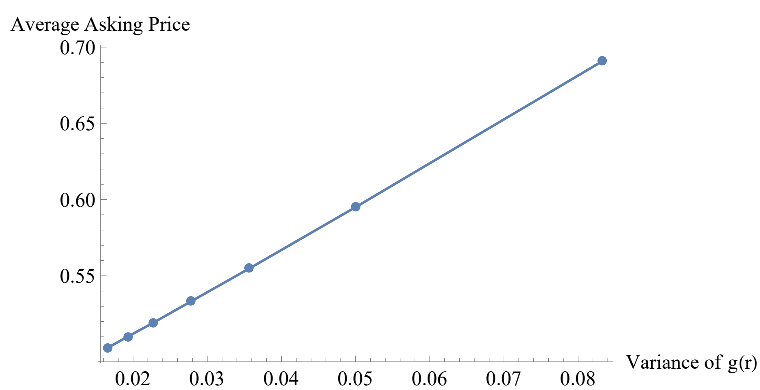

Figure 8: Relation between Variance of Bidding Distribution and Asking Price

Figure 8 shows that as variance increases, so too does the optimal asking price. The intuition is that when potential buyers have a bidding distribution with greater variance, the probability of receiving an upper tail offer becomes larger, which incentivizes sellers to be consistent with their asking prices. To confirm our finding is not driven by the loss aversion (λ) effect, we also consider a loss "neutral" case ($\lambda = 1$), and find a similar result.

2 Empirical Tests

In section 1, we develop a theory to model a potential seller's pricing strategy under different loss/gain exposures. In this section, before reporting our empirical results, we first list the four key findings from the model: 1) The three components in the prospect theory jointly predict a non-linear and non-monotonic pricing curve along seller's potential loss/gain exposure, as shown in the right panel of Figure 3; 2) the asking price decreases when waiting cost increases; 3) the heterogeneity of asking prices among sellers tends to decrease when market price is higher[9]; and 4) the asking price tends to increase with greater bidding heterogeneity. We test these four hypotheses using a comprehensive housing transaction dataset from Hampton Roads, a region of southeastern Virginia composed of seven cities: Virginia Beach, Norfolk, Portsmouth, Chesapeake, Hampton, Newport News, and Williamsburg.

2.1 Data

Our housing transaction data are based upon the complete record of single-family transactions in Hampton Roads over the period 1993(Q1)-2013(Q1), as provided Real Estate Information Network (REIN). Due to the strength of the data, which includes detailed records of housing characteristics in terms of structure and neighborhood information, we are able to obtain a more accurate estimate of the expected market price when using a hedonic model. We drop observations with missing hedonic characteristics, resulting in 227,384 bidding and selling records during the sample period to estimate the hedonic model. Within the data 32,160 observations reflect transactions involving houses with at least two selling records.

[9]We do not report the regression result on the price-volume relation as this phenomena has been well documented in the literature (Stein 1995, Berkovec and Goodman 1996, Genesove and Mayer 2001). The result is available upon request.

Hence, we can use these repeat sales for the subsequent tests.

2.2 Methodology

Define V_i as unit i's expected log market value at time t:

$$V_{it} = X_i\beta + \delta_t \tag{18}$$

where X_i is a vector of hedonic characteristics, and δ_t is a time dummy for period t. However, in reality, we cannot observe this expected market value. Instead, what we observe is the selling price at time t, in log form P_{it}, which we express as:

$$P_{it} = X_i\beta + \delta_t + e_{it} = V_{it} + e_{it} \tag{19}$$

where the additional component e_{it} is the amount that is over or under-paid by the buyer. In the theory section, we assume housing units are ex-ante identical in terms of its structural characteristics and quality. That is, all housing units should have the same expected market price. To control for quality differences in real data, we perform a two-stage process. In stage 1, we estimate a hedonic regression through which we can generate the expected market price for each unit. In stage 2, using the log of asking price L_{it} as our dependent variable, we then regress it on seller's loss/gain exposure, after controlling for the expected market prices of different housing units. One key prediction from our theory is that L_{it} depends on the potential loss/gain exposure, which reflects the seller's heterogeneous reference value. We measure it using a variable called $Loss_{ist}$, to be consistent with Genesove and Mayer [2001]. The relation is specified as:

$$L_{it} = \alpha V_{it} + f(Loss_{ist}) + \phi c_{it} + \gamma\sigma_t + \varepsilon_{it} \tag{20}$$

where ϵ_{it} is the error term with the usual assumptions, c_{it} refers to the seller's waiting cost upon the sale, and σ_t measures the perceived period t bidding heterogeneity in the market. As is typically done in the literature, we use the original log purchase price P_{is} at time s as a reference value and, hence, $Loss_{ist}$ is defined as the difference between the log prior transaction price and the log of the current expected value:

$$Loss_{ist} = P_{is} - V_{it} = \delta_s - \delta_t + e_{is} \tag{21}$$

Substituting equation (21) into equation (20) yields our ideal econometric specification:

$$L_{it} = \alpha V_{it} + f(\delta_s - \delta_t + e_{is}) + \phi c_{it} + \gamma \sigma_t + \varepsilon_{it} \tag{22}$$

The standard treatment in the literature is to censor the potential gainer's loss exposure at zero and examine the behavior of the potential losers (Genesove and Mayer, 2001). However, the theoretical justification for this censoring treatment is unclear. As our model covers a full range of potential losses ($loss > 0$) and gains ($loss < 0$), we choose to conduct our empirical test without censoring. As a result, a negative value on $Loss_{ist}$ indicates a potential gain to house seller i.

Our theory in section 1 predicts that the coefficient associated with holding cost, ϕ, shall be negative. One difficulty in testing the waiting cost effect is that one is unable to observe an individual seller's moving pressure. Nevertheless, holding other factors constant, a smaller waiting cost shall imply less stress with regard to moving and a longer duration time in the current home. Fortunately, for each repeat-sale seller, we have information on the length of time between her initial purchase and her next move, so we can measure tenure in the current house before a successful sale is realized. Ideally, if we can observe the demographic information of house sellers, we can use it to estimate the moving pressure conditional to this demographic information. However, such information is unavailable in our data. Because we have detailed information on housing characteristics, we use it as a proxy of household characteristics and are able to get the systematic relations between housing attributes and a household's expected duration time. Accordingly, we conduct a Cox proportional hazard model to estimate a seller's hazard rate of moving, conditional on the given housing characteristics that are used in our hedonic regression. We then use the predicted hazard rate as a proxy for the underlying holding cost of each seller. Since a higher hazard rate implies a greater likelihood of moving and a higher holding cost, we should expect a negative coefficient when we regress the realized transaction price on this rate. The results from the first stage hedonic and Cox proportional hazard regressions are reported in the appendix.

With regard to the perceived time t bidding heterogeneity, σ_t, we construct a measure using a GARCH model. In particular, from our stage 1 hedonic model, we firstly generate a quarterly return index for the overall Hampton Roads housing market and set the level of base quarter (1993Q1) house price index as 100. We then perform a simple GARCH (1,1) model on the return series and use the implied volatility as the proxy for σ. The intuition is that when the implied market return volatility is higher, there is a greater chance of observing extreme values, an indication of larger bidding heterogeneity. To ensure our measure of perceived bidding heterogeneity is forward-looking, we use the lag of volatility throughout our analysis. Our theory predicts a positive impact of bidding heterogeneity on asking price, thus we anticipate the coefficient associated with our implied volatility measure to be positive.

In the second stage regression, as shown in equation (22), in order to remove outliers, we omit 1.5 percent of the loss/gain observations at both tails. Furthermore, we drop the observations that have more than one sale within a year to rule out potential housing flippers. This screening leaves 27,584 observations for use in stage 2 of the analysis.

2.3 Estimation Results

2.3.1 OLS Analysis

We first estimate a simple two-stage analysis using Ordinary Least Square (OLS). Our empirical second stage regression equation is $L_{it} = \alpha V_{it} + f(Loss_{ist}) + \phi c_{it} + \gamma \sigma_t + \psi Control_{it} + e_{it}$. The difference between the empirical second stage and the ideal specification in equation (22) is that we add additional control variables (via the vector $Control_{it}$) to account for empirical irregularities caused by unobserved housing quality, general market price level and neighborhood effects. Table 1 presents our stage 2 result on the relation between the asking price and a seller's potential loss and other control variables. Here, we use a polynomial function form $F(Loss_{it}) = \sum_{j=1}^{n} \gamma_j Loss_{ist}^{j}$, where n is 1, 2 and 7 in the regression.

In model 1, we include only the linear term of loss exposure. As our loss exposure variable is not censored at zero, a negative value indicates a potential gain. The coefficient is 0.147 and is significant at 1 percent, which implies that a 1 percent increase in potential loss (or

Table 1: Asking Price and Loss Exposures

OLS Equations, Dependent Variable: Log of Asking Price

Explanatory Variables	Model 1	Model 2	Model 3
Loss	0.1472***	0.1389***	0.2686***
(robust std)	(0.0054)	(0.0085)	(0.0215)
$Loss^2$		-0.0147	-0.0568
		(0.0101)	(0.0670)
$Loss^3$			-1.309***
			(0.2803)
$Loss^4$			-0.6899*
			(0.4073)
$Loss^5$			2.615***
			(0.7245)
$Loss^6$			3.043**
			(1.240)
$Loss^7$			0.8967
			(0.5486)
Expected Log Selling Price	0.7656***	0.7655***	0.7669***
	(0.0081)	(0.0081)	(0.0081)
Moving Hazard Rate	-0.0226***	-0.0225***	-0.0225***
	(0.0009)	(0.0009)	(0.0009)
Market Volatility (lag)	0.1507***	0.1539***	0.1369***
	(0.0210)	(0.0210)	(0.0216)
Market Index When Listing	0.0020***	0.0020***	0.0020***
	(0.00005)	(0.00005)	(0.00005)
Last Residual	0.2468***	0.2467***	0.2452***
	(0.0111)	(0.0111)	(0.0111)
Constant	2.397***	2.397***	2.396***
	(0.1073)	(0.1074)	(0.1071)
Neighborhood Fixed Effect	Yes	Yes	Yes
Observations	27,584	27,584	27,584
R^2	0.8336	0.8336	0.8342

Note: 1) *Significant at 0.10 level. **Significant at 0.05 level. ***Significant at 0.01 level.
2) Robust standard errors are in parentheses.

1 percent decrease in potential gain) will increase the asking price by 0.147 percent. We then add the quadratic loss term in model 2. The quadratic $loss^2$ term is negative but not significant, and the joint test on $loss$ and $loss^2$ is significant at 1 percent. Finally, in model 3 we estimate a septic polynomial model. The joint test on all polynomial terms is now significant at 1 percent. To delve deeper into the joint curvature of selling price on reference values, in Figure 9 we plot the predicted selling price based on the septic polynomial fit[10], conditional to different loss/gain exposures.

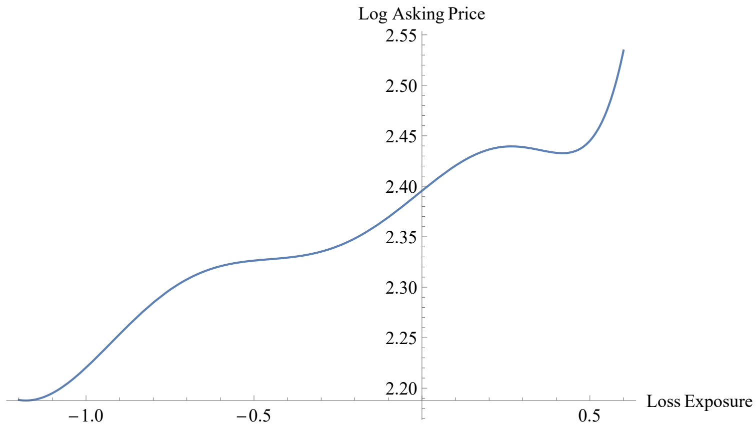

Figure 9: The Joint Curvature of Selling Price from the Septic Polynomial Fit.

Both Proposition 1 and the simulation show that, under the prospect theory, the optimal asking price tends to increase as potential gain declines and as potential loss increases. However, when potential loss further increases, the optimal asking price decreases. Eventually, when the potential loss is further increasing and large enough, the optimal asking price becomes increasing again. The septic polynomial fit in model 3 matches this non-linear and non-monotonic pattern well, particularly when it accurately captures the range of declining asking price when perceived loss exposure is positive but moderate. Therefore, the non-monotonic empirical pricing curve supports the existence of the marginally diminishing effect. As discussed in simulation section of 1.2.3, the loss aversion effect (i.e., when $\lambda > 1$), implies an increasing slope in the seller's pricing curve around the break-even point. It is clear from Figure 9 that the slope of the pricing curve is steeper in this range, as predicted. With regard to the holding cost, the coefficient on the moving hazard rate is negative and significant in all models. Consistent with theory, this implies that people with a higher probability of moving tend to sell their houses at lower prices. Furthermore, the positive and significant coefficient on the implied return volatility echoes our model prediction that when the market is subject to greater bidding heterogeneity, house sellers tend to mark up

[10] The functional form here is $f(loss) = 0.2686loss - 0.0568loss^2 - 1.309loss^3 - 0.6899loss^4 + 2.615loss^5 + 3.043loss^6 + 0.8967loss^7 + 2.396$

their asking prices.

Our control variables are also consistent with the extant literature. For example, the residual from the last sale, which controls for potential unobservable house quality intuitively shows a significant positive effect on the current asking price. A positive last residual means the seller was willing to pay a higher than expected market price when she purchased the unit. Hence, it is very likely that the house may have an unobservable quality premium, which may make the current asking price high. Finally, a positive and significant coefficient on Market Index When Listing indicates that when the anticipated market price is high, in general, sellers tend to ask for a correspondingly higher price.

Our simple OLS analysis in this section is subject to some econometric challenges. First, as our measures on potential loss/gain, holding cost (via moving hazard rate) and bidding heterogeneity (via implied market return volatility) are all based on estimates from auxiliary regressions, we need to take the potential estimation error into consideration in order to make valid statistical inferences. Second, using a high order polynomial to fit a non-linear curve, such as in model 3, may be inaccurate and overfitting, and any bias in the mean and standard error of loss may be amplified in the high order term, leading to high oscillations in the regression. Also, using a high order polynomial model may only fit our specific sample rather than generalize to the overall population (Good and Hardin [2012]).

2.3.2 Semiparametric Analysis in Two-stage Bootstrap

To address both the "generated regressor" problem and the concern with using a simple polynomial to fit a non-linear pricing curve, we adopt a semi-parametric approach in a two-stage bootstrap setting. In stage 1, in addition to hedonic regression, we also estimate a Cox proportional hazard regression and GARCH (1,1) in order to obtain all needed control variables. In stage 2 (i.e., for $L_{it} = \alpha V_{it} + f(Loss_{ist}) + \phi c_{it} + \gamma \sigma_t + \psi Control_{it} + e_{it}$), we use Robinson's [1988] partially linear regression semi-parametric model. In particular, we maintain the linear specification on V, c, σ and $Control$, and leave $f(Loss_{ist})$ as non-parametrized.

There is a vast literature purporting the advantages of using semi-parametric analysis to model non-linear specifications (Verardi and Debarsy [2012]; Yatchew [2003]; Simar and Wilson [2007]). The standard errors for linear parameters are constructed through a two-stage housing unit stratified bootstrap procedure with 1000 iterations. Table 2 reports the coefficients for the linear component of the stage 2 regression.

Table 2

Asking Price and Loss Exposures: Semi-parametric Model

Explanatory Variables	Dependent Variable: Log of Asking Price
Expected Log Selling Price	0.7844***
(std)	(0.0121)
Moving Hazard Rate	-0.0201***
	(0.0032)
Market Volatility (lag)	0.0449
	(0.0465)
Market Index When Listing	0.0021***
	(0.0001)
Last Residual	0.2521***
	(0.0102)
Neighborhood Fixed Effect	Yes
Observations	27,584

Note: 1) * Significant at 0.10 level. ** Significant at 0.05 level. *** Significant at 0.01 level.
2) The reported standard errors are constructed through a two-stage housing unit stratified bootstrap procedure.

The results in Table 2 are largely consistent with the previous OLS findings with coefficients significant and carrying the expected signs. The only exception is the coefficient for the implied volatility. Although still positive, it is no longer significant. To test whether our previous septic polynomial fit works reasonable well, we plot the parametrically fitted pricing curve in Figure 10 and compute Härdle and Mammen's [1993] specification test to assess whether the nonparametric fit can be approximated by a parametric adjustment of order 7. The result shows a p-value of 0.83, which means the parametric and non-parametric septic model fits are not significantly different. The general curvature from the semi-parametric fit is very close to the septic polynomial model in the previous section, providing supporting evidence of non-linearity and an up/down/up trending pricing curve along the seller's potential loss/gain exposure, which is consistent with the prospect theory based model predications.

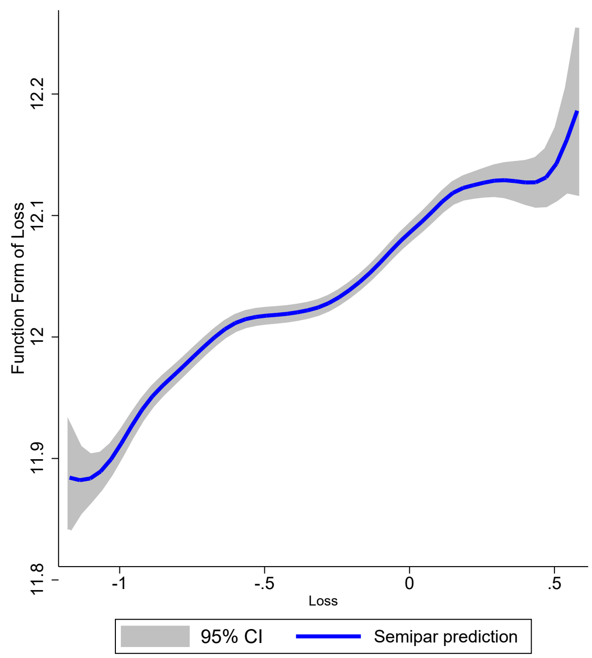

Figure 10: The Joint Curvature of Asking Price from the Semi-Parametric Fit

Our analysis thus far focuses on the seller's asking price. To investigate whether the loss/gain dependent pricing strategy materializes in the marketplace, rather than merely reflecting wishful thinking from the seller, we re-estimate our two-stage semi-parametric analysis using the realized transaction price instead of the seller's asking price. We report the coefficients for the linear portion of the stage 2 regression in Table 3.

Our findings, based on the realized transaction price, are qualitatively similar to those associated with the asking price. Figure 11 plots the non-parametrically fitted pricing curve on transaction price.

Table 3: Selling Price and Loss: Semi-parametric Model

Explanatory Variables	Dependent Variable: Log of Realized Transaction Price
Expected Log Selling Price	0.7906***
(std)	(0.0148)
Moving Hazard Rate	-0.0222***
	(0.0038)
Market Volatility (lag)	-0.0127
	(0.0356)
Market Index When Listing	0.0021***
	(0.0001)
Last Residual	0.2596***
	(0.0128)
Neighborhood Fixed Effect	Yes
Observations	19,752

Note: 1) * Significant at 0.10 level. ** Significant at 0.05 level. *** Significant at 0.01 level.
2) The reported standard errors are constructed through a two-stage housing unit stratified bootstrap procedure.

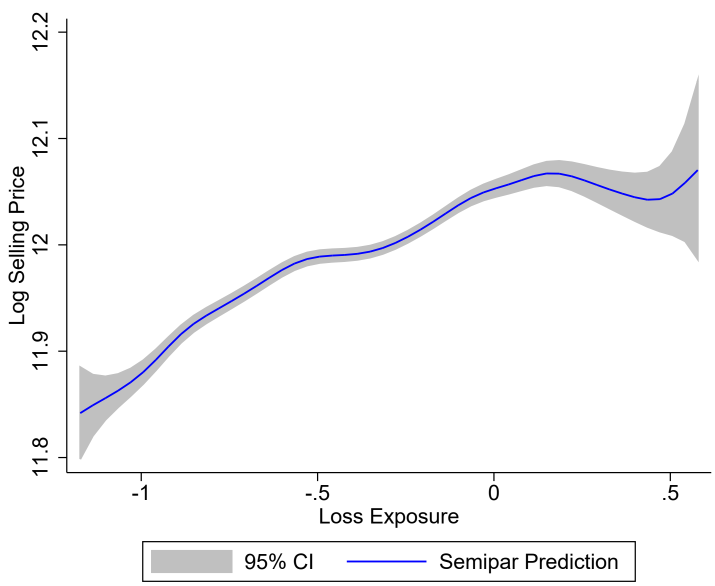

Figure 11: The Joint Curvature of Realized Transaction Price from the Semi-Parametric Fit

2.3.3 Price Dispersion Effect

The last predication from our theory relates to the price dispersion effect. If we interpret the difference between the realized transaction price and expected market price as noise, our theory predicts that the higher the expected market price, the smaller the noise should be since there would be fewer and fewer losers in the market. To test this prediction, in each quarter, we first compute the variance of the stage 1 hedonic residuals and then regress them on the level of price index in that given quarter. One point to note is that our theory has different implications for existing home sales versus sales from a developer. Individual sellers generally bought their houses at different times and are thus subject to different initial purchase prices, even after controlling for quality. That is, there is greater heterogeneity in repeat sellers' reference values. As a result, we should expect greater price dispersion for repeat sellers. However, for developers, this may not be true. Firstly, a new house is typically sold by real estate developers, instead of individual households. And the prospect theory is more relevant for an individual decision-making process. Secondly, even with the assumption that real estate developers follow the exact same decision process as individual sellers, we should still expect less price dispersion from these sellers because developers should face very similar costs in terms of construction materials, financing, labor, and so forth, which represents possibly similar reference values for developers. However, conditional on a common v_i, they will also have the same asking price. In this case, our model implies a much weaker price dispersion effect. Accordingly, to test for a price dispersion effect, we calculate two variances for the hedonic residuals in each quarter. One is for the repeat-sellers and the other is for new house transactions, assuming they were sold by developers. We also include a dummy variable which is equal to 1 if transactions occurred after 2007. Finally, we drop the observations that have tenure duration less than a year to rule out potential housing flippers. Table 4 reports the regression results for both groups. The standard errors are calculated by Biased-Reduced Linearization (BRL) method (Bell and McCaffrey [2002]), which is robust to both heteroscedasticity and small sample size.

Consistent with our theoretical prediction, the coefficient on the house price index of the full model for individuals is significantly negative at 5 percent, which means that when the market price increases, market noise (as measured by the variance in the hedonic residuals) becomes smaller. Meanwhile, as expected, we observe no significant dispersion effect for developers. The R^2 in the developers regression is also much lower than the case for individual sellers, indicating a much less systematic pattern on price dispersion. Taken together, the

Table 4: Price-dispersion Effect

Dependent Variable: Variance of Hedonic Residuals in Each Quarter

Variables	Individual Sellers	Developers
House Price Index	-0.00018**	-0.00008
	(0.00009)	(0.00011)
Post-2007	0.05550***	-0.01011
	(0.01292)	(0.01400)
Constant	0.09998***	0.07391***
	(0.01606)	(0.01786)
Observations	80	80
R^2	0.3561	0.0920

Note: 1) * Significant at 0.10 level. ** Significant at 0.05 level. *** Significant at 0.01 level.
2) Biased-Reduced Linearization (BRL) corrected standard errors are reported.
3) Variance is only generated for quarters that have at least 10 transactions from the corresponding group.

overall finding suggests that for developers, the dispersion of the realized price is much less sensitive to the level of the expected market price, due to the lack of reference value heterogeneity among developers. With regard to the post-2007 dummy, the coefficient is positive and significant at 1 percent in individual sellers sample, and insignificant for the developers sample. Hence, the data imply that after the year 2007, average price dispersion increased significantly. This is probably not surprising given that many house sellers are subject to losses which tends to increase the mark up when they sell.

2.4 Potential Evidence on the Varying Marginal Sensitivity

We have thus far found a close connection between our prospect theory driven model prediction and empirical findings. However, a closer comparison on the overall curvature between the theoretical pricing curve (i.e., the right panel of Figure 3) and the empirical one (i.e., Figure 10) still reveals a notable difference. The empirical curve shows that sellers in a large gain or loss position tend to mark up the asking price much faster than theory suggests, as indicated by the steep slope of the curve when "Loss" is further away from the origin from both sides. This finding suggests that somehow house sellers in large gain/loss positions behave more aggressively than a static prospect theory based model predicts. As the incremental (marginal) effect is affected by α, one potential implication is that α might not be a constant throughout all loss/gain positions. To check if a changing α can potentially explain this empirical discrepancy, we perform another simulation in which we change α from the base value of 0.88 to 0.50 when "Loss" is greater than 0.25 (25 percent) and change the base value to 0.20 when "Gain" is greater than 0.30 (30 percent). We then plot both the empirical pricing curve and our new predicted curve in Figure 12.

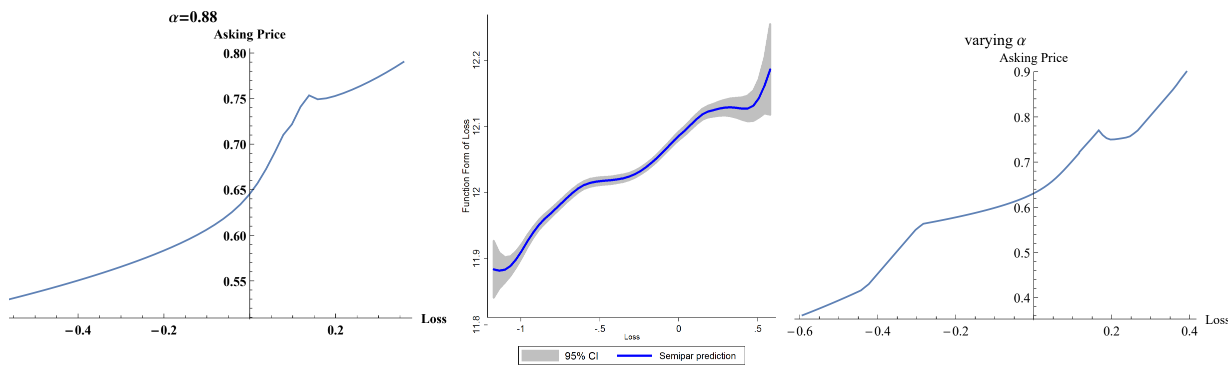

Figure 12: Comparison of Empirical Result and Simulation Result by Constant or Varying α

Interestingly, when we allow α to change, we are able to achieve a better match between the theoretical pricing curve and its empirical counterpart. Thus, there appears to be evidence that the marginal diminishing effect, a key component of the prospect theory, could be changing based on the loss/gain position of the agent. We should emphasize, however, that we have let α change in an ad hoc fashion in order to illustrate its potential as an explanation. Notably, Yao and Li [2013] investigate trade patterns in the stock market and suggest that a smaller α in the gain region as compared to the loss region can better explain the observed disposition effect. As the extension of the prospect theory itself is not the central focus in this study, we defer this as a future research topic and suggest interested researchers further investigate this possibility and provide a justification for why a context dependent α could be the case.

3 Conclusion

This study improves upon the Genesove and Mayer [2001] testing of loss aversion behavior in the housing market. Specifically, we build a search model that better enables us to separately examine the impact from the three components of prospect theory. We conclude that both findings in Genesove and Mayer [2001] offer evidence to support a reference-dependence value function. As such, they are valid tests of the first component of the prospect theory. However, finding one does not have a necessary relation with loss aversion, nor does finding two have a necessary relation with diminishing sensitivity in the value function. Thus, there is a conceptual mismatch between these two empirical findings and their theoretical counterparts.

Our paper contributes to the ongoing debate on the connection between the prospect theory and observed trader behavior in asset markets. Specially, our model provides a clear correspondence between each component of the prospect theory and its unique empirical implication. Overall, under the prospect value function, we predict a non-linear, non-monotonic pricing curve with changing curvature. In particular, we show that reference dependence generates a disposition effect, which is magnified by loss aversion. One striking prediction from our model is that diminishing sensitivity may lead to a local reverse disposition effect. That is, when a prospect-utility seller is subject to a range of moderately sized losses, her asking price can be decreasing when the potential loss is increasing. Using a multiple listing service dataset in Virginia, we find evidence that supports these predictions from prospect utility. Finally, our model also helps to explain the positive price-volume relation and why the price dispersion in a cold market is greater than in a hot market.

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A Mathematical Appendix: Proof of Proposition 1

(1)We have already proven $\frac{dF(r^*)}{dr^*} < 0$. So, when $\alpha > 1$, if $v_i - r^* < 0$:

$$\frac{\partial r^*}{\partial v_i} = \frac{1 - \frac{(H+c)(\alpha-1)}{\beta}(r^* - v_i)^{-\alpha}}{1 - \frac{(H+c)(\alpha-1)}{\beta}(r^* - v_i)^{-\alpha} - \frac{dF(r^*)}{dr^*}} \begin{cases} > 0 & \text{if} \quad (r^* - v_i)^{\alpha} < \frac{(H+c)(\alpha-1)}{\beta(1-\frac{dF(r^*)}{dr*})} \\ < 0 & \text{if} \quad \frac{(H+c)(\alpha-1)}{\beta(1-\frac{dF(r^*)}{dr^*})} < (r^* - v_i)^{\alpha} < \frac{(H+c)(\alpha-1)}{\beta} \\ > 0 & \text{if} \quad (r^* - v_i)^{\alpha} > \frac{(H+c)(\alpha-1)}{\beta} \end{cases}$$

Notice that the $\frac{\partial r^*}{\partial v_i} > 1$ at all times, so when v_i increases, $(r^* - v_i)$ increases. This means that for the case of $\alpha > 1$ and $r^* - v_i > 0$, when v_i increases, the r^* firstly increases, and decreases and finally increases.

And if $v_i - r^* > 0$

$$\frac{\partial r^*}{\partial v_i} = \frac{1+\frac{(H+c)(\alpha-1)}{\beta\lambda}(v_i-r^*)^{-\alpha}}{1+\frac{(H+c)(\alpha-1)}{\beta\lambda}(v_i-r^*)^{-\alpha}-\frac{dF(r^*)}{dr^*}} > 0$$

For the case of $\alpha < 1$, if $v_i - r^* < 0$:

$$\frac{\partial r^*}{\partial v_i} = \frac{1+\frac{(H+c)(1-\alpha)}{\beta}(r^*-v_i)^{-\alpha}}{1+\frac{(H+c)(1-\alpha)}{\beta}(r^*-v_i)^{-\alpha}-\frac{dF(r^*)}{dr^*}} > 0$$

And if $v_i - r^* > 0$

$$\frac{\partial r^*}{\partial \mathrm{v}_i} = \frac{1-\frac{(H+c)(1-\alpha)}{\beta\lambda}(v_i-\mathrm{r}^*)^{-\alpha}}{1-\frac{(H+c)(1-\alpha)}{\beta\lambda}(v_i-\mathrm{r}^*)^{-\alpha} - \frac{dF(r^*)}{dr^*}} \begin{cases} > 0 & \text{if} \quad (v_i-\mathrm{r}^*)^{\alpha} < \frac{(H+c)(1-\alpha)}{\beta\lambda(1-\frac{dF(r^*)}{dr^*})} \\ < 0 & \text{if} \quad \frac{(H+c)(1-\alpha)}{\beta\lambda(1-\frac{dF(r^*)}{dr^*})} < (v_i-\mathrm{r}^*)^{\alpha} < \frac{(H+c)(1-\alpha)}{\beta\lambda} \\ > 0 & \text{if} \quad (v_i-\mathrm{r}^*)^{\alpha} > \frac{(H+c)(1-\alpha)}{\beta\lambda} \end{cases}$$

Here, as v_i increases, $v_i - r^*$ increases, and the curve is firstly increasing and then decreasing and finally increasing. However, the range of the decreasing zone is based on the functional form of $G(r)$ among other parameters. For our simulation result with $G(r) = Beta(2, 2)$ and $\alpha = 0.88$, we find this range to be small. This is the reason why the right graph of Figure 3 only shows a small zone of decreasing relation between r^* and v_i (or $v_i - \overline{P}$).

(2)For the relation between r^* and c, when $\alpha > 1$ and $r^* - v_i > 0$, $\frac{\partial r^*}{\partial c} = \frac{-\frac{1}{\beta}(r^*-v_i)^{1-\alpha}}{-\frac{dF(r^*)}{dr^*}+1-\frac{(c+H)(\alpha-1)}{\beta}(r^*-v_i)^{-\alpha}}$.
If $(r^* - v_i)^{-\alpha} < \left[1 - \frac{dF(r^*)}{dr^*}\right] / \left[\frac{(c+H)(\alpha-1)}{\beta}\right]$, we get $\frac{\partial r^*}{\partial c} < 0$.

When $\alpha > 1$ and $v_i - r^* > 0$, $\frac{\partial r^*}{\partial c} = \frac{-\frac{1}{\lambda\beta}(v_i - r^*)^{1-\alpha}}{-\frac{dF(r^*)}{dr^*} + 1 + \frac{(c+H)(\alpha-1)}{\lambda\beta}(v_i - r^*)^{-\alpha}} < 0.$

When $\alpha < 1$ and $r^* - v_i > 0$, $\frac{\partial r^*}{\partial c} = \frac{-\frac{1}{\beta}(r^* - v_i)^{1-\alpha}}{-\frac{dF(r^*)}{dr^*} + 1 + \frac{(c+H)(1-\alpha)}{\beta}(r^* - v_i)^{-\alpha}} < 0.$

when $\alpha < 1$ and $v_i - r^* > 0$, and if $(v_i - r^*)^{-\alpha} < \left[1 - \frac{dF(r^*)}{dr^*}\right] / \left[\frac{(c+H)(1-\alpha)}{\beta\lambda}\right]$, we get $\frac{\partial r^*}{\partial c} = \frac{-\frac{1}{\lambda\beta}(v_i - r^*)^{1-\alpha}}{-\frac{dF(r^*)}{dr^*} + 1 - \frac{(c+H)(1-\alpha)}{\lambda\beta}(v_i - r^*)^{-\alpha}} < 0.$

When $\alpha > 1$, the only exception for $\frac{\partial r^*}{\partial c} < 0$ is $v_i - r^* < 0$ with $(r^* - v_i)^{-\alpha} > \left[1 - \frac{dF(r^*)}{dr^*}\right] / \left[\frac{(c+H)(\alpha-1)}{\beta}\right]$. For the case of $\alpha < 1$, the only exception for $\frac{\partial r^*}{\partial c} < 0$ is $(v_i - r^*)^{-\alpha} > \left[1 - \frac{dF(r^*)}{dr^*}\right] / \left[\frac{(c+H)(1-\alpha)}{\beta\lambda}\right]$ with $v_i - r^* > 0$. In our simulation, $c = \beta = 0.05$ and H is quite small. As $\lambda \geq 1$, the right hand side term is relatively large and probably much greater than 1. So, $\frac{\partial r^*}{\partial c} > 0$ is only possible when $|v_i - r^*|$ is very close to zero.

(3)For the relation between r^* and λ, we firstly notice that it only matters when $loss > 0$ ($v_i - r^* > 0$). Therefore, we find $\frac{\partial r^*}{\partial \lambda} = \frac{\frac{c+H}{\beta\lambda^2}(v_i - r^*)^{1-\alpha}}{-\frac{dF(r^*)}{dr^*} + 1 + \frac{(c+H)(\alpha-1)}{\lambda\beta}(v_i - r^*)^{-\alpha}}$. Notice that compared with $\frac{\partial r^*}{\partial c}$ when $v_i - r^* > 0$, the expression of $\frac{\partial r^*}{\partial \lambda}$ has the same denominator but a positive numerator. Thus $\frac{\partial r^*}{\partial \lambda} > 0$ holds only except for $(v_i - r^*)^{-\alpha} > \left[1 - \frac{dF(r^*)}{dr^*}\right] / \left[\frac{(c+H)(1-\alpha)}{\beta\lambda}\right]$ and this exception is only possible when $(v_i - r^*)$ is very close to zero.

(4) For the case of $\alpha = 1$, when $v_i - r^* \neq 0$, equations (13) now simplify to:

$$v_i = r^* + \frac{(c+H)}{\beta} - F(r^*) \qquad \text{if } v_i - r^* < 0$$

$$v_i = r^* + \frac{(c+H)}{\beta\lambda} - F(r^*) \qquad \text{if } v_i - r^* > 0$$

As $\frac{\partial r^*}{\partial v_i} = 1/[1 - \frac{dF(r^*)}{dr^*}]$, we could prove $\frac{\partial r^*}{\partial v_i} > 0$ based on the fact $\frac{dF(r^*)}{dr^*} < 0$. In regard to the relation of r^* with c, $\frac{\partial r^*}{\partial c} = -\frac{1}{\beta}/(1 - \frac{dF(r^*)}{dr^*})$ when $loss < 0$ and $\frac{\partial r^*}{\partial c} = -\frac{1}{\beta\lambda}/(1 - \frac{dF(r^*)}{dr^*})$ when $loss > 0$. Thus we could prove that $\frac{\partial r^*}{\partial c} < 0$. Meanwhile, as $\frac{\partial r^*}{\partial \lambda} = \frac{c+H}{\beta\lambda^2}/(1 - \frac{dF(r^*)}{dr^*})$, $\frac{\partial r^*}{\partial \lambda} > 0$ is easily proved.

B Supplemental Tables

Table B.1: Hedonic Regression:

Dependent Variable: Log of Transaction Price

age	-0.00752***
	(0.000251)
age^2	0.0000369***
	(0.00000327)
age^3	-5.23e-08***
	(6.96e-09)
age>= 120	0.348***
	(0.0520)
Baths_Full	0.171***
	(0.00976)
Baths_Half	0.0704***
	(0.0104)
Bedrooms	0.0870***
	(0.00571)
Square_Feet_Approx	0.0000521***
	(0.0000107)
Fireplaces_Number	0.0677***
	(0.00832)
Stories_Number	0.0160**
	(0.00581)
Cool_CENT	0.130***
	(0.00267)
Cool_WIN	0.0724***
	(0.00516)
Cool_OTHER	0.239***
	(0.0521)
ATTdummy	-0.321***
	(0.00538)
PoolDummy	0.0983***
	(0.00355)
SewerDummy	-0.0760***
	(0.00550)
HeaterDummy	-0.0256***
	(0.00190)
Waterdummy	0.146***
	(0.00460)
WaterCityDummy	-0.0226***
	(0.00571)
Parkingscale=1	0.0701***
	(0.00317)

Parkingscale=2	0.161***
	(0.00349)
Parkingscale=3	0.226***
	(0.0137)
Viewscale=1	0.0402***
	(0.00207)
Viewscale=2	0.172***
	(0.00752)
Viewscale=3	0.167***
	(0.00475)
Floorscale=2	-0.00588
	(0.0160)
Floorscale=3	0.127***
	(0.00965)
Floorscale=4	0.271***
	(0.00985)
Floorscale=5	0.318***
	(0.0142)
Floorscale=6	0.169***
	(0.0113)
Floorscale=7	0.337***
	(0.0143)
Constant	10.33***
	(0.0447)
Neighbourhood Fixed Effect	Yes
Quarterly Fixed Effect	Yes
Observations	156,531

Note: 1) * Significant at 0.10 level. ** Significant at 0.05 level. *** Significant at 0.01 level.
2) Robust Standard errors are in parentheses
3) Cool: Cent = Central air conditioning; WIN = Window unit
4) Floor: 1=worst; 7=best

Table B.2: Cox Proportional Hazard Regression

Independent Variables	Hazard Ratios
age	1.0013***
	(0.00051)
age>= 120	0.5847
	(0.2064)
Baths_Full	1.0416***
	(0.0133)
Baths_Half	1.0415***
	(0.0066)
Bedrooms	1.00315
	(0.0112)
Square_Feet_Approx	0.9995***
	(0.000021)
Fireplaces_Number	1.0261***
	(0.0068)
Stories_Number	1.0379***
	(0.0084)
Cool_CENT	0.9487***
	(0.0191)
Cool_WIN	0.8861***
	(0.0326)
Cool_OTHER	4.88e-19
	(.)
ATTdummy	1.2703***
	(0.0265)
PoolDummy	0.9457
	(0.0326)
SewerDummy	1.091
	(0.0604)
HeaterDummy	1.029*
	(0.0169)
Waterdummy	0.9166**
	(0.0344)
WaterCityDummy	1.271***
	(0.0753)
Parkingscale=1	0.9307***
	(0.0223)
Parkingscale=2	0.9243***
	(0.0212)
Parkingscale=3	0.4457**
	(0.1838)
Viewscale=1	1.0457**
	(0.0235)
Viewscale=2	1.333***

	(0.1143)
Viewscale=3	0.9669
	(0.0398)
Floorscale=2	1.4780***
	(0.1587)
Floorscale=3	1.1763***
	(0.0688)
Floorscale=4	1.0678
	(0.0635)
Floorscale=5	1.1471
	(0.1359)
Floorscale=6	1.2227**
	(0.1013)
Floorscale=7	1.2059
	(0.1422)
Neighbourhood Fixed Effect	Yes
Observations	147,597

Note: 1) * Significant at 0.10 level. ** Significant at 0.05 level. *** Significant at 0.01 level.
2) Robust Standard errors are in parentheses
3) Cool: Cent = Central air conditioning; WIN = Window unit
4) Floor: 1=worst; 7=best