Hyperbolic Discounting, Reference Dependence and its Implications for the Housing Market

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Abstract

The influential work of Genesove and Mayer (2001) uses loss aversion theory to explain several puzzling behaviors in the housing market. In this study, we present an alternative theory, which does not require an asymmetric value function, to observe the same “loss aversion” behavior. Specifically, this paper presents a model in which a reference-dependent home seller has a symmetric value function, but faces an inter-temporal decision problem. Furthermore, the framework presented in this paper also helps explain the positive price-volume relationship and price dispersion effect, two observations that are well-documented in the housing market.

Keywords: Hyperbolic Discounting, Loss Aversion, Repeat-Sales Index

JEL Classification: D01, R21, R20
1. Introduction

The prevalent theoretical foundation for loss aversion is the prospect theory from Kahneman and Tversky (1979) and Tversky and Kahneman (1991). A central feature of this theory is the assumption that consumers treat losses and gains asymmetrically in their value functions. In particular, they are more sensitive to losses than gains\(^1\), as shown in Exhibit 1.

Countless studies have used loss aversion theory to help explain anomalous results across a number of disciplines. In residential real estate, the most widely cited work is Genesove and Mayer (2001) who examined seller behavior in the Boston market during the 1990s. The authors argue that loss aversion is responsible for explaining the following findings: When expected market price is lower than the seller’s reservation value, the seller will list at higher than market price, attain a higher realized selling price, experience a greater time on the market, and exhibit a much lower sale hazard. Genesove and Mayer (2001) continue by attributing the positive price-volume relationship to loss aversion as well.

We argue that there is a conceptual mismatch between the theoretical definition of loss aversion as presented in the seminal study by Kahneman and Tversky (1979) and what was empirically tested in Genesove and Mayer (2001). Specifically, we show that asymmetry in the value function is not necessary to achieve the same results as Genesove and Mayer (2001). As such, loss aversion is only potentially responsible for explaining
seller behavior in their model. To demonstrate our supposition, we show that the “loss aversion” behavior observed in Genesove and Mayer (2001) can be driven by an inter-temporal choice problem. Specifically, we present a model in which consumers have present-biased preferences (Laibson, 1997; O’Donoghue and Rabin, 1999). That is, their preferences are dynamically inconsistent in the way choices are made between two payoffs in the future. This feature, known as hyperbolic discounting, describes how consumers discount short horizon payoffs with higher rates than longer horizon payoffs. Acknowledging the existence of this effect, we show that people may exhibit what appears to be loss aversion behavior even when they treat losses and gains in a symmetric way in their value functions.

1.1 The Positive Price-Volume Relationship

Stein (1995) documents that a 10% drop in prices is associated with a reduction in transaction volume by over 1.6 million housing units – what has been termed the positive price-volume relationship. To explain the phenomenon, Stein (1995) proposes the down payment constraint theory. The intuition is that when home prices decline, sellers cannot afford to sell, and then buy another home because the proceeds from the sale do not yield sufficient cash to make a down payment on the next home. As a result, existing homeowners are forced to ride out the market until prices recover. More formally, a decline in home prices will constrain household mobility and hence reduce contemporaneous market demand.
Genesove and Mayer (2001) provide an alternative explanation to the positive price-volume relationship, specifically attributing it to loss aversion. The authors find that after controlling for loss aversion, the coefficient on equity constraint becomes much smaller. Engelhardt (2003) confirms this conclusion by examining the factors that influence household mobility. He finds that after controlling for loss aversion, there is little evidence that equity the constraint restricts mobility3. In our model, we do not require the asymmetric treatment of gains and losses, yet we still find a positive price-volume relationship. This result casts further doubt on the ability to attribute the Genesove and Mayer (2001) findings solely to loss aversion.

1.2 Our Model

O'Donoghue and Rabin (1999) present a famous example of hyperbolic discounting behavior as it relates to the dynamic inconsistent choice problem. In February, when asked to choose between a seven hour task to be performed on April 1 and an eight hour task with similar intensity to be performed on April 15, most people will choose the earlier date. However, as the April date approaches, people tend to change their choices by selecting the longer eight hour work period at a later time4. This dynamic inconsistent behavior was first characterized by Strotz (1955) who found that people will depart from their original choice if they are allowed to revise their consumption plan in the future.

In this paper, we adopt a special functional form, quasi-hyperbolic discount model, which is widely used in the hyperbolic discounting literature due to its close approximation and
mathematical tractability. In particular, we assume that a person’s inter-temporal value function at time $t$ can be express as:

$$U_t(c_t, c_{t+1}, c_{\tau}) = E_t[c_t + \beta \sum_{\tau=1}^{T-t} \delta^\tau c_{\tau+1}],$$

where $0<\beta<1$ and $\delta \leq 1$ (1.1)

Here $\delta$ represents the long-run, time consistent discounting rate and $c_t$ denotes the payoff.

The present-biased preference is characterized by $\beta$. Because it is less than one, for a payoff in period $\tau$, the consumer will put less weight on it when the current time is before $\tau$. However, when period $\tau$ actually arrives, she will place a higher weight on this payoff, which reflects that she is biased toward the current payoff. If $\beta=1$, the preference becomes the regular exponential discounting case, which is dynamically consistent. Clearly, (1.1) is symmetric between losses and gains, a condition not associated with loss aversion.

In sum, we document that many of the puzzling behaviors in the housing market such as loss aversion, the positive price-volume relationship, the existence of fishing behavior in housing markets, and diminishing effects of this fishing behavior along house price levels, all follow naturally in our model. In addition, we also find that the horizon constraint for the seller plays an important role in driving pricing behavior. For example, we show that even with the same amount of net loss, two otherwise identical sellers, but with different time horizons may list at different prices.

The remainder of the paper is structured as follows. Section II describes the two-period model for a seller’s decision problem. Section III extends the model to a multi-period
case. Section IV presents simulation results, while Section V discusses its implications on the housing market. Finally, Section VI concludes the paper.

2. Two-Period Problem

Consider the problem that a seller must sell her house either now or in the next period. Assume that in period 0, the expected price is \( P_0 \). Additionally, the seller has a psychological reference value associated with her house, \( V_0 \).

Conditional on the current expected price, the seller believes the future expected price follows a stochastic process:

\[
P_t = P_{t+1} + \sigma \varepsilon,
\]

where \( \varepsilon \sim N(0,1) \) and \( \sigma \) is standard deviation. Furthermore, we make two assumptions in the model:

**Assumption 1:** Conditional on the expected price \( P_t \), the potential buyer’s evaluation of the house in that period follows an exponential distribution. The density function is:

\[
p(x) = \begin{cases} 
\lambda e^{-\lambda(x-P_t)}, & \text{if } x \geq P_t \\
0, & \text{otherwise}
\end{cases}
\]

An implicit assumption being made is that if a seller asks the expected price, she can sell her home within that period with certainty. Further, buyers in the market will mark up their bid prices following an exponential distribution. Meanwhile, we also assume that in each period, one seller will meet one and only one buyer. If the buyer’s bid price is higher than the seller’s asking price, a sale is transacted at the asking price.
Assumption 2: In the last period, the seller must sell her house at the expected price in that period. Further, there is no carrying cost or benefit associated with the house before the transaction occurs.

Assumption 2 substantially simplifies the solution process in our model. While it may seem restrictive to assume the seller must dispose of the property in a finite period, in the next section of the paper we consider a multi-period model where we allow the selling horizon to approach infinity. In this less restrictive environment, we demonstrate that the seller’s asking price will converge. Alternatively stated, there are costs to holding the property such as paying property taxes, perhaps paying two mortgages simultaneously, and the cost of keeping the property in showroom condition. Realistically, the marginal holding cost rises with the holding period. In this sense, the finite holding period assumption is an extreme version of this model: marginal costs are 0 until the period ends, and then become infinite. As a result, seller must seek a sure sale to avoid such a huge penalty\(^{11}\).

In the two-period case, the seller faces a maximization problem by setting an asking price today of \(x\):

\[
\begin{align*}
\max_x \quad & \mathbb{E}[U] = \int_x^\infty \lambda e^{-\lambda(y-p_0)} \, dy \cdot (x - V_0) + \beta \delta (1 - \int_x^\infty \lambda e^{-\lambda(y-p_0)} \, dy) \{ (P_0 - V_0) + \sigma \varepsilon \} \\
& \quad \int_x^\infty \lambda e^{-\lambda(y-p_0)} \, dy \cdot (x - V_0) + \beta \delta (1 - \int_x^\infty \lambda e^{-\lambda(y-p_0)} \, dy) \{ (P_0 - V_0) + \sigma \varepsilon \}
\end{align*}
\]

Equation 2.4 implies that over time the seller maximizes the discounted expected payoff from the following decision problem. First, it is possible that one buyer, who is willing to
pay $x$, will arrive. In this case, if the transaction is completed, the seller draws a reference-dependent utility, $x - V_0$. The first term of equation 2.4 measures this effect.

Likewise, $(1 - \int_x^\infty \lambda e^{-\lambda(y-P_0)}dy)$ refers to the probability of remaining unsold and rolling over to the next period. In this case, the seller has no choice, but to sell the property at the guaranteed price, $P_0$. The second term measures the corresponding discounted payoff.

Solving this problem is straightforward. The first order condition gives:

$$U' = e^{-\lambda(x - P_0)} \times [\beta \delta \lambda (P_0 - V_0) + V_0 \lambda - x \lambda + 1] = 0$$

(2.5)

Solving, we get

$$x^* = \frac{1}{\lambda} + \beta \delta (P_0 - V_0) + V_0$$

(2.6)

The second order condition requires:

$$x^* \leq \frac{2}{\lambda} + \beta \delta (P_0 - V_0) + V_0$$

(2.7)

which is automatically satisfied by (2.6). Substituting (2.6) into (2.4), the expected payoff is:

$$E[U^*] = \frac{1}{\lambda} e^{-\lambda(\frac{1}{\lambda} + (1 - \beta \delta) (V_0 - P_0))} + \beta \delta (P_0 - V_0)$$

(2.8)

Now define the “fishing margin” as the difference between a seller’s asking price and the expect market price:

$$D(P_0, V_0) = x^* - P_0 = \frac{1}{\lambda} + (1 - \beta \delta)(V_0 - P_0)$$

(2.9)
A positive value is associated with the existence of fishing, whereas the size of the associated value measures the extent of the seller’s fishing behavior. The binding condition in the probability density function requires \( D(P_0) \geq 0 \), i.e.,

\[
P_0 \leq V_0 + \frac{1}{(1-\beta\delta)\lambda}
\]

The conclusion is clear: it is never optimal for a seller to ask a lower than market price in our model since she is guaranteed to be able to sell at the expected market price, which would generates a higher payoff.

Three important comparative static results avail themselves when we take partial derivatives with respect to the current market price and reservation value:

\[
\frac{\partial D}{\partial P_0} = \beta\delta - 1 < 0 \quad (2.11)
\]

\[
\frac{\partial D}{\partial V_0} = 1 - \beta\delta > 0 \quad (2.12)
\]

\[
\frac{\partial D}{\partial \beta} = \delta(P_0 - V_0) \begin{cases} > 0 & \text{if } P_0 - V_0 > 0 \\ < 0 & \text{if } P_0 - V_0 < 0 \end{cases}
\]

From (2.11) we can see that the fishing margin becomes smaller when market price increases. Moreover, (2.12) shows that a higher reservation value is associated with a larger fishing margin, in equilibrium. Finally, (2.13) illustrates the effect of discounting. If the seller is subject to a potential loss, i.e., \( P_0 - V_0 < 0 \), her incentive of fishing becomes stronger due to the discounting effect, i.e., a lower \( \beta \). Intuitively, because the discounting effect implies that future losses are preferred to current ones, the seller would be better off fishing for a higher price today even though the probability of sale is lower.
The above results can be summarized in the following proposition:

**Proposition 1:** If the current market price is no smaller than \( V_0 + \frac{1}{(1-\beta \delta)\lambda} \), the seller will always sell the house now at the market price; there is no fishing behavior. If it is smaller than \( V_0 + \frac{1}{(1-\beta \delta)\lambda} \), the seller will ask a higher than market price, and the fishing margin will be positive. The equilibrium asking price in this case is \( \frac{1}{\lambda} + \beta \delta (P_0 - V_0) + V_0 \) and the fishing margin is \( \frac{1}{\lambda} + (1 - \beta \delta)(V_0 - P_0) \). Moreover, the fishing margin declines with the price level, and increases with the seller's reservation value.

To the extent our assumptions hold in the real world, Proposition 1 sheds light on many observed behaviors in the housing market. One implication is the existence of loss aversion. When \( P_0 < V_0 \) (i.e., when the seller is in a loss position), her asking price will be \( \frac{1}{\lambda} + (1 - \beta \delta)(V_0 - P_0) \) higher than the expected market price. A greater loss position is associated with a higher than market asking price and a much lower sale hazard rate. A second implication of Proposition 1 is that it supports a positive price-volume relationship. Since the fishing margin declines with the price level and eventually goes to zero, when the market price is high enough, sale hazard rates will be positively correlated with the level of market prices. Thirdly, Proposition 1 also explains the puzzling behavior noted by Williams (1999) that in a hot market, sellers ask prices that are near the
expected market prices, whereas in cold markets many sellers withdraw their listings after setting substantially higher than market prices\textsuperscript{12}. A fourth implication from this proposition relates to price dispersion. Specifically, in a hot market, the observed transaction prices will be less dispersed (with respect to the expected market price) than in a cold market.

A final, much more subtle implication relates to fishing behavior. Proposition 1 maintains that the existence of fishing is not necessarily associated with a loss position. Specifically, if the expected market price is not substantially greater than the reservation value, i.e., \( V_0 \leq P_0 < V_0 + \frac{1}{(1-\beta\delta)^\lambda} \), fishing behavior may still exist, although the margin will be smaller than in a loss position.

3. Multi-Period Problem

In the two-period problem, hyperbolic discounting is trivial because the joint discounting effect (i.e., \( \beta\delta < 1 \)) is not qualitatively different from the classical inter-temporal problem of \( \delta < 1 \). However, the hyperbolic discounting assumption is important in a multi-period setting. Now consider a multi-period problem with hyperbolic discounting where there are \( T+1 \) periods which are indexed by \( t=0,1,\ldots,T \). A parallel presentation to equation 2.4 within a multi-period framework gives:
\[
\max_{x_0, x_1, \ldots, x_{T-1}} E[U] = \int_{y_0}^{y_T} \lambda e^{-\lambda(y-y_0)} dy (x_0 - V_0) + (1 - \int_{y_0}^{\infty} \lambda e^{-\lambda(y-y_0)} dy) \beta \\
\quad \left\{ \delta \int_{y_0}^{y_T} \lambda e^{-\lambda(y-y_0)} dy (x_1 - V_1) + (1 - \int_{y_0}^{\infty} \lambda e^{-\lambda(y-y_0)} dy) \right\} \\
\quad \left\{ \delta^2 \int_{y_0}^{y_T} \lambda e^{-\lambda(y-y_0)} dy (x_2 - V_2) + (1 - \int_{y_0}^{\infty} \lambda e^{-\lambda(y-y_0)} dy) \delta^T P_0 - V_0 \right\} \ldots \right\}
\]  
(3.1)

Equation 3.1 appears quite complicated due to its nested probability structure. It is the expected utility in which the likelihood of being carried over to the next period depends on the nested probability generated by all previous asking prices.

An important lesson learned from the hyperbolic discounting literature is that the sequence of asking prices, \( x_0, x_1, \ldots, x_{T-1} \), even if they can be solved, are proven to be invalid due to dynamic inconsistent preferences. Alternatively stated, the optimal pricing rule derived at day 0 may not be optimal if the sale is indeed carried over to the next period.

Due to the dynamic inconsistent preferences stemming from hyperbolic discounting, it is common in the literature to treat the situation as a multi-period game. In particular, it is a game that the current homeowner plays against herself in the future. The person in each period is modeled as a separate player. In our model, it is a T-period pricing game\(^{13}\) in which the seller in each period from 0 to T-1 chooses an asking price which maximizes her expected payoff based on the preference at that time. In addition, we assume sellers are sophisticated\(^{14}\) (i.e., they foresee that they will have the same present-biased preference problem in the future period).
This game can be solved by backward induction. The seller in period T-1 faces exactly the same decision as in a two-period case. Since she knows she will sell at the expected price in period T, she must choose an asking price to maximize her expected payoff, which is equivalent to the problem in equation (2.3). The maximized expected payoff is provided in equation (2.8). Knowing the expected payoff, the seller in period T-2 will choose her asking price to maximize her expected payoff. This process continues until period 0, yielding a backward inducted equilibrium pricing strategy (See the appendix for a more mathematically detailed explanation).

Since the expected payoff is decreasing with respect to t, conditional on a given set of \( P_0, V_0 \), it follows that the asking price and fishing margin will also be decreasing with respect to t.

As in our two-period case, the binding condition in period T-1 requires (2.10) to hold, i.e.,

\[
P_0 \leq V_0 + \frac{1}{\beta \delta \lambda (1-\beta \delta)}
\]

If (2.10) holds, following (A.5), the expected payoff prior to period T-1 is monotonically decreasing with respect to t. Therefore, all prior payoffs are guaranteed to be larger than \( P_0 - V_0 \). As a result, all binding conditions from period 0 to T-1 are automatically satisfied. If (2.10) fails, the solution becomes a trivial case:

\[
x_0^* = P_0
\]

(3.2)

In this case, the transaction is completed in the current period.
We now characterize some properties of equilibrium asking price and expected payoff in the following lemma:

**Lemma 1:** If the current expected market price is no smaller than $V_0 + \frac{1}{(1-\beta\delta)\lambda}$, then $x_0^* = P_0$, $E[U_0] = P_0 - V_0$ and transaction occurs in the current period. If the expected market price is smaller than $V_0 + \frac{1}{(1-\beta\delta)\lambda}$, both the equilibrium asking price $x_t^*$ and the expected payoff $E[U_t]$ are decreasing with respect to $t$. In addition, the sequence $\{E[U_T | t = 0], E[U_{T-1} | t = 0], ..., E[U_1 | t = 0], E[U_0]\}$ converges when $T$ goes to infinity.

**Proof:** We only prove the convergence of the sequence $\{E[U_T | t = 0], E[U_{T-1} | t = 0], ..., E[U_1 | t = 0], E[U_0]\}$. Other results follow from the above discussions. We know that the expected payoff is monotonically decreasing with respect to $t$. Thus, there exists an $N$ such that for all $n<N$, $E[U_n | t = 0] > 0$. In addition, $E[U_{n+1} | t = 0] < \frac{1}{(1-\beta\delta)\lambda}$. This is a contradiction since a diverged increasing sequence will not be bounded above. **QED.**

If we define this limit as $U^*$, it can be obtained by solving the following nonlinear equation:

$$(1-\beta\delta)U^* - \frac{1}{\lambda}e^{-\frac{1}{\lambda} + \beta U^* - \nu_0(V_0 - V_0)} = 0 \quad (3.3)$$

The limit of the asking price is:
\[ X^* = \lim_{t \to \infty} x_t^* = \frac{1}{\lambda} + \beta \delta U^* + V_0 \]  \hspace{1cm} (3.4)

Accordingly, the fishing margin will converge to \( X^* - P_0 \).

Now we can summarize our major results from the multi-period model in the following proposition:

**Proposition 2:** If the current market price is no smaller than \( V_0 + \frac{1}{(1-\beta \delta)\lambda} \), the seller will always sell her house now at the current expected market price, and there is no fishing behavior. If it is smaller than \( V_0 + \frac{1}{(1-\beta \delta)\lambda} \), an equilibrium pricing strategy is characterized by (A.2) and fishing behavior exists. Specifically, the fishing margin is expressed in (A.6). In addition, the expected fishing margin declines along \( t \) (i.e., the expected subsequent asking price is always smaller than the prior asking price). Meanwhile, the expected payoff is bounded by \( U^* \), the expected asking price from 0 to \( T-1 \) is bounded by \( X^* \), and the expected fishing margin is bounded by \( X^* - P_0 \).

One implication from Proposition 2 is that the horizon constraint for the seller plays an important role in determining the equilibrium pricing strategy. Depending on how far away the seller is from the ending period \( T \), she will choose different asking prices even though her net position of gain or loss is the same. Genesove and Mayer (2001) find that the fishing margin for owner-occupants is roughly twice as large as for investors. A more recent study by Neo, Ong and Somerville (2005) finds similar results by using an auction.
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dataset in Singapore. Our theoretical model supports these empirical findings if it is the case that investors have tighter horizon constraints than owner-occupants.\textsuperscript{15} In addition, Proposition 2 predictions also have important econometric implications for empirical studies, which we will discuss in the next section.

Continuing, Proposition 2 predicts that conditional on a given T, the expected subsequent asking price will be smaller than the prior one (i.e., asking price declines along t). This is also consistent with the empirical findings in Genesove and Mayer (2001). In their study the authors find that sellers subject to nominal losses set higher asking prices of 25-35 percent of $V_0 - P_0$ and get 3-18 percent of that difference if the house is sold at a later time.\textsuperscript{16} While exogenous factors could explain a large part of this difference, our theory supports this finding as well. Finally, all implications as discussed in the two-period case remain valid in the multi-period model.

4. Simulation Results

The most striking behavior in the housing market is the significant price-volume relationship. We first perform a simulation on the price-volume relationship based on our multi-period model. In particular, we assume the current market price is $100,000 and it evolves stochastically from period 1 to period 100 following equation (2.1), where $r=0$, $\sigma=1500$, $\beta\delta = 0.75$, and $\lambda = 0.0003$. We generate 300 sellers starting from period 1 (now). Their reference values uniformly range from $90,000 to $110,000 and evolve following equation (2.2). In addition, we let their horizons range uniformly from 2 to 100.\textsuperscript{17} In each period, if the homeowner transacts the property, we generate a new seller
in the subsequent period. Therefore, in each period the total number of sellers in the market remains at 300. For comparison purposes, the historic price-volume relationship in the U.S. from 1968 to 1992 is presented in Exhibit 2, Panel A, while our simulation results are presented Panel B.

As is evident from the exhibit, our simulation results are visually consistent with the empirical findings in the actual housing market. In fact, the correlation between current price and transaction volume is 0.7612, and the 95% confidence interval using Fisher’s bias correction is (0.6554, 0.8283). When incorporating the observation that prices lead volume changes, the correlation between past price and contemporaneous transactions further increases to 0.8132, with the 95% confidence interval of (0.7258, 0.8667). We also run the Steiger’s Z one-tailed test for the null hypothesis that the second correlation, (i.e., between prior price and current volume, is higher than the correlation between current price and volume). The test is significant at 5%.

There are two additional interesting and important questions. First, conditioning on a reference value \( V_0 \) and horizon \( T \), how does the asking price and fishing margin change relative to expected market price? Second, conditioning on a net gain or loss exposure, how does the asking price and fishing margin change with horizon flexibility? Exhibit 3 presents a simulation result that sheds light on both questions. Consistent with the simulation on the price-volume relationship, we still assume \( \beta \delta = 0.75 \) and \( \lambda = 0.0003 \). Also, we allow horizon ranges from 2 to 100 and let \( V_0 = \$100,000 \).
Exhibit 3 presents several meaningful implications for the above two questions. First, conditioning on a given loss position, asking price and fishing margin increase as seller’s maximum holding horizon, \( T \), increases; and the differences across \( T \)s could be large. This result has important implications for empirical studies. For example, it suggests that the measure of loss aversion alone, as discussed in Genesove and Mayer (2001), is not sufficient to explain why a seller chooses to fish that particular amount. Behavior also depends on the horizon flexibility faced by each individual seller. Suppose there are two otherwise identical sellers who have the same net loss position, but very different horizon constraints. Although the measures of loss exposure are the same for these two sellers, their asking prices could be very different due to the horizon effect. Similarly, the same magnitude of fishing margin could be associated with sellers who have very different net loss positions due to their different horizon constraints. As a result, there is no clear meaning for the coefficient of loss aversion when observed in isolation. In addition, there could be omitted variable biases in the regressions estimated by Genesove and Mayer (2001) since they did not control for the horizon effect. Of course, we agree that it is generally difficult to find a good way to measure this horizon constraint since it is disaggregated and presumably unobservable. However, the econometric issue arising from horizon constraint measurement should be more adequately addressed in empirical studies dealing with loss aversion.

The second implication from Exhibit 3 is that as the expected market price increases, the discrepancy between asking price and expected market price becomes smaller, and eventually disappears if the expected market price becomes sufficiently high. As a result,
the fishing margin also declines and eventually approaches zero. In addition, from the simulation, we can see that sellers with a small net gain may still fish somewhat above market, a prediction which could be tested empirically. From Exhibit 3, we also observe that the price dispersion increases when prices decrease, which is also an empirically testable hypothesis.

Finally, this dispersion effect can easily generate a cross-sectional pattern of concave fishing behavior, as indicated in Genesove and Mayer (2001)\(^1\) and directly assumed by the prospect theory. To show the effect more concretely, we estimate a regression with the log measure of fishing margin as the dependent variable and a quadratic term of net loss on the right hand side of the equation. The result is presented in Exhibit 4, Panel A. The corresponding fitted curve of the fishing margin is plotted in Panel B.

The intuition for this finding is straightforward. Due to the existence of sellers who have tighter horizon constraints, the scattered asking prices should have more downward outliers when loss amount becomes larger. This will generate a cross-sectional pattern of concave fishing behavior. Note that this effect exists even when each individual response is linear or slightly convex along the size of loss, which is not presented in the current simulation. Therefore, an empirical finding of cross-sectionally concave fishing margin should be explained with some caution since it does not necessarily mean that each individual has the same concave fishing behavior.

5. **Empirical Implications**
5.1 Testing for the Price Dispersion Effect

One predication from our theory is the price dispersion effect. If we regard the difference between the realized transaction price and the expected market price as noise, our theory predicts that the higher the expected market price, the smaller the noise should be. This results because there would be more deep gainers and fewer losers in the market. To test this prediction, we use data based on the complete record of single-family transactions in the Vancouver metropolitan area for the period 1980(Q1)-2005(Q2), which is provided by Landcor from the British Columbia Assessment Authority (BCAA). The strength of the data is that it includes detailed records of housing characteristics in terms of its structure and neighborhood information, which helps when estimating the hedonic price model. After dropping observations due to missing values, we have 255,445 complete transaction records during the sampling period available for hedonic estimation. To perform the test, in each quarter we compute the variance of the hedonic residuals and regress it against price levels in that quarter. One point to note is that our theory only applies to repeat-sellers who have already bought the house at some price. Therefore, our model provides no prediction on the similar dispersion effect for the first-time transactions of new houses. Accordingly, we compute two variances for hedonic residuals in each quarter. One is for the repeat-sellers and the other is for new home transactions. Exhibit 5 reports the regression results for both groups, where the price level is measured by an inflation-adjusted hedonic price index.

As expected, the coefficient on real house price index is negative and significant at 1%, which means when market prices increase, market noise (measured by the variance of
hedonic residuals) becomes smaller. This negative relationship is also supported by the correlation between variance and price level. Interestingly, we do not find a similar dispersion effect for new home transactions. Price noise for new home transactions appears to be insensitive to the market price level.

5.2 Measurement Issue with a Repeat-Sales Index

One of the most commonly used methods to construct a house price index is the repeat-sales method. This technique only examines transactions in which the same house was sold more than once during the time period under examination. However, one key implication from our theory is that for those repeat sellers who face a potential loss, they tend to ask a higher than expected market price and experience a greater time on the market. This causes problems when we calculate the price difference for two sequential transactions, which are then used as the dependent variable in repeat-sales regression. This idea is better depicted graphically as in Exhibit 6.

Suppose we observe in the dataset a negative price pair in which a seller who purchases a house in period 1 at $10 sells her house in period 5 at $8. The observed data tells us that this seller realized a 20% loss from period 1 to period 5. As established earlier in the paper, since this seller experiences a loss in the transaction it is very likely that the observed loss reflects fishing behavior. Therefore, it may be a biased reflection of true market dynamics. The true market could have dropped 30%, but we cannot observe the drop from the data. As a result, two potential biases can occur when we use repeat-sales data. One is the level bias due to the standard fishing or discounting effect which will
generate an upward bias when we observe a negative price pair and either upward or downward biases for positive price pairs. This argument is similar to Bourassa et al. (2009) who show biases in repeat-sales indexes exist because households’ search strategies differ over time depending on the nature of the housing market. This implies the nature of selection bias differs in a repeat-sales index when comparing first and second sales environments.

The second potential bias is a lagging bias due to the timing effect after fishing. As previously discussed, if a seller asks for a higher than expected market price, the expected waiting time for her to sell increases, which causes our data to be a lagging indicator of true market dynamics. One implication from these two potential biases is that a repeat-sales index tends to underestimate the market volatility and, therefore, the risk level of the housing market. To assess this prediction, Exhibit 7 plots both hedonic and repeat-sales price indices for the Vancouver single-family housing market during our sample period.

As the hedonic index includes information from both repeat-sellers and first-time transactions, we expect the hedonic index to have a better measure of true market volatility when compared to the repeat-sales index. The standard deviation of the hedonic index is 152.33. Consistent with our prediction, the standard deviation of the repeat-sales index is only 139.85, which is 8.2% lower. To summarize, we find evidence that the repeat-sales index generally underestimates true market volatility.
6. Concluding Remarks

The theory of loss aversion relies heavily upon the assumption that the agent’s value function is asymmetric between gains and losses. One potential problem with current loss aversion theory is that it actually uses outcome to explain outcome (i.e., the reason people exhibit loss aversion is because their value function is loss averse). In this paper, we show that this asymmetric assumption is not necessary to generate observed “loss aversion” behavior. Alternatively stated, many behaviors, although they are observationally equivalent to loss aversion, can be explained by alternative theories. For example, a homeowner’s unwillingness to sell at a loss could be due to an inter-temporal tradeoff between current and future expected payoffs. To demonstrate this supposition, we present a model with a discounted future payoff. In particular, we examine a housing market model in which the agent has a symmetric value function, but faces an inter-temporal decision problem: she must form a pricing strategy to sell her house within a finite period. Our model shows that several puzzling behaviors in the housing market which were argued to show evidence of Kahneman and Tversky style loss aversion, follow naturally from our model, as well. For example, in our model, a seller will ask a higher than expected market price and will experience greater time on the market if she is in a loss position. Moreover, our model also predicts the commonly observed positive price-volume relationship as well as diminishing fishing behavior along home price level.

Our model further predicts that the horizon constraint for the seller plays an important role in determining a seller’s pricing behavior. For example, we show that even with the same level of loss exposure, two sellers with different time horizons may ask different
prices in the meantime. This prediction supports the previously unexplained observation that investors generally appear to be less loss averse than owner-occupants. Finally, we also raise an econometric concern when examining repeat-sales indexes. Specifically, a repeat-sales index will tend to understate the true market volatility. In sum, our model generates a rich set of empirically testable predictions in the housing market and possibly in the markets for other heterogeneous goods.
References


Exhibit 1. Graphical Depiction of the Value Function in the Prospect Theory
Exhibit 2. The Historic and Simulated Price-Volume Relationship


Panel B: Simulated Price-Volume Relationship

Source of Figure: Stein (1995)
Exhibit 3. Asking Price and Fishing Margin by Price Level
Exhibit 4. Understanding Fishing Behavior

Panel A: Simulated Regression Results

<table>
<thead>
<tr>
<th>Dependent Variable: Log (Fishing Margin)</th>
<th></th>
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<tbody>
<tr>
<td>Explanatory variables</td>
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<tr>
<td>Constant</td>
<td>1.819704***</td>
</tr>
<tr>
<td>(0.0042)</td>
<td></td>
</tr>
<tr>
<td>Loss</td>
<td>0.079531***</td>
</tr>
<tr>
<td>(0.0000)</td>
<td></td>
</tr>
<tr>
<td>$Loss^2$</td>
<td>-0.000767***</td>
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<tr>
<td>(0.0000)</td>
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</tbody>
</table>

Note: Numbers in parentheses are standard errors.
*** denotes statistical significance at the 1% level.

Panel B: Estimated Fishing Margin
Exhibit 5. Price Dispersion Effects

Dependent Variable: Variance of Residuals in Each Quarter

<table>
<thead>
<tr>
<th>Variables</th>
<th>Repeat Sellers</th>
<th>New House</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>0.0718*** (0.0046)</td>
<td>0.2131*** (0.0228)</td>
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<tr>
<td>Real House Price Index</td>
<td>-0.0108*** (0.00027)</td>
<td>0.0061 (0.0206)</td>
</tr>
<tr>
<td># observations</td>
<td>102</td>
<td>97</td>
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<tr>
<td>R²</td>
<td>0.1362</td>
<td>0.0009</td>
</tr>
<tr>
<td>ρ(σ², Index)</td>
<td>-0.3691</td>
<td>0.0301</td>
</tr>
</tbody>
</table>

Note: Numbers in parentheses are standard errors.
* Significant at 0.10 level, ** Significant at 0.05 level, *** Significant at 0.01 Level
Exhibit 6. Fishing Effect in Repeat-Sales Data
Exhibit 7. Figure VII: Hedonic and Repeat-Sales Index
Appendix. Further Details of the Multi-Period Model

In general, in period $t$, the seller’s decision problem is:

$$\max_{x_t} \mathbb{E}[U_t] = \int_{y_t} \lambda e^{-\lambda(y_t - \beta)} dy_t (x_t - V_t) + \beta \delta (1 - \int_{y_{t+1}} \lambda e^{-\lambda(y_{t+1} - \beta)} dy_{t+1}) \mathbb{E}[U_{t+1}]$$  \hspace{1cm} (A.1)

where, $\mathbb{E}[U_{t+1}]$ is the expected payoff if deferred to the next period and $\mathbb{E}[U_t | t=0] = P_0 - V_0$. As in the two-period model, taking the first order condition and solving for $x$ yields:

$$x_t^* = \frac{1}{\lambda} + \beta \delta \mathbb{E}[U_{t+1}] + V_0$$  \hspace{1cm} (A.2)

The second order condition requires:

$$x_t^* \leq \frac{2}{\lambda} + \beta \delta E[U_{t+1}] + V_0$$  \hspace{1cm} (A.3)

which is again satisfied by (3.2).

Substituting (3.2) into (3.1), the expected payoff is:

$$\mathbb{E}[U_t^+] = \frac{1}{\lambda} e^{-\lambda t} + \beta \delta \mathbb{E}[U_{t+1}]$$  \hspace{1cm} (A.4)

Taking the partial derivative with respect to $\mathbb{E}[U_{t+1}]$, we get

$$\frac{\partial \mathbb{E}[U_t^+]}{\partial \mathbb{E}[U_{t+1}]} = \beta \delta (1 - e^{-\lambda t}) \geq 0, \text{ if } \frac{1}{\lambda} + \beta \delta \mathbb{E}[U_{t+1}] + V_0 - P_0 \geq 0$$  \hspace{1cm} (A.5)

The expected fishing margin becomes:

$$D_t(\mathbb{E}[U_{t+1}]) = x_t^* - P_0 = \frac{1}{\lambda} + \beta \delta \mathbb{E}[U_{t+1}] + V_0 - P_0$$  \hspace{1cm} (A.6)
1 That is, \(U(x) < -U(-x)\). See Loewenstein and Prelec (1992) for further discussion.

2 Ortalo-Magne and Rady (1998) shows a similar relationship in the U.K.

3 See Chan (2001) for evidence of the existence of both an equity constraint and loss aversion.

4 See Loewenstein and Thaler (1989) and Loewenstein and Prelec (1992) for more experimental evidence on hyperbolic discounting behavior with positive payoffs.

5 The quasi-hyperbolic model was first developed by Phelps and Pollak (1968) and was later employed by Laibson (1997), Fischer (1999), and O’Donoghue and Rabin (1999), among others.

6 For general hyperbolic discount factors, see Loewenstein and Prelec (1992).

7 Since \(U_t(c_t, c_{t+1}, \ldots, c_T) = -U_t(-c_t, -c_{t+1}, \ldots, -c_T)\).

8 Later in the paper the seller is allowed to ask a higher than expected market price and still have a positive probability of successfully selling her house. This can be thought of as the case where there is asymmetric information between a seller and potential buyers.

9 For example, it could be the initial purchase price. See Neo, Ong and Somerville (2005) for a further discussion on the choice of reference value.

10 In this case, we assume the buyer is strictly a “price taker”.

11 We thank an anonymous referee for identifying this alternative method of considering the idea of a special holding cost assumption.

12 Williams (1999) observes similar behavior in commercial real estate and rental markets as well.

13 In period T, the seller has no choice but to sell at the market price. So a T+1 period problem reduces to a T-period pricing game.
See O’Donoghue and Rabin (1999) for more discussion on the implications with and without this assumption.

We leave this empirical question to future studies, but suggest this relationship due to investors having higher holding costs.


Since we assume they must sell at the market price in the last period, we set $T \geq 2$ to rule out the trivial case.

The horizon effect appears to be more significant when $T$ is small since it converges relatively quickly in the simulation.

This means the coefficient associated with the squared of loss is negative.

For gainers, we expect a downward bias since they may sell at a lower than expected market price.