Loss Aversion and Seller Behavior:

Evidence from the Housing Market

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We show that loss aversion is an important feature in explaining sellers' behavior in the housing market. Data from the 1990-97 boom-bust cycle in downtown Boston show that condominium owners subject to nominal losses 1) set higher asking prices of 25-35 percent of the difference between the expected selling price of a property and their original purchase price; 2) attain higher selling prices of 3-18 percent of that difference; and 3) exhibit a much lower hazard rate of sale than other sellers. The list price results are roughly twice as large for owner-occupants as investors, although they hold for both groups. We also show that the larger the prospective loss, the smaller the marginal mark-up of list price over expected selling. These findings are consistent with the shape of the value function in prospect theory as first proposed by Kahneman and Tversky (1979). They also help explain the strong positive correlation between aggregate prices and volume in this and other real estate markets.

1. Introduction

Twenty years ago, Kahneman and Tversky (1979) developed prospect theory to explain the growing body of experimental evidence showing that individuals make choices that violate expected utility theory. Prospect theory argues, in part, that individuals make financial decisions relative to some reference point, suggesting that otherwise identical persons might act differently based on the price they paid for an asset. To explain the asymmetric treatment of gains and losses, also known as loss aversion or the disposition effect, prospect theory suggests that an individual's value function is concave in gains (as for a risk averse individual in expected utility theory), but convex in losses. In addition, it argues that the function is much more sensitive to losses relative to equivalent-sized gains. While prospect theory has garnered considerable attention from economists, statisticians, and psychologists alike, much of the evidence in its favor remains experimental.

In many ways, the housing market is an ideal place to look for evidence of loss aversion. While the housing market is quite large and important, representing about 10 trillion dollars—one-quarter of the total net worth of US households and non-profits in 1997— it is primarily a consumer market, with individual, non-professional, buyers and sellers involved in almost all transactions.[1] While our sample includes both owner-occupied and investor owned condominiums, even the investors are likely to own no more than a few properties. Although professional real estate agents have influence in this process, individuals make the final decision about listing prices and accepted offers. In addition, most individuals are relatively inexperienced in buying and selling a house. Finally, arbitrage is quite expensive. Transaction costs include the brokerage fee, typically between 5 and 7 percent, moving expenses, and the

[1]Source: Flow of Funds data (6/11/98) from the Board of Governors of the Federal Reserve System

costs associated with holding a vacant property for sale or living in a house that is a poor match with the owner's preferences.[2]

By investigating loss aversion, we hope to explain a number of puzzling features of the real estate market. A number of authors have documented the strong positive correlation between aggregate prices and trading volumes in the US, Great Britain, and France (Ortalo-Magne and Rady, 1998 and Stein, 1995). This positive price-volume correlation is often attributed to downpayment requirements in the mortgage market. In Stein (1995), down payment requirements add a self-reinforcing mechanism to demand shocks, and so generate a positive price-volume correlation at the aggregate level. Owners with limited home equity choose not to sell because they would have little money left for a down payment on a new property and would thus be forced to trade down if they moved.[3] Using a dynamic life-cycle model with down payment constraints, Ortalo-Magné and Rady (1998) show how shocks to credit availability and current income affect the timing of young households in moving up the property ladder, and thus generate the observed correlation between prices and sales volume.

However, equity constraints fail to explain the order of magnitude of the changes in trading volume and the number of unsold listings that remain on the market, when prices fall. Consider the Boston condominium market, where we have collected quite extensive data on asking prices, selling prices and transaction volume. Between 1982 to 1997 this market went through a large boom-bust cycle. As Figure 1 shows, during the 1980s housing prices rose over 150 percent, then fell by 40 percent in the early 1990s, only to rise above their previous peak by 1997. Trading volume at the trough (1990) was less than one-third its level at the neighboring

[2]Using data on military movers–involuntary and known in advance–, Gill and Haurin, 1998, estimate the non-broker costs associated with moving to exceed 10 percent.

[3] Surveys from Chicago Title and Trust Company show that more than one-half of the down payment for repeat buyers comes from equity obtained from the sale of the previous home.

peaks. New properties coming on the market in the trough years of 1991 and 1992 had average list prices that exceeded their expected selling price at the quarter of entry by an astounding 35 to 39 percent.[4] At the bottom of the market, between 1990 and 1992, more than one-half of all units listed for sale were eventually withdrawn from the market, unsold, for at least 6 months.

In a previous paper, (Genesove and Mayer 1997), we document that liquidity constraints are an important factor in determining list prices, selling prices, and time on the market for potential sellers. While all of the above-mentioned stylized facts are consistent with liquidity-constrained sellers choosing to wait rather than sell at the trough of the market, the order of magnitude of these changes greatly exceed the estimates in that paper. In fact, our previous estimates on the impact of equity constraints can explain less than 20 percent of the observed time series variation in deviation of price to list prices or time on the market.

Our sample covers a useful time period for investigating loss aversion. We have collected data on downtown Boston condominiums listed for sale between 1990 and 1997 whose sellers originally purchased their property after 1982. In this sample period, 55 percent of all potential sellers were faced with a prospective loss when they first placed their property on the market. Many of them had made large down payments when purchasing their home, and so are not likely to be equity constrainted. Cross-sectional variation in the loan to value ratio and gain or loss position of individual sellers at a given point in time allows us to isolate loss aversion and equity constraints from other time effects such as owner expectations about the future path of house prices or macroeconomic conditions.

In exploring loss aversion, we focus on the previous nominal purchase price as the reference point around which sellers are sensitive to gains and losses. In this regard, we draw

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[4] The expected selling price was estimated by a hedonic regression with a sample of sold properties.

from other research that concludes that individuals focus on nominal targets, even with positive levels of inflation. Shafir, Diamond, and Tversky (1995), for example, present evidence from a number of surveys suggesting that money illusion ("a deviation from 'real' decision making") is common in a wide variety of contexts and does not go away with learning.

The support for loss aversion in the data is quite striking. Sellers whose expected selling price is below their original purchase price set an asking price that exceeds the asking price of other sellers by between 25 and 35 percent of the difference between the two. This mark-up exists though we control for the remaining loan to value (LTV) of the seller. In addition, we find that sellers facing a smaller loss have a much higher marginal mark-up of list price over expected selling price than sellers facing a larger loss. This finding is consistent with a convex slope of the value function for losses, as predicted by prospect theory. Finally, we show that both investors and owner-occupants behave in a loss averse fashion, although investors exhibit about one-half of the degree of loss aversion as owner-occupants.

We develop an empirical model to address the possibility of a correlation between unobserved quality in a unit and the measure of loss aversion. The model implies that estimates from two OLS regressions will bound the true coefficient for loss aversion. As a further check on our results, we also instrument for the amount of the loss with the change in the aggregate house price level between the original purchase date and the date the property is listed for sale. The estimated coefficient on the amount of the loss, although lower, remains positive and statistically significant even after these measures.

The evidence on loss aversion is not confined to asking prices and is not driven only by unsuccessful sellers. While the sensitivity of asking price to nominal loss among successful sellers is about half that of owners that eventually withdraw from the market, the coefficient remains large and statistically significant. This finding also shows that loss aversion has the additional effect of driving those most sensitive to losses out of the market. Second, the estimated coefficients on nominal loss in non-linear transaction price regressions are also positive, although only the upper bound is large and significant.

Since the cost of demanding a higher price is a longer expected time to sale, an immediate corollary to these results is that those at risk of a nominal loss should also face a longer time on the market. Indeed, we find that a 10 percent difference between the previous selling price and current market value for sellers facing a loss results in a 3 to 6 percent decrease in the weekly hazard rate of sale. Thus the high asking prices set by these are not simply brief and irrational 'wish' statements that the market quickly corrects.

The paper proceeds as follows. A more detailed discussion of the previous literature follows in the next section. The data is described in the third section. Section 4 develops the econometric framework. The next section presents the empirical results from list prices, followed by a section that explores the impact of loss aversion on selling prices and time on the market. The paper concludes with a discussion of the empirical findings, a future research agenda, and possible policy implications.

2. Previous Literature

Loss Aversion

The theory of loss aversion, as might be applied to the real estate market, relies on two behavioral principles; prospect theory, and money illusion.[5] Prospect theory suggests that individuals are more sensitive to losses than to gains around a reference point (Tversky and

[5]See the May, 1997 Special Issue of the Quarterly Journal of Economics in Memory of Amos Taversky, as well as Rabin (1998) and Kahneman, Knetsch, and Thaler (1991) for a more detailed listing of articles relating to the behavioral issues summarized here.

Kahneman, 1992). Shafir, Diamond, and Tversky (1997) argue that the reference point (the "origin" in the value function) and losses or gains be calculated in nominal terms since "...people often think about economic transactions in both nominal and real terms, and that money illusion arises from an interaction between these representations, which results in a bias toward a nominal evaluation." (P. 1)

A couple of studies have explored whether the experimental behavior of subjects that is the empirical basis supporting prospect theory can be generalized to real world markets.[6] One set of studies goes part of the way to addressing this concern by exploring the sensitivity of the results to the presence or amount of actual monetary payouts to subjects. Grether and Plott (1979) conclude that the behavioral anomaly that they were studying (preference reversal) was, if anything, more prevalent in a group playing for real money than in a group that faced no monetary consequences for their choices. Similarly, Kachelmeir and Sheeta (1992) find evidence of subtle differences between participants based on whether and how much money is involved in an experiment. Because budget limits deter most studies from offering large monetary incentives, these authors conduct a number of experiments in the People's Republic of China, where differences in the standard of living allow them to offer very substantial monetary incentives to some study participants, and confirm these experiments with supplementary studies in the US and Canada. Kachelmeir and Sheeta conclude that subjects behave in a more risk-averse manner when large amounts of money are at stake, particularly through overvaluing low

[6] Some authors have criticized the experimental evidence that forms the basis of prospect theory. For example, Coursey, Hovis, and Schultze (1987) argue that learning and a market setting can eliminate differences between willingness to pay and willingness to accept in experiments. Knez, Smith, and Williams (1985) suggest that this discrepancy may be explained by the subjects employing simple bargaining strategies. Kahneman, Knetsch, and Thaler (1990) counter with evidence that these disparities continue to hold even when participants play a game multiple times, but are eliminated when the experiments involve goods with no consumption value.

probability events.

Despite this evidence, a number of questions remain. First, few studies look at losses in the experimental literature. Experimenters are (justifiably) reluctant to have subjects run the risk of leaving an experiment with less money than they arrived with. Second, there is no guarantee that subjects would behave in the same manner in a real world market with large amounts of money on the line. Even if they were to behave so, the presence of rational arbitragers should limit the impact of loss averse behavior on actual market outcomes.

While experimental and survey evidence about loss aversion is plentiful, empirical evidence of its importance in real world markets is very recent and limited to publicly-traded equities. Odean (1998) analyzes the stock trading activity of individual investors obtained from a discount brokerage firm and shows that these investors are much more likely to sell winners than losers, despite the capital gains tax cost associated with realizing gains and the tax benefit associated with realizing losses. Odean rejects other explanations for this behavior, including portfolio re-balancing or lower trading costs associated with low-priced stocks. Grinblatt and Keloharju (1999) obtain similar results using records of virtually all trades on the Finnish stock market over a 2-year period. Finally, Shapiro and Venezia (1998) use trading records from both individuals and professionals to show that the disposition effect (loss aversion) holds in Israel as well.

We focus on nominal, not real, losses because survey evidence suggests that people often focus on nominal levels as a reference point. For example, households exhibit a strong preference for nominal wages that increase over time, rather than a flat or declining earnings pattern. (Lowenstein and Sicherman 1991) Shafir, Diamond, and Tversky (1995) present surveys results that document a clear pattern of money illusion. One question is indicative of their findings and is especially relevant for our study. Respondents were asked to rank the success of three hypothetical individuals: Adam owned a house during a time of 25 percent deflation and sold it for 23 percent less than he paid, Ben owned a house when prices were flat and sold it for a 1 percent nominal loss, and Carl owned a house during a time of 25 percent inflation and sold it for 23 percent more than he paid. Their results show that nearly one-half of the respondents thought that Carl did the best, although his real gain was the lowest of the three individuals, and only 37 percent ranked Adam's position as the best, despite his having the highest real gain.

In addition to the evidence in favor of a (nominal) disposition effect in the stock market, other empirical evidence on the relevance of nominal reference points comes from Garcia, Lusardi, and Ng (1997). These authors show that consumption is more sensitive to expected nominal declines in income than to nominal increases. Shea (1997) finds that consumption is more sensitive to expected drops in income than to gains, but he uses real gains/losses, rather than nominal gains/losses.

Evidence from the Housing Market

Most papers that explore efficiency in real estate markets rely on aggregate sales price data. The much-cited Case and Shiller (1989) argue on the basis of house price changes in four cities over 15 years that the residential housing market is inefficient. They show that prices do not fully incorporate predictable events such as forecastable changes in interest rates, and that aggregate prices exhibit positive short-run serial correlation and negative long-run serial correlation. Meese and Wallace (1993) further buttress the claim of inefficiency using data on house prices and rents in San Francisco. A number of papers rely on regional differences in the cyclicality of house prices to explore the determinants of inefficiency. Lamont and Stein (1996) find that house prices in cities with high average debt levels are more responsive to income shocks. Using a panel of U.S. cities, Capozza, Mack and Mayer (1997) show that house prices are less efficient in smaller markets (less information), markets with higher construction costs (slower supply response to demand shocks) and faster income growth (euphoria).

Relatively little research exploits differences in seller characteristics. Our previous paper (Genesove and Mayer 1997) utilized a more limited version of this data (listings from 3/90-12/92) to show that equity constrained owners set higher reservation prices than other sellers. An owner with an LTV of 100 percent sets an asking price that is 4 percent higher than an owner with an LTV of 80 percent, and also sells the property for 4 percent more. However, the former property will be on the market 15 percent longer, or an average of 6 weeks at the sample average. Glower, Haurin, and Hendershott (1998) use surveys to determine the reason that a seller is moving, and show that relatively impatient sellers set lower asking prices and sell more quickly than other sellers. Both papers highlight that housing markets are far from perfect asset markets by showing that otherwise identical houses can sell at different prices depending on the reservation price of the seller.

3. Data; Sources and Summary

Our data track individual property listings in the Boston Condominium market between 1990 and 1997. The most unusual data are from LINK, a privately owned listing service. Over this time period, LINK claims to have had a 90 to 95 percent market share in its coverage area, which is a well-defined and geographically segmented market area in downtown Boston. LINK has weekly records of all properties listed, including the *original* asking price in the week that the condo first entered the market, property attributes, and the property's street address. We supplement the LINK data with other data described below.

In LINK, properties can be listed simultaneously by as many as three brokers. In addition, many sellers will switch brokers at some time while their property is on the market.

However, a buyer would still view multiple listings as just a single property for sale and should only be concerned about the total time the property has been on the market. Thus we create a single record for each property showing the date it is first listed (the entry date), the date it exits the market, whether by sale or by withdrawal, and the listing price at entry. Since brokers sometimes try to game the system by withdrawing a property and then relisting it soon after so as to designate it as a "new listing," a new spell is considered to have begun only if there was at least an eight-week window since the property last appeared in LINK. There are a number of properties with multiple spells in the data.[7] When a property exited from LINK, its destination is labeled either "sale" or "off-market," according to whether a sale record was found in LINK.

To supplement LINK, we use information on property characteristics and assessed tax valuations from the City of Boston Assessor's Office. The Assessor's data indicate for some years whether the owner applied for a residential tax exemption. Banker and Tradesman provides data on all transactions since 1982, and includes information on the sales price, sales date, and mortgage amount. This source provides us with the previous selling price and current mortgage of the property.

The LINK database has several advantages over other data sets that might be used to study the market microstructure of residential real estate. First, and most importantly, LINK includes information on all listings, whether or not the property was sold. Using the LINK data, we have discovered that well over one-half of all listings in the housing cycle trough (1990-1992) were withdrawn from the market without being sold. Withdrawn properties tend to have higher listing prices (after adjusting for quality differences) and a longer time on the market than sold properties, suggesting that using only sold properties to compute statistics such as time-on-the-market and discount from asking price gives a misleading picture of actual market conditions.

[7] In the analysis, we adjust the standard errors for clustering within a given property.

All other published studies, as well as other databases that we know of from various local multiple listing services (MLS), rely on data for sold properties only.

In addition, because the LINK database includes all listings for a property, we can compute a correct time-on-the-market from the date of earliest listing, whereas other databases compute time-on-the-market based on the beginning of the last contract with the current broker. Because of such biases, data from local MLS's will understate the actual expected time-on-the-market that a typical homeowner experiences. Finally, LINK reports the original, and not only the final, asking price, and has a well-defined geographic market.

According to LINK records, 13,983 condominiums were listed for sale between 1990 and 1997, out of a total stock of a little more than 30,000 units. In order to be included in this study, a listed condominium must meet three conditions: 1) no missing information in LINK, 2) at least one previous sale in the deeds records—with the previous mortgage and sales price, and 3) match with the assessor's data— containing property attributes and property tax records.[8] These restrictions reduce the sample to 5,773 listings. Other than the requirement that a property have been previously sold between January 1, 1982 and the listing date, none of the other restrictions impose any particular bias on the results.[9] Just to be sure, we have re-run much of the estimation that follows without the requirement of a previous sale (setting all variables requiring a previous

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[8]This matching process is not as straightforward as it might seem. Brokers list the address of a condominium as visitors would find it, not necessarily its legal address. For example, a 6th floor condo might be listed in LINK as a penthouse unit, but as apartment #6 in the assessor's data. Similarly, a condo project will have a name (e.g., Parkside), but a different legal address. Also, the deeds records do not have computerized information on properties whose last sale occurred prior to 1982 or new properties (without a previous sale).

[9] To be sure about any data matching biases, we have had research assistants match the LINK data with the other dat sets by hand after completing a round of computer matching. This quite-costly process increased the match rate, but had no effect on estimated coefficients in previous work.

sale equal to zero and including a dummy variable for no match in the deeds records). The results are unchanged.

Table 1 summarizes the data. Clearly this is not a cross-section of typical properties in the U.S. The average property has an assessed value on January 1, 1990 of $212,833, despite having only 936 square feet, and well above the average value of about $180,000 for Boston area single-family homes. Owners also have high incomes, and presumably high levels of non-housing wealth, and thus should be relatively sophisticated compared to most US home owners.

Even so, 55 percent of listed properties had a current expected selling price in the quarter of listing that was lower than the previous purchase price, thus subjecting their owners to a potential loss. The data also show that the typical listed condominium has a mortgage whose balance at the time of listing is 63 percent of the estimated value of the property at that date, well above the US average of about one-third.[10] The loan to value (LTV) ratio is high in this market for three reasons: market prices fell over 40% during the sample period, high prices lead buyers to utilize more debt when initially purchasing a home (see Engelhardt, 1998), and many households in the area are young with steep age-earnings profiles (i.e., yuppies).

The difference between the first and second columns in Table 1 highlights the potential biases in exploring the impact of market conditions on sellers without considering withdrawn properties. Fewer than 60 percent of properties put on the market in this time period were sold. Given that the inventory level on January, 1998 was less than 500 condominiums, most of these unsold properties were withdrawn from the market without sale. Withdrawal rates for properties

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[10] The estimated value is for the quarter that the property enters the market and is calculated from a hedonic regression over the sample period using all sold properties. Regression results are available from the authors. The current loan balance is computed by amortizing the original mortgage amount (or a refinanced amount) using average mortgage rates prevailing in the market in the month of origination. The deeds records contain information on both original mortgages as well as refinancings.

listed in 1990-1992 were especially high, and exceeded 50 percent in all of these years. In addition, sold properties have lower overall debt levels and are less likely to have last sold at a high price. Analysis in Section 6 will explore the determinants of the hazard rate of sale for new listings.

4. An Empirical Model of List Price and Loss Aversion

To understand seller behavior over this time period, we start by looking more formally at the determinants of the original asking price for the first week that a property enters the market. In this section, we first lay out our ideal econometric formulation for the relationship between list price and potential loss. Estimation of this `true' relationship is infeasible, since for any given unit we can not separately identify the unit's unobserved quality from extent to which the owner over- or underpaid relative to the market value at the time of purchase. We provide three alternative, feasible estimators. The first is the ordinary least squares (OLS) estimator in which observed loss, which includes the unobservable quality, substitutes for loss. This provides an upper bound for the true coefficient on loss. The second feasible estimator is the OLS estimator of this same equation but with the previous sale price added as a control. The estimate of the coefficient on observed loss yields a lower bound for the true effect of a loss. The third is an instrumental variables (IV) estimator analogue of the first estimator, in which a loss term based only on changes in the market index is used as an instrument in place of the loss term itself. This provides a biased estimate of the true effect, although it should provide a consistent estimate of the test statistic for the null of zero effect.

Our ideal econometric specification states that the log asking price, L, is a linear function of the expected selling price in the quarter of listing, μ, an indicator of potential loss, $LOSS^*$, plus a constant and an error term:

$$(1) \qquad L_{ist} = \alpha_0 + \alpha_1 \mu_{it} + m\, LOSS^*_{ist} + \epsilon_{it}.$$

Here, *i* indicates the unit, *s* the period of the previous sale, and *t* the period of listing.

In turn, we assume that the expected selling price is a linear function of observable attributes, the quarter of listing (entry on the market), and an unobservable component:

$$(2) \qquad \mu_{it} = X_i \beta + \delta_t + v_i,$$

where X_i is a vector of observable attributes, δ_t is a time-effect that shifts expected price proportionally, and v_i summarizes the effect of unobservable attributes. We will refer to v in the following as unobservable quality.

$LOSS^*$ is simply the difference between the previous selling price, P^0, and the expected selling price, truncated from below at zero:

$$(3) \qquad LOSS^*_{ist} = \quad (P^0_{is} - \mu_{it})^+,$$

where $x^+ \equiv max\,(0,x)$. Note that this is not a measure of loss actually incurred on the books, but the amount the potential seller would lose, were he to sell at the current average price in the market.

Since we assume that equation (2) holds for all periods, we can also write the previous selling price as:

$$(4) \qquad P^0_{is} = \mu_{is} + w_{is} = X_i \beta + \delta_s + v_i + w_{is},$$

where w_{is} is the difference between the previous selling price and its expected value, conditional on all quality attributes. Thus the true loss term is

(5) $$LOSS^*_{ist} = (\mu_{is} + w_{is} - \mu_{it})^+ = ((\delta_s - \delta_t) + w_{is})^+.$$

Notice that $LOSS^*$ is composed of two terms. The first, $(\delta_s - \delta_t)$, the change in the market price index between the quarter of original purchase and the quarter of listing. The second term, w_{is}, is the over or underpayment by the current owner when he originally bought the house and thus is idiosyncratic to the particular transaction.

Combining the above equations yields the model

(6) $$L_{ist} = \alpha_0 + \alpha_1 X_i \beta + \alpha_1 \delta_t + m (\delta_s - \delta_t + w_{is})^+ + \alpha_1 v_i + \epsilon_{it.}$$

This model can not be estimated because v and w, and so $LOSS^*$, are not observed. Thus we are led to consider alternative, feasible models.

Model I

Since we do not observe the true prospective loss ($LOSS$*), our first feasible model substitutes a noisy measure of loss for true loss:

(7) $$L_{ist} = \alpha_0 + \alpha_1 (X_i \beta + \delta_t) + m\, LOSS^I_{ist} + \eta_{it}$$

(8) $$LOSS_{ist} = (P^0_{is} - X_i \beta - \delta_t)^+ = (\delta_s - \delta_t + v_i + w_{is})^+.$$

LOSS is estimated as the difference between the purchase price and the predicted price from a hedonic equation. When we substitute (8) into (7), the error term, η_{it}, contains two terms in addition to ϵ_{it}:

$$(9) \qquad \eta_{it} = \alpha_1 v_i + m\,((\delta_s - \delta_t + w_{is})^+ - (\delta_s - \delta_t + v_i + w_{is})^+) + \epsilon_{it}.$$

These additional terms lead to two biases in this model. The first bias arises from the simultaneous occurrence of the unobserved quality term, v_i, in both the error term and observed loss term. This leads η_{it} to be positively correlated with *LOSS* and so will tend to bias upwards the estimate of *m*, the coefficient on *LOSS*. Intuitively, our problem is that when we observe a large positive discrepancy between the previous sale price and the unit's expected selling price, beyond that accounted for by movements in the market, we can not know if this gap exists because the unit is more valuable than its measured attributes would indicate, or because the current seller "overpaid" for the unit. A unit with high unobserved quality will also have a high list price, leading to the upwards bias.

The second bias is the standard errors in variable (EIV) bias, albeit in nonlinear form. The well know attenuation result for the linear EIV problem leads one to expect EIV to bias downwards the absolute value of the OLS estimate of *m*. However, the general case for attenuation can not be made, both because of the presence of other variables, and because of the non-linearity. (Indeed, one can construct cases in a bivaraite regression where the bias is upwards, although the inflation is quite small). Nonetheless, given the empirical distribution of $\delta_s - \delta_t$, and assuming normality of *w* and *v*, the simulations discussed in the Appendix show that EIV always leads to attenuation. Those same simulations show the first bias always dominates the second, so that the estimate is biased upwards. Also, note that under the null of no loss effect, the EIV bias does not exist.

Here, and in the following two models, we follow a two stage estimation procedure. We first obtain consistent estimates of β and δ from an auxiliary regression, by regressing selling price on attributes and the quarter of entry dummies, corresponding to equation (2), and then substitute these estimates into equation (7) to obtain estimates of *m*, and the other coefficients[11]. Standard errors are corrected for this two-stage approach by the method described in Newey and McFaddden (1994, p. 2183). We do not impose the restriction that the coefficients on the predicted baseline price and the market index are equal.

<u>Model II</u>

Our second feasible model adds the residual of the previous selling price from the price regression, *v+w*, as a noisy proxy for unobserved quality:

$$(10) \quad L_{ist} = \alpha_0 + \alpha_1 (X_i \beta + \delta_t) + \alpha_1 (P^0_{is} - X_i \beta - \delta_s) + m\, LOSS_{ist} + u_{it}$$
$$= \alpha_0 + \alpha_1 X_i \beta + \alpha_1 \delta_t + \alpha_1 (v_i + w_{is}) + m\, LOSS_{ist} + u_{it},$$

However, because we cannot separately identify *v+w*, we overcompensate and now run into the opposite problem as in Model I. In this case, the residual, u_{it}, contains two additional terms:

$$(11) \quad u_{it} = - \alpha_1 w_{is} + m ((\delta_s - \delta_t + w_{is})^+ - (\delta_s - \delta_t + v_i + w_{is})^+) + \epsilon_{it}.$$

In this specification, there are again two separate biases. As in the previous model there is measurement error, which disappears under the null, and tends to bias the OLS estimate downwards in absolute value in our simulations. Now, instead of $\alpha_1 v_i$ in the error term, $-\alpha_1 w_{is}$

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[11] We obtain similar results when the index of the quarter previous to the entry quarter is used instead.

appears, and as this is negatively correlated with *LOSS*, it will tend to bias downwards the coefficient on the *LOSS* term. The argument is a little tricky, because $-\alpha_1 w_{is}$ is also correlated with the noisy proxy $(v_i + w_{is})$, and in principle this can offset the negative bias on m that one would expect from the correlation with *LOSS*. However, our simulations show that this is not a serious concern.

Model III

In our final model, we return to the specification of model I, but instead of estimating the coefficients by OLS, we use IV where the list of instruments includes

(12) $$LOSS_{st}^{AGG} = (\delta_s - \delta_t)^+,$$

plus all the regressors except *LOSS*. That is, we include the change in the market index between the purchase date and the date of listing. Since the instruments are uncorrelated with *v*, the upward bias in the OLS estimation does not appear. However, it remains the case that the instrument is correlated with the EIV component of the regressor error term, because of the nonlinearity in that component. Our simulations show that bias to be positive throughout, and small in the relevant region. Of course, under the null of no loss effect, the estimates are consistent. Note that the power of the model depends on the correlation between $LOSS^{AGG}$ and $LOSS^*$.

5. Estimates From List Price Regressions

Basic Results

Table 2 presents our basic results on the responsiveness of list price to prospective losses.

The standard errors correct for the estimation of the 1990 baseline value and the market index, as well as for correlation among properties listed more than once, and are robust to heteroskedacticity. The correction for the use of the auxiliary regression is quantitatively unimportant. Column (1) reports the regression of list price on *LOSS*, the excess of LTV (the loan-to-value ratio) over 0.8, the market index at time of listing ($\hat{\delta}_t$), and the 1990 baseline value of the home ($X_i\beta$).[12] The estimated coefficient of 0.35 on LOSS has the interpretation that a ten percent increase in a prospective positive loss, leads a seller to set a list price 3.5 percent higher. As argued in the previous section, this estimate should be viewed as an upper bound to the true effect of loss aversion on list prices.

Column (2) adds the difference between the previous sale price and its predicted value in its year of previous sale. As noted earlier, this is a noisy proxy for unobserved quality. Since the added noise is itself a component of the expected loss, the estimated coefficient on *LOSS* in this column, which is 0.25, should provide a lower bound for the true effect. Taking the two columns together, then, we conclude that the true effect is greater than 0.25, but less than 0.35, a result confirmed by the simulations reported by the Appendix.

As noted in the Introduction, prospect theory suggests a more specific functional form on the shape of an individual's value function. It suggests that the marginal disutility of a loss declines with the size of the loss (i.e. individuals have a diminishing marginal dis-utility of losses). We would thus expect the list price to be an increasing, but convex function of loss. To see if this is true, we add a quadratic term in loss in columns (3) and (4). Whether we include the previous selling price residual as in (4), or not, as in (3), we find that both the quadratic and the linear terms are separately and jointly significant, and that the estimates indeed imply a positive,

[12]See Genesove and Mayer (1997) for a justification of the use of a measure of LTV truncated at 0.8.

but falling, marginal response to the expected loss for most of the range of the data.

Considering the control variables, we find a positive response to LTV. We expected to find this from previous work (Genesove and Mayer 1997). However, at 0.06, the effect is less than half what we previously found. The higher estimate in the earlier work derives in part from the absence of *LOSS* in those regressions, where LTV was obviously picking up some of the loss aversion effect. However, the two estimates are not directly comparable, because of the different time periods, the inclusion of all, not only sold, properties here, and the need to define market value somewhat differently here. Inclusion of the quadratic term cuts the LTV coefficient in half, while maintaining its statistical significance.

The coefficient on the Estimated Value in 1990 is 1.09, significantly greater than one, across all the columns. This result is consistent with simple bargaining theory, given that the distribution of the regressor is right skewed. With higher quality units selling in a thinner market, list prices are set more than proportionately higher to allow greater room for bargaining.

Interestingly, the coefficient on the market index is significantly less than one. This indicates that list prices do not immediately adjust to changes in market prices. Further investigation shows that this adjustment takes 4 quarters.[13]

Table 3 considers three alternative robustness checks on our estimate. Columns (1) and (2) substitute quarterly dummies of entry for the quarterly market index. This is a more general specification that nests the linear market index derived from the price regression. Use of the quarterly dummies has no effect on the upper or lower bound estimates. Columns (3) and (4) adds the price index of the date of the previous sale. Recall that this term, δ_s in the model, enters positively (and nonlinearly) into the calculation of the prospective loss. Including it separately in the regression addresses any concern that the coefficient on the prospective loss might somehow

[13] We plan to examine the adjustment rate in future work.

be capturing the effect of δ_s, which might in turn be proxying for some unknown selection effect. Its inclusion, in fact, pushes the upper and lower bound estimates up slightly.

Finally, columns (5) and (6) restrict the sample to properties with a loan to value ratio of less than half. We do so to answer two possible criticisms. First, *LOSS* and LTV might interact in highly non-linear ways, making identification of the separate effects difficult in the full sample. Second, as we measure loan balance with error (since we do not have the exact interest rate on each mortgage), the coefficient on *LOSS* may really be picking up declines in the market that raise LTV. In addition, these estimates show that loss aversion is unrelated to overall wealth or credit constraints. The average owner in this sub-sample has at least $110,000 in housing wealth. Yet, the coefficients on expected loss remain remarkably similar to their previous estimates.

Table 4 presents the Instrumental Variables estimates (Model III), in which the truncated change in the market index, (δ_s - δ_t) is used as an instrument for *LOSS*.[14] We find a positive and significant coefficient on expected loss of 0.11, which falls beneath the range established by the corresponding OLS estimates of the upper and lower bounds. The remaining columns present the robustness checks that we explored in Table 3. Adding the market index for the previous sale date pushes up the estimate to 0.23, insignificantly different from our estimate of the lower bound from column (2) of Table 1. Replacing quarterly dummies for the date of entry reduces the coefficient substantially; it remains positive but is insignificantly different from zero. Finally, column (4) restricts the sample to the sub-sample of properties with loan-to-value of less than a half. This has the effect of increasing the IV estimate substantially, to 0.47.

Overall, the IV results are much less stable than the OLS estimates. In three of the four columns, the coefficients are positive and statistically significant, but are on both sides of the

[14]The t-statistic on the instrument in the first-stage regression is 41.

OLS upper and lower bounds. In general, these estimates may be less well identified than in the OLS specification. For example, consider the results in column (3), the only insignificant coefficient on *LOSS* so far. Although, in principle, identification of the loss effect at the aggregate level comes from variation in the combination of quarters of entry and previous sale, in practice, once the quarter of entry is controlled for, there may be insufficient variation in the latter to identify the loss effect. Also, the effect of a potential loss may be greater when the loss is incurred because of the seller's overpayment at the time of selling, than when it derives from movements in the overall market, which are out of control of the individual seller. Obviously, the IV estimates capture only the latter case.

Do Investors Behave Differently Than Owner-Occupants?

Approximately 40 percent of the units in our sample are owned by investors; the rest are owned by their occupants. It is interesting to ask whether we see differences in behavior between the two groups of owners. Perhaps the psychological pain in selling the house one lives in exceeds that in selling a mere investment. Or large investors might calculate the loss on their entire portfolio of houses, or even their entire portfolio of investment assets, although the vast majority of investors in this market are small ones.[15]

The sole evidence on the effect of ownership status on loss aversion is provided by Shapiro and Venezia (1998) who show that the disposition effect among professionally managed brokerage accounts, although it exists, is less than that of self-managed brokerage accounts.

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[15]Many of the investor owned units were acquired in the 1980s, a period of rising prices, by small investors (often the owner-occupant of a neighboring property) in anticipation of further capital gains. Others were originally purchased as owner-occupied units, but then rented out when the owner moved out. In some cases, the decision to rent rather than sell may have been related to the severe decline in prices and the thin market for sales in the early 1990s. However, market factors have not had a disproportionately large effect on owner-occupancy in downtown Boston. This area has had an active rental market throughout the 1980s and the 1990s and the percentage of investor-owned units did not increase greatly in the 1990s.

Bernartzi and Thaler (1995) had earlier argued that prospect theory should apply to professional investment managers whose performance is judged by individuals who apply the same behavioral principals when assessing their investments as to other aspects of their behavior. We know of no experimental evidence on this point. Our situation is somewhat different than that of brokerage accounts, however, for in the Boston condominium market, both types of sellers manage the sale of their property. Rather, investors and owner-occupants differ only according to whether the asset provides the owner with a direct consumption stream or not.

We classify a unit as owner-occupied if the Assessor's Office's record of 1/1/92 notes that the property owner applied for and was granted a property tax exemption, which the City of Boston grants to owner-occupants. This definition leads to two additional conditions on an observation's inclusion in the sub-sample used in the next set of regressions: 1) the listing date on the property must be after 1/1/92 and 2) there must be no sale between 1/1/92 and the listing date. An important maintained assumption is that a property does not change status between 1/1/92 and the date of listing. Discussions with Assessor's Office employees suggest that filings for a change of occupancy not associated with a sale are relatively rare. Of course, any mis-classification bias will make distinguishing between the behavior of both sets of owners more difficult.

The regressions in Table 5 compare owner-occupants to investors and strongly reject the null hypothesis that the two groups behave the same (p-value of .04). For example, in column (1) the coefficient on loss for owner-occupants is 0.50, about twice as large as the coefficient on investors. Nonetheless, the loss coefficient for investors of 0.24 is statistically significant and indicates that investors still raise their asking prices by about one-quarter of their prospective loss. Surprisingly, low equity has a larger impact on the asking price of investors than owner-occupants, although the difference is not statistically significant. Among those who are neither equity constrained nor face a potential loss, investors also set slightly lower asking prices than owner occupants. This result is a little bit surprising given that owner-occupants face higher direct costs of listing a property over time--and higher asking prices should lead to a longer expected time to sale--because potential buyers traipse through their house, interrupting meals and requiring a constantly clean home. Perhaps owner-occupants are overly optimistic in their listing behavior.

Correcting for possible unobserved quality in column (2) reduces the coefficients on prospective loss somewhat. The owner-occupant *LOSS* coefficient remains large and highly significant, while the investor *LOSS* coefficient, while remaining economically large, becomes statistically insignificant. Columns (3) and (4) add quadratic terms for the expected loss, with and without controls for unobserved quality. We find that the joint test on the linear and quadratic loss terms is statistically significant not only for owner-occupants but also for investors, with a p-value of .001 for each test. Strikingly, the major difference between the two groups is in the quadratic terms, indicating that differential behavior arises only for large losses, for which investors mitigate their marginal response much more than owner-investors do.

6. Selling Prices and Time on the Market

Skeptics might question the economic importance of asking prices, since these are not transaction prices. One might imagine that loss averse sellers set an asking price near their old purchase price, but have their thinking quickly corrected by the market, and so quickly cut their asking price. In this scenario, neither prices nor time on the market would show the influence of loss aversion.

The data indicate otherwise. Some degree of correction does occur, but it is only partial. The estimated coefficients on the final transaction prices are not as large as those earlier estimated for the asking price, but they are positive, although significant only for the upper bound. Part of the difference between the two sets of coefficients is explained by a lesser sensitivity to *LOSS* in asking price among those who eventually sell their property, rather than withdraw it from the market; part reflects a reduction in the loss effect from list price to sale price among realized sellers. There are effects in the time domain as well, with properties facing a prospective loss exhibiting a lower hazard rate of sale.

Sellers versus Non-Sellers

As a first test of the hypothesis that realized sellers exhibit less loss aversion than those who withdrawn their property from the market (withdrawers), Table 6 reports the results of rerunning the earlier list price regressions, conditioning on whether or not the property eventually sells.[16] Note that since the list price we use is that of the day of first listing, it reflects the seller's perceptions at that point. Columns (1) and (2) show that realized sellers exhibit a lower degree of loss aversion than withdrawers. An F-test rejects that the coefficients on *LOSS* are the same for the two subgroups at the 10 percent level. As in the earlier list price regressions, the coefficients in column (2) provide a lower bound for the coefficient on *LOSS*. Note also the coefficient on the dummy for a sold property, which indicates that among units not subject to a loss or equity constraints, properties that eventually sell had been listed at a 3 to 4 percent lower list price.

Columns (3) and (4) include a quadratic term for *LOSS*, which is highly statistically significant. As with investors versus owner-occupants, most of the difference in loss aversion for these two groups stems from the quadratic term. In both columns, the marginal effect of loss aversion diminishes much more quickly with the size of the loss for realized sellers than for withdrawers.

[16]A small fraction, x percent, of the properties that are not observed to sell, are actually right censored, rather than withdrawn from the market. Their inclusion does not affect our results.

Final Selling Prices

In considering the effect of loss aversion on transaction prices, we need to simultaneously estimate the market value, μ_{it}, and the loss. Thus we are unable to estimate the relationship using an auxiliary regression, as for the asking price, and must estimate the model in a single stage. We use nonlinear least squares to estimate[17]

$$
\begin{aligned}
(15)\quad P_{ist} &= \alpha_0 + \alpha_1 (X_i \beta + \delta_t) + m\, LOSS_{ist} + u_{it} \\
&= \alpha_0 + \alpha_1 X_i \beta + \alpha_1 \delta_t + m\,(P^0_{is} - X_i \beta - \delta_t)^+ + u_{it}
\end{aligned}
$$

and

$$
\begin{aligned}
(16)\quad P_{ist} &= \alpha_0 + \alpha_1 X_i \beta + \alpha_1 \delta_t + m\,(P^0_{is} - X_i \beta - \delta_t)^+ + \alpha_1 (v_i + w_{is}) + u_{it}, \\
&= \alpha_0 + \alpha_1 X_i \beta + \alpha_1 \delta_t + m\,(P^0_{is} - X_i \beta - \delta_t)^+ + \alpha_1 (P^0_{is} - X_i \beta - \delta_s) + u_{it}.
\end{aligned}
$$

These regressions yield upper and lower bounds, respectively, of the true LOSS coefficient, *m*. Table 8 shows our results. Column (1) shows our estimate of the upper bound on the coefficient on prospective loss to be 0.18, with a standard error of 0.02. This effect is about half of what we found in asking prices for the whole sample of owners. Two factors account for the difference. First, as the previous table showed, owners who withdraw from the market are more sensitive to loss than those who eventually sell. Second, although, as that table showed, the asking prices of eventual sellers also reflect loss aversion, with an upper bound coefficient of 0.27, that phenomenon is partially "corrected" by the market. Nonetheless, at least in the upper

[17] We write equation (16) in two ways to indicate that in estimating equation (16), we treat observations with a previous sale prior to 1990 differently than those with a prior sale after that date. For the first group, we use the residual from a price regression on the pre-1990 observations from Banker and Tradesman as our quality proxy, labeled in Table 7. For the second group, we use the term $P^0_{is} - X_i \beta - \delta_s$. We adopt this approach so as not to be forced to estimate quarter effects for pre-1990 observations on the basis of post-1990 prices.

bound, loss aversion is still present, and noticeably so, in the transaction prices.

Column (2) shows the results from estimating equation (16). The coefficient on LOSS, .03, is an estimate of the lower bound on the true effect. It is small and insignificant.

Finally, the coefficient on LTV in these equation is 0.06-0.07, and highly significant. It is interesting to note that, unlike LOSS, LTV has a similar effect on price as on listing price. As it represents an institutional constraint on sellers' behavior , rather than a psychological reluctance to sell, its effect does not diminish with learning or exposure to market conditions.

Evidence from the Estimated Hazard Rate of Sale

From the perspective of a search market, we would expect that if sellers facing a potential loss have higher reservation prices, as suggested above, then these sellers must also face a longer average time on the market, or equivalently, a lower hazard rate of sale. In fact, it would be quite puzzling if we did not find that sellers who obtained higher prices also had a longer time on the market.

This section estimates the contribution of loss aversion to the hazard rate of sale--the probability that a property sells in any given week given that an owner has listed the property for sale in LINK and that it has not yet sold. We specify the hazard rate as:

$$(16) \qquad h(t) = h_0(t)\exp(\theta Z)$$

where Z is a vector of attributes of the property and owner, and θ is a conformable vector of parameters. We also include other property attributes in equation (16) to allow for the possibility that the offer arrival rate varies according to quality or other unit characteristics.

We estimate the parameters by Cox's partial likelihood method. (Cox and Oakes, 1984). Units that remain listed but unsold at the end of our sample period, December 1997, are treated as right censored. Units that are de-listed without sale (go "off-market") are considered to be censored at their time of exit. Although some properties go "off market" because of exogenous changes in the conditions of the household, others exit when the owners become discouraged. Under the null hypothesis of no loss aversion effect on selling, the treatment of "off market" properties should have no effect on the estimated coefficients. Under the alternative that loss aversion does matter, the likely bias is positive if, precisely because they are less likely to sell, high loss properties are more likely to go off market. The presence of this bias will make the presence of loss aversion more difficult to establish.

As expected, the coefficients on the prospective loss terms in Table 7 are negative and highly statistically significant. To understand the difference in the estimates in Columns (1) and (2) first note the positive and significant coefficient on the Estimated Value in 1990, which indicates that high-quality properties have a higher hazard rate of sale. Thus the positive correlation between unobserved quality in the error term and in the *LOSS* term leads to a positive bias on *LOSS* in column (1). Following this line of reasoning, including our noisy proxy for quality in Column (2) would lead to a negative bias on *LOSS*. The results in the first two columns are consistent with that reasoning, and with our earlier findings on the bounds on the true coefficient estimates in the previous sections. The coefficients suggest that an owner facing a 10 percent prospective loss on a property will have between a 3 ($1\text{-}e^{-.033}$) and 6 ($1\text{-}e^{-.063}$) percent reduction in the weekly sale hazard, or an equivalent increase in the expected time to sale.

We add quadratic terms for *LOSS* in the columns (3) and (4) and once again get coefficients that are consistent with our previous results. Larger losses have a positive, but diminishing effect on the hazard rate of sale. This makes sense, given that sellers' marginal increase in their list price falls with the size of the prospective loss.

7. Concluding Remarks

This paper has shown that loss aversion affects seller behavior in the residential real estate market. Data from a boom-bust cycle in downtown Boston from 1990-1997 shows that sellers subject to losses: 1) set higher asking prices of 25-35 percent of the difference between the expected selling price of a property and their original purchase price; 2) attain higher selling prices of 3-18 percent of that difference, and 3) have a lower hazard rate of sale. The list price results are roughly twice as large for owner-occupants as investors, although they hold for both groups. For a given loss, the list price markup of realized sellers lies between the markup of withdrawers and the markup the sellers receive in the transaction price.

Our findings are relevant to two, seemingly disparate areas of economic research. That sellers in such a large market display loss averse tendencies gives added credence to papers that document such behavior in experimental settings. In addition, the shape of the implied "loss function" in our results is consistent with the convex shape of the value function in prospect theory. Future research should look to get parameter estimates for other markets.

The results of this paper also have broader implications for our understanding of real estate markets, and why they differ from perfect asset markets. First, the mere fact that transactions prices are determined by seller characteristics, whether that be through loss aversion or equity constraints, indicates that the market is far from being a perfect asset market. Second, a major finding of previous research is that volume falls when prices decline. This phenomenon cannot be explained by perfect asset models. Loss aversion and equity constraints can explain it, and we have shown in this paper that both forces are present. But the large size and significance of year dummies in the asking price regressions indicates that some third force must operate as well. We suspect that sellers' lagged adjustment to new market conditions is this third force, and we intend to explore that hypothesis in future research. At the same time, our findings make housing markets more difficult to understand. The presence of loss aversion and equity constraints imply that buyer valuations are more volatile than observed transaction prices , because at the trough of the cycle, many sellers are setting relatively high reservation prices.

Finally, from a policy perspective, our findings have important implications for the real estate market in the current macroeconomic environment. In the US, if regional economies begin to slow, an increasing number of sellers may face the prospect of a loss on their property. Given the current low level of US inflation, real estate markets will suffer large declines in trading volume as prices begin to fall. In Japan, real estate prices have fallen as much as 70 to 90 percent causing severe problems for the banking sector. Many policy observers have suggested that the Japanese government can solve the problem by injecting public money in the banking system and having banks write down the value of real estate debt. However, if potential sellers care about realizing a loss on their property, writing down debt levels will not be sufficient to lead to a quick or full recovery in the real estate market. Our evidence from Boston suggests that the possibility of a loss is a more important factor in explaining seller behavior than liquidity constraints.

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Appendix

This appendix describes our calculation of the expected biases in the coefficient on LOSS in the basic model of list price. Our primary purpose in calculating these biases is to ensure that our intutition on the sign of these biases, as described in the text, is correct. We also discuss the likely size of the biases.

In calculating the biases for each of the three models, we assume that the unobserved quality and idiosyncratic component, v and w, are each normally distributed, with mean zero and variances σ_v^2 and σ_w^2, respectively. By construction, the two are independent of each other. Although these variables are latent, we do observe their sum, so we will be interested in the conditional distribution of v, given $v + w$. This is a normal distribution with mean

$$(v+w)\sigma_v^2/(\sigma_v^2+\sigma_w^2)$$

and variance

$$\sigma_w^2\sigma_v^2/(\sigma_v^2+\sigma_w^2)$$

(Thus, e.g.,when the distribution of w is degenerate, knowing $v + w$ is equivalent to knowing v: the conditional mean of v is $v + w$ and its variance is zero; in contrast, when the variance of v is small compared to the variance of w, the conditional distribution is close to the unconditional distribution.) As our estimate of the variance of $v + w$, $\sigma_v^2 + \sigma_w^2$, we take the mean of the square of the residual from the first stage price regression described in Section 4, which is equal to $.35^2$.

We calculate the biases on a grid of σ_v^2, from zero (for which all the biases are zero) to $.35^2$. We drew 100,000 draws from the data set with repetition. With each draw, we associated a random draw of v from the distribution described above, conditional on the observed value of $v + w$ for that observation.

Let X be the $kX100,000$ matrix of data, where k is the number of regressors. Let $\widehat{m}^j$ be the estimate of the *LOSS* coefficient in model j. Thus $\widehat{m}^I = .35$, from Column (1) of Table 2. Our estimate of the first bias term in Model I is $B_1^I = (X'X)^{-1}X'v$. (We are asssuming that $a_1 = 1$.) Define the second error component (the errors-in-variable component) $\eta_1 = \max(0,\delta_s-\delta_t+w) - \max(0,\delta_s-\delta_t+w+v)$. Our estimate of the second bias term in Model I is $mB_2^I = m(X'X)^{-1}X'\eta_1$. Thus the overall bias for Model I is

$$\begin{aligned} B^I &= \widehat{m}^I - m = B_1^I + mB_2^I \\ &= (\widehat{m}^I B_2^I + B_1^I)/(1+B_2^I) \end{aligned}$$

(where we have left out the plims).

Likewise, our estimate of the first bias term in Model II is $B_1^{II} = -(X'X)^{-1}X'w$. Our estimate of the second bias term in Model II is $mB_2^{II} = m(X'X)^{-1}X'\eta_1$. (Note that $B_2^I \neq B_2^{II}$, since the set of regressors in the two models differ.) The overall bias for Model I is

$$B^{II} = (\widehat{m}^{II} B_2^{II} + B_1^{II})/(1+B_2^{II})$$

Finally, the bias in model III is

$$B^{III} = \widehat{m}^{II} B_2^{III}/(1+B_2^{III})$$

where $B_2^I = (Z'X)^{-1}Z'\eta_1$, and the Z is the matrix of instruments.

We find that B^I is always positive and increasing in σ_v, while B^{II} is negative and decreasing in the same. This accords with the intuition given in Section X, which is drawn from well known results of an unincluded regressor and errors-in-variables in bivariate regression model. Thus $\widehat{m}^I$ is indeed an upper bound, and $\widehat{m}^{II}$ a lower bound, for a consistent estimate of the true coefficient.

If the model of Section X is true, $p\lim(\widehat{m}^I - B^I) = p\lim(\widehat{m}^{II} - B^{II})$. This identifies a unique value of $\sigma_v : B^I - B^{II} = \widehat{m}^{II} - \widehat{m}^I = .1$ at $\sigma_v = .07$. As a check on this value, consider the coefficient on $(v + w)$ in Model II, which we estimate in Column (2) of Table 2 at .11. we calculated the bias on this coefficient in an analagous manner to the above. This bias increases from $-.97$ to $-.08$, as σ_v increases from zero to .35. At $\sigma_v = .07$, the calculated bias on the coefficient is $-.93$, which accords well with an estimated value of .11, and a ”true” value of 1.

B^{III}, the bias on the IV estimate of m, is always positive, increasing exponentially from zero to .03 at the maximum value. At $\sigma_v = .07$, the bias equals .001.

Table 1
Sample Means

Standard deviations in parentheses

Variable	All Listings	Listings That Were Sold
Number of Observations	5,785	3,408
1991 Assessed Value[a]	\$212,833 (132,453)	\$223,818 (135,553)
Original Asking Price	\$229,075 (193,631)	\$242,652 (202,971)
Sales Price	N.A.	\$220,475 (180,268)
Loan/Value (LTV)[b]	0.63 (0.42)	0.59 (0.41)
Percent with LTV[b] > 80%	38%	32%
Percent with LTV[b] > 100%	19%	15%
Percent with Last Sale Price > Predicted Selling Price[b]	55%	50%
Square Footage	936 (431)	977 (444)
Bedrooms	1.5 (0.7)	1.6 ().7)
Bathrooms	1.2 (0.4)	1.2 (0.4)
Months Since Last Sale	66 (37)	66 (38)

[a] The 1991 assessed value comes from the City of Boston Assessor's Office. It is the estimated market value of the property as of 1/1/90, the beginning of the sample period, and contains no information from sales after that date.

[b] The predicted value is for the quarter that the property enters the market and comes from a hedonic regression over the sample period using all sold properties. Regression results are available from the authors.

Table 2
Loss Aversion and List Prices

Dependent Variable: Log(Original Asking Price)
OLS equations, standard errors in parentheses

Variable	(1) All Listings	(2) All Listings	(3) All Listings	(4) All Listings
LOSS	0.35	0.25	0.63	0.53
	(0.06)	(0.06)	(0.04)	(0.04)
LOSS-squared			-0.26	-0.26
			(0.04)	(0.04)
LTV	0.06	0.05	0.03	0.03
	(0.01)	(0.01)	(0.01)	(0.01)
Estimated Value in 1990	1.09	1.09	1.09	1.09
	(0.01)	(0.01)	(0.01)	(0.01)
Estimated Price Index at Quarter of Entry	0.86	0.80	0.91	0.85
	(0.03)	(0.03)	(0.03)	(0.03)
Residual from Last Sale Price		0.11		0.11
		(0.02)		(0.02)
Months Since Last Sale	-0.0002	-0.0003	-0.0002	0.0004
	(0.0001)	(0.0001)	(0.0001)	(0.0002)
Constant	-0.93	-0.91	-0.97	-0.94
	(0.10)	(0.10)	(0.10)	(0.19)
R-Squared	0.85	0.86	0.86	0.86
Number of Observations	5,792	5,792	5,792	5,792

LOSS is defined as the greater of the difference between the previous selling price and the estimated value in the quarter of entry, and zero. LTV is the greater of the difference between the ratio of loan to value and 0.8, and zero. The standard errors are heteroskedasticity robust and corrected both for the multiple observations of the same property and for the estimation of Estimated Value in 1990, Estimated Price Index at Quarter of Entry and Residual of Last Sale.

Table 3
Loss Aversion and List Prices: Alternative Specifications

Dependent Variable: Log(Original Asking Price)
OLS equations, standard errors in parentheses

Variable	(1) All Listings	(2) All Listings	(3) All Listings	(4) All Listings	(5) L/V<0.5	(6) L/V<0.5
LOSS	0.35	0.24	0.40	0.29	0.37	0.28
	(0.06)	(0.06)	(0.07)	(0.07)	(0.10)	(0.11)
LTV	0.06	0.05	0.07	0.06		
	(0.01)	(0.01)	(0.01)	(0.01)		
Estimated Value in 1990	1.09	1.09	1.09	1.09	1.09	1.09
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Estimated Price Index at Quarter of Entry			0.90	0.83	0.75	0.72
			(0.03)	(0.04)	(0.05)	(0.05)
Residual from Last Sale Price		0.11		0.10		0.06
		(0.02)		(0.02)		(0.02)
Estimated Price Index at Quarter of Last Sale			-0.10	-0.06		
			(0.02)	(0.02)		
Months Since Last Sale	-0.0002	-0.0003	-0.0004	-0.0004	0.0004	0.0003
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0002)
Dummy Variables for Quarter of Entry	Yes	Yes	No	No	No	No
Constant			-0.94	-0.91	-0.99	-0.95
			(0.10)	(0.10)	(0.17)	(0.17)
R-Squared	0.86	0.86	0.86	0.86	0.84	0.84
Number of Observations	5,792	5,792	5,792	5,792	1,999	1,999

See Notes to Table 3.

Table 4
Loss Aversion and List Prices: Instrumental Variables Estimates

Dependent Variable: Log(Original Asking Price)
IV equations, standard errors in parentheses

Variable	(1) All Listings	(2) All Listings	(3) All Listings	(4) L/V<0.5
LOSS	0.11	0.23	0.02	0.47
	(0.05)	(0.06)	(0.05)	(0.08)
LTV	0.10	0.08	0.11	
	(0.01)	(0.01)	(0.01)	
Estimated Value in 1990	1.08	1.08	1.07	1.09
	(0.01)	(0.01)	(0.01)	(0.01)
Estimated Price Index at Quarter of Entry	0.78	0.84		0.79
	(0.03)	(0.04)		(0.05)
Estimated Price Index at Quarter of Last Sale		-0.06		
		(0.02)		
Months Since Last Sale	-0.0003	-0.0004	-0.0003	0.0004
	(0.0001)	(0.0001)	(0.0001)	(0.0002)
Dummy Variables for Quarter of Entry	No	No	Yes	No
Constant	-0.76	-0.83		-1.08
	(0.11)	(0.12)		(0.17)
Number of Observations	5,792	5,792	5,792	1,999

See Notes to Table 2. LOSS is treated as endogenous. Instruments include exogenous variables as well as the greater of minus the change in the aggregate price index between the quarter of previous sale and the quarter of listing, and zero.

Table 5
Loss Aversion and List Prices: Owner-Occupants versus Investors

Dependent Variable: Log(Original Asking Price)
OLS equations, standard errors in parentheses

Variable	(1) All Listings	(2) All Listings	(3) All Listings	(4) All Listings
LOSS X Owner-Occupant	0.50	0.42	0.66	0.58
	(0.08)	(0.09)	(0.08)	(0.08)
LOSS X Investor	0.24	0.16	0.58	0.49
	(0.12)	(0.12)	(0.06)	(0.06)
LOSS-squared X Owner-Occupant			-0.16	-0.17
			(0.14)	(0.14)
LOSS-squared X Investor			-0.30	-0.29
			(0.02)	(0.02)
LTV X Owner-Occupant	0.03	0.03	0.01	0.01
	(0.02)	(0.02)	(0.01)	(0.01)
LTV X Investor	0.05	0.05	0.02	0.02
	(0.03)	(0.03)	(0.02)	(0.02)
Dummy for Investor	-0.019	-0.020	-0.029	-0.030
	(0.014)	(0.013)	(0.012)	(0.011)
Estimated Value in 1990	1.09	1.09	1.09	1.09
	(0.01)	(0.01)	(0.01)	(0.01)
Estimated Price Index at Quarter of Entry	0.84	0.80	0.86	0.82
	(0.04)	(0.04)	(0.03)	(0.03)
Residual from Last Sale Price		0.08		0.08
		(0.02)		(0.02)
Months Since Last Sale	-0.0002	-0.0003	-0.0001	-0.0002
	(0.0002)	(0.0002)	(0.0001)	(0.0001)
Constant	-0.98	-0.96	-1.02	-1.00
	(0.13)	(0.13)	(0.13)	(0.13)
R-Squared	0.85	0.85	0.86	0.86
Number of Observations	3,687	3,687	3,687	3,687
P-value for test: Coefs on Loss and LTV are equal, Owner-Occupants & Investors	0.04	0.03	0.03	0.02

See Notes to Table 2.

Table 6
Loss Aversion and List Prices: Sold and Unsold Properties

Dependent Variable: Log(Original Asking Price)
OLS equations, standard errors in parentheses

Variable	(1) All Listings	(2) All Listings	(3) All Listings	(4) All Listings
LOSS X Unsold	0.45	0.34	0.61	0.50
	(0.06)	(0.06)	(0.06)	(0.06)
LOSS X Sold	0.27	0.16	0.60	0.49
	(0.08)	(0.08)	(0.04)	(0.04)
LOSS-squared X Unsold			-0.16	-0.16
			(0.09)	(0.09)
LOSS-squared X Sold			-0.29	-0.29
			(0.02)	(0.02)
LTV X Unsold	0.04	0.04	0.03	0.03
	(0.02)	(0.02)	(0.01)	(0.01)
LTV X Sold	0.06	0.06	0.03	0.02
	(0.02)	(0.02)	(0.01)	(0.01)
Dummy for Sold	-0.03	-0.03	-0.03	-0.04
	(0.01)	(0.01)	(0.01)	(0.01)
Estimated Value in 1990	1.09	1.09	1.09	1.10
	(0.01)	(0.01)	(0.01)	(0.01)
Estimated Price Index at Quarter of Entry	0.88	0.81	0.93	0.86
	(0.03)	(0.03)	(0.03)	(0.03)
Residual from Last Sale Price		0.11		0.11
		(0.02)		(0.02)
Months Since Last Sale	-0.0002	-0.0003	-0.0002	-0.0003
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Constant	-0.98	-0.96	-1.01	-0.99
	(0.10)	(0.10)	(0.10)	(0.10)
R-Squared	0.86	0.86	0.86	0.86
Number of Observations	5,792	5,792	5,792	5,792
P-value for test: Coefs on LOSS and LTV are equal, Sold and Unsold Properties	0.09	0.06	0.07	0.06

See Notes to Table 2.

Table 7
Loss Aversion and Transaction Prices

Dependent Variable: Log(Transaction Price)
NLLS equations, standard errors in parentheses

Variable	(1) All Listings	(2) All Listings
LOSS	0.18	0.03
	(0.03)	(0.08)
LTV	0.07	0.06
	(0.02)	(0.01)
Residual from Last Sale Price		0.16
		(0.02)
Months Since Last Sale	-0.0001	-0.0004
	(0.0001)	(0.0001)
Dummy Variables for Quarter of Entry	Yes	Yes
Number of Observations	3,413	3,413

Nonlinear least squares estimation of the equation $P = X\beta + T\theta + m\text{LOSS} + g\text{LTV}$, where $\text{LOSS}=(P^0 - X\beta - T\theta)$, X is a vector of property attributes, T is a set of dummies for the quarter of sale, P^0 is the previous sale price and LTV is as defined in Tables 2. In column (2), the right hand side is expanded to include a term that for observations with a previous sale prior to 1990 equals the Residual from the Last Sale, as in the previous tables, and for the remaining observations is equal to $(P^0 - X\beta - S\theta)$ where S is a set of dummies for the quarter of previous sale, of the same dimension and mapping as T. LTV is the greater of the difference between the ratio of loan to value and zero. The standard errors are heteroskedasticity robust and corrected for multiple observations of the same property.

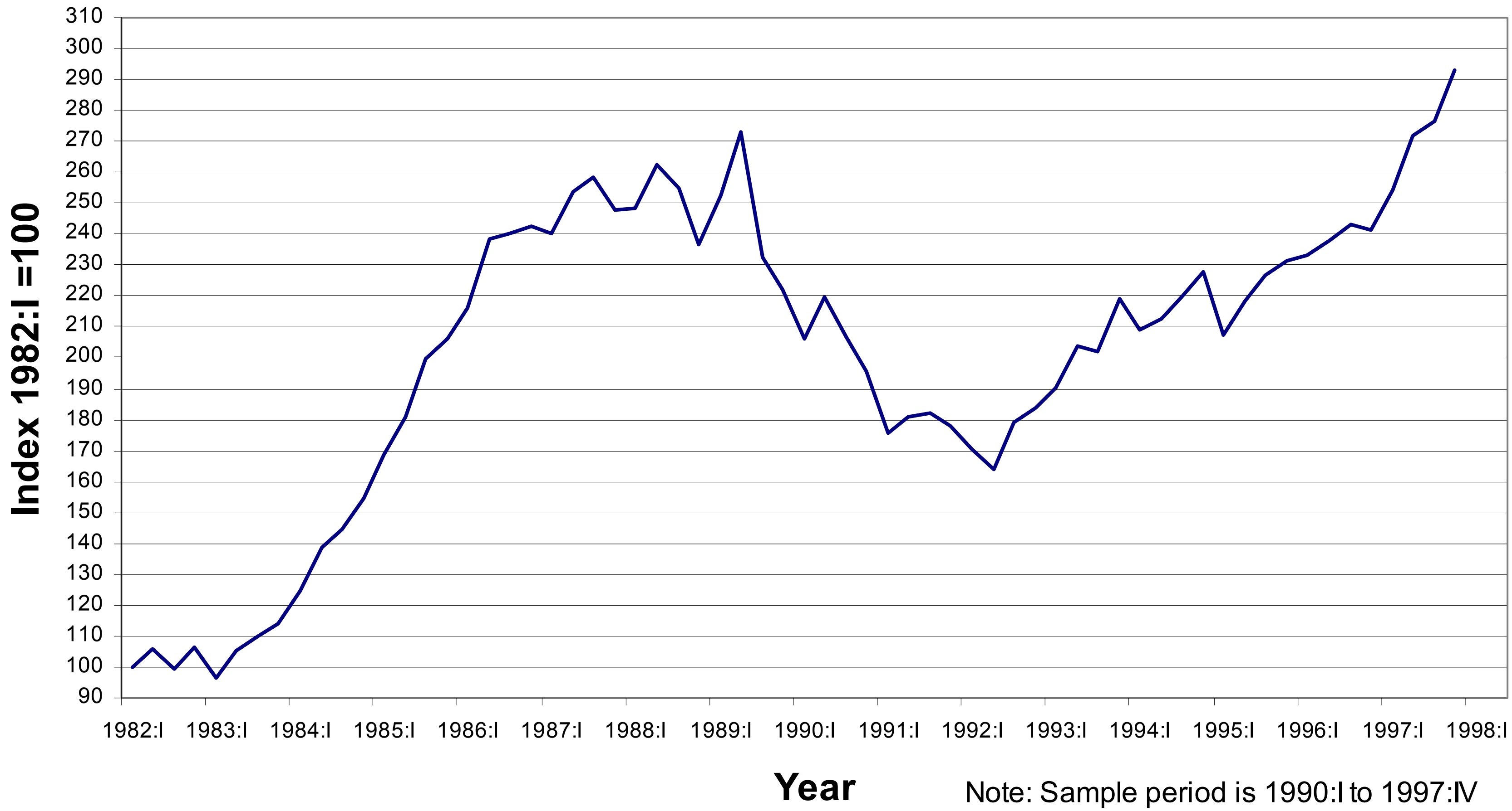
Table 8
Hazard Rate of Sale

Duration variable is the number of weeks the property is listed on the market
Cox proportional hazard equations, standard errors in parentheses

Variable	(1) All Listings	(2) All Listings	(3) All Listings	(5) All Listings
LOSS	-0.33	-0.63	-0.59	-0.90
	(0.13)	(0.15)	(0.16)	(0.18)
LOSS-squared			0.27	0.28
			(0.07)	(0.07)
LTV	-0.08	-0.09	-0.06	-0.06
	(0.04)	(0.04)	(0.04)	(0.04)
Estimated Value in 1990	0.27	0.27	0.27	0.27
	(0.04)	(0.04)	(0.04)	(0.04)
Residual from Last Sale		0.29		0.29
		(0.07)		(0.07)
Months Since Last Sale	-0.003	-0.004	-0.003	-0.004
	(0.001)	(0.001)	(0.001)	(0.001)
Dummy Variables for Quarter of Entry	yes	yes	yes	yes
Log Likelihood	-26104.4	-26094.1	-26101.8	-26091.3
Number of Observations	5,792	5,792	5,792	5,792

See Notes to Table 2.

Figure 1
Boston Condominium Price Index



Note: Sample period is 1990:I to 1997:IV