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Abstract

This paper investigates whether sellers in the housing market are loss averse, which is argued to be the source for the positive correlation between prices and volume in housing markets. With a sample of repeated purchases-to-listings covering the period 2005-2020 and using observed appraisal values to measure sellers' price expectations, estimation yields no loss aversion effect. The results suggest that sellers who receive appraisal values suffer less from loss aversion bias than what previous studies find. In contrast, using hedonic predictions yields a significant effect, highlighting the issue of substituting price expectations with predictions. I interpret the findings as indicating that sellers who receive appraisals and know that buyers can observe these, are not only better informed than others, but also feel constrained in their list price choice.

Keywords: *Loss aversion; Housing market; Bias; Price expectation*
JEL classification: *D91; R21; R31*

1 Introduction

This paper asks whether sellers in the Oslo housing market are nominally loss averse in the list price choice. In housing market busts, the positive price-volume correlation can be explained by sellers not willing to sell their housing units at the current expected market prices, thus giving longer time-on-market and list prices above expected market prices. This accumulates to a larger unsold inventory. Similarly in booms, housing markets are characterized by shorter time-on-market and smaller unsold inventory.

A possible reason for this kind of seller behaviour is that they are loss averse: they expect a utility loss from selling when their market price expectations are below some reference points.

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Facing this prospective loss makes the sellers put list prices above the price expectations, hoping to match with buyers willing to pay the higher prices.[1]

To investigate whether sellers are loss averse, I use data from the Oslo housing market and utilize a new measure of sellers' own market price expectations, namely the appraisal values provided by surveyors shortly before the units are listed. In short, the results suggest that sellers do not exert loss aversion in the list pricing in this particular market. The findings suggest that institutional factors are important for loss aversion exertion in list prices, and also highlights potential issues with identifying loss aversion when trying to capture price expectations using hedonic predictions.

Loss aversion is rooted in prospect theory by Kahneman and Tversky (1979). They present an alternative model of expected utility which captures behavioral effects when economic agents are facing risk. Loss averse people dislike losing more than they like gaining, so that their decision making is affected by their aversion against losing. In the housing market literature, the seminal paper using micro-level data of listings and transactions to identify the effect are Genesove and Mayer (2001) (hereafter GM). They present an empirical framework to identify loss aversion among sellers, which consists of modelling the list price as the expected price and the potential prospective loss. Thus, the loss aversion effect in the market are estimated on the intensive margin choice of list price. GM find a significant loss aversion effect in the 1990s Boston condominium market. Using a sample of repeated purchases-to-listings in the Oslo housing market in the 2005 to 2020 period, consisting of 32,000 observations, I estimate the GM model with the extension of adding the prospective gain to the model, as proposed by Bokhari and Geltner (2011). The GM approach is to use hedonic predictions as substitutes for the expected market price, which with the Oslo sample results in a significant loss aversion effect. The estimates suggest that a seller facing a prospective loss of 10 percent is associated with increasing the list price by between 4.2 and 6.1 percent. In comparison, in the Boston condominium market, GM estimates the effect to be between 2.5 and 3.5 percent.

In studies of loss aversion in housing markets, hedonic predictions or indices are used to capture the unobserved market price expectation. By construction, predictions fail to account for all variation in the true values, making the predictions suffer from measurement error. The measurement error consists of three unobserved parts, the constant heterogeneity, the time-varying heterogeneity, and the deviation between the expected market price and the actual selling price. These are all omitted variables that may lead to bias in the estimates of the effect, which is apparent from the two estimation results consisting of a lower and an upper bound of the true effect. A recent paper investigating loss aversion and addressing the unobserved heterogeneity problem is Andersen et al. (2022). They use a structural model approach

[1]A fishing strategy; higher list prices are put at the expense of longer time-on-market. See Figure C.1 in Appendix C for a visualization of the positive price-volume correlation in Oslo.

to quantify the effect of loss aversion among Danish homeowners, and assess the measurement error issues by implementing different approaches of predicting prices, giving a kink at zero prospective gains for all approaches. Yet, some sources of bias still remains even with their implementations, so that the question about unobserved heterogeneity remains. Their proposed alternative methods reveal the difficulties of inferring from prediction-based models, thus motivating the use of an observed price rather than a predicted price.[2] In turn, this leads me to use appraisal values to capture the price expectations.

Until mid-2016, appraisal values were used as supplements in marketing and indicating the market value of housing units. Appraisal values were supplied by surveyors as part of evaluating the technical condition of the units.[3] There are several advantages of using the appraisal values compared to hedonic predictions. From an econometric point-of-view, the appraisal value is decided upon by an expert that actually visits the housing unit. Considering the appraisal values as a prediction, more of the heterogeneity absent from the data are available to the surveyor, such as quality and view. Moreover, the fact that sellers are supplied with appraisal values is a key institutional factor playing into the list price setting for two reasons. First, the sellers' expectations may shift when given expert opinions (Northcraft & Neale, 1987; Tversky & Kahneman, 1974). Second, when buyers can observe these appraisal values, sellers feel constrained in their list price setting, so that they do not put list prices above their respective appraisal values. Therefore, the low degree of asymmetric information, and that sellers update their expectations according to the expert opinion, mitigate the effect from potential loss aversion on list prices. This is evident from the estimation results, which suggests that there is no such loss aversion effect on list prices once the appraisal value is taken into account.

A new question arises, namely why there is a difference between the hedonic-based and the appraisal-based outcomes? In principle, the appraisal-based outcome should yield an estimate between the lower and upper bound from estimating the hedonic-based model. One possibility for this gap is the usage of predictions as explanatory variables. If appraisal values are the true determinants of list prices and sellers are not affected by loss aversion in the list price setting, then the key to this gap must be that there are issues with the hedonic model. To provide some insights into the difference between the two, I build upon the reduced form investigation of GM, and find that when accounting for unobserved time-varying heterogeneity, this could explain why the proposed lower bound may not be a lower bound. Estimating a model with

[2]For instance, as presented in Andersen et al. (2022), autocorrelated unobserved heterogeneity could still bias the estimates when applying the repeated sales models. Also, in the case of only a single repeated sale, the feasible variables of interest reduces to be the same as studied by Bracke and Tenreyro (2021), meaning prospective gains/losses in aggregate prices. Hence, the choice of prediction method is important for inference of the causal relationship.

[3]The practice of using surveyors is very common in Norway. In mid-2016 surveyors stopped providing appraisal values but surveyors are still hired for technical evaluations.

hedonic predictions that take more information into account results in lower estimates of the effect, indicating that unobserved heterogeneity indeed could be important for inference.

When using fitted values of appraisal values instead of observed values, the estimates suggest that the choice between selling price and appraisal values cannot alone be what drives the gap. The fitted appraisal-based results are about the same as the selling price prediction-based results, being the hedonic-based results. Adding the residual from the appraisal value model estimation as a control variable for unobserved heterogeneity in the hedonic model, and using the resulting predictions in the main list price model, makes the loss aversion effect disappear, supporting the claim that unobserved heterogeneity is the most important driver of the gap.

Furthermore, I estimate models in which I add the different expectation substitutes as the main list price determinant and in the prospective loss and gain, so that the models mix between the substitutes. For instance, a model is estimated using hedonic predictions as the main list price determinant and using appraisal values as substitutes in the prospective loss and gain. This is done to establish whether the measurement error in the prospective terms, or in the main list price determinant, is what produces the wedge. Coefficient estimates suggests that there is a spillover effect from the main determinant to the prospective terms. Interestingly, adding more noise to this main determinant, while keeping the hedonic-based prospective terms unchanged, gives higher estimates of loss aversion for the hedonic-based model. Together with unit-fixed effects estimations, the investigation of the gap supports the notion that the size of the loss aversion estimates may come from measurement error in predictions, and that the hedonic-based list price model suffers from differential Berkson error (Berkson, 1950; Haber et al., 2021).

To test the robustness of the results, I show that appraisal values serve as an upper bound for the list price. Appraisal values explain more of the variation in list prices than other substitutes, including hedonic predictions. By following Graddy et al. (2022) in their approach to identify endowment effects in art auctions, I split the data into a short holding time and long holding time, making it possible to assert the potential effect of more unobserved heterogeneity for the estimates. There is a stronger effect for those with long holding time. Rather than interpreting this being due to the endowment effect, I propose that the stronger effect for longer holding time comes from the tendency of these units suffering more from unobserved heterogeneity. Further, as a robustness check of the hedonic-based models, I estimate a model with appraisal values as the dependent variable. Surveyors are professionals and should not be affected by sellers' preferences. However, if some surveyors are biased, one may expect smaller effects than what the list price model produces. The results indicate that the surveyors are as loss averse as sellers, even in the lower bound estimate, which again suggests that the hedonic-based model produce too high estimates. Finally, sensitivity test of functional forms suggest that using predictions in estimations of the relationship creates a reference dependence effect, and that the hedonic-based loss aversion effect comes from choice of functional form.

My findings nuance the current literature on the subject matter. Although replication with some adjustments give results encompassing the existing literature, utilizing an observed price expectation substitute results in insignificant loss aversion. Supplying sellers and buyers with third-party estimates of the market prices, no matter how precise these estimates are, could shift expectations and incentivize constraining-like behavior in the list price decision. Considering these sellers as more informed than those not getting appraisal values, if they truly are loss averse, this bias is mitigated by the new information and the fact that buyers would also observe this prediction, making the heuristic bias disappear in the list price setting. Thus, the deviation from previous studies may simply be explained by institutional differences. Yet, I find evidence suggesting that unobserved heterogeneity may play a sizable role for the difference. While the positive price-volume correlation prevails in the Oslo market, even when sellers are not exerting loss aversion in list prices, a more fitting explanation for the correlation may be the local market information friction explanation provided by Anenberg (2016).

This paper contributes to mainly two different strands in the literature, namely the loss aversion in housing markets literature (e.g., Andersen et al., 2022; Anenberg, 2011; Bokhari and Geltner, 2011; Einiö et al., 2008; Genesove and Mayer, 2001; Lamorgese and Pellegrino, 2022) and the more loosely related literature applying the GM intuition of measuring prospective terms based on predictions (e.g., Bracke and Tenreyro, 2021; Giacoletti and Parsons, 2021). The contribution to these strands is two-fold. First, the evidence suggests that sellers in the Oslo housing market are not exerting loss aversion in the list price setting, highlighting the importance of the institutional factors for the market. Second, the gap between the results from the hedonic-based and the appraisal-based models exemplify the issues with omitted variables and unobserved heterogeneity when estimating the effect. As presented in this paper, using hedonic predictions could have consequences for inference.

The rest of the paper is structured as follows. Section 2 describes the data, the cleaning of the data, and the institutional background. Section 3 presents the identification framework and the estimation results from the Oslo market. This is followed by an investigation of the differing estimation results between the hedonic-based model and appraisal based model in section 4. Robustness testing is presented in 5, and the conclusion in 6.

2 Data and Institutional Details

2.1 Description

The data used in this paper come from two sources. Housing transactions are provided by Eiendomsverdi AS, a private firm that provides, among other things, market price predictions of real estate properties in commercial banks' mortgage portfolios, and a tool for assessing values of other properties often used by financial advisors and realtors.[4] The data set include unique consistent identifiers for housing units and individual sellers and buyers, and covers the period 2003 to 2021 for the 20 largest municipalities in Norway, as measured by population size. There are only sold dwellings in the data and no withdrawn listings. The other variables included are the roles of each individual in each transaction and their ownership share, selling and list prices, but no revisions, dates for when the units are listed and sold, different attributes, such as zip code, dwelling type, and ownership type.

Background information about sellers and buyers consists of administrative data from Statistics Norway (SSB). The data have a panel structure for the period 2005 to 2019, and are only gathered for people actually being actors in the housing markets in the municipalities in the transaction data. The variables included are different income, debt, and wealth variables, all being measured at the end of the year.

To avoid errors in the data to spill into estimation results, the data were cleaned. There are different ownership types in Norway. The most usual type is self-ownership, but co-ops are also common and in practice not much different from self-ownership.[5] Typically, in larger cities, there are a large share of apartments that have co-op ownership. Both these types are included in the data. Before 2007, there were no organized registration of ownership of co-ops, but after 2007 all co-op units were registered in the Land Registry just like self-owned units. Transaction data of co-ops before 2007 are therefore removed from the data.

The data cleaning process continued as summarized in Table C.1 in Appendix C. The sample containing dwellings sold once, or more, are used to fit hedonic regressions in order to predict prices.[6] In order to get a repeated structure, the transactions sample are reduced to contain only repeat purchases-to-listings, i.e., only listings in which the seller(s) are the same as the buyer(s) in the preceding sale of that same housing unit. Naturally, there are few observations in the first couple of years. Also, there are no debt available for 2020, which is information needed for the analysis, so I restrict the data to the period 2005Q1 to 2020Q4.

Previous studies typically use loan-to-value (LTV) to control for effects of being equity-constrained. The actual mortgage related to the dwellings are not available in the data, so I use debt-to-value (DTV), meaning the total debt relative to an estimated market value,[7] in

[4]Eiendomsverdi AS is owned by some of the largest commercial banks in Norway. The value assessment tool is based on an automatic valuation model of house prices. Eiendomsverdi AS gathers information from different public sources and realtor firms, and combines these data to a unique commercial data set.

[5]The main difference between the two is the ownership structure. Self-owners own their own housing units. With co-ops, the co-op association owns the building, each homeowner owns a share of the association with a unique right-to-reside to their respective housing unit. Also, there is no stamp duty for buyers of co-op units, while self-owner units have a stamp duty tax of 2.5 percent.

[6]More information of these regressions are given in Appendix A.1.

[7]DTV is truncated from below at 0.85, so that $DTV^{trunc} = (DTV - log(0.85) - 1)^{+}$, with DTV being the difference between the log of total debt and log market value. This difference is subtracted with $log(0.85) + 1$ (≈ 0.85), the log-equivalent to a 85 percent DTV cutoff. While the current equity requirement of 15 percent is for the actual mortgage (meaning a maximum LTV of 85 percent), the 0.85 cut-off on the DTV is chosen

which the total debt is all registered debt aggregated on sellers of each transaction as of the end of the year preceding the listing. This introduces some lag to the debt but ensures that I have a measure of the equity-debt situation when listing.

The data include appraisal values, meaning market price estimates given by surveyors that have inspected the housing units prior to listings. There is a structural break in these values, due to a transition in mid-2016 from using appraisal values to an alternative estimation method among realtors in Norway. There are a few observations with appraisal values after June 2016, which I remove from the sample when estimating models with appraisal values.

Effectively, this means that I am left with two subsamples, one that is used when not needing appraisal values and one for models including appraisal values. The hedonic subsample consists of 32,044 observations and covers the period January 2005 to December 2020, and the appraisal value subsample consists of 16,111 observations and covers the period January 2005 to June 2016. Summary statistics of the repeated purchases-to-listings samples are presented in Table 1.[8] Note that all prices include common debt, if any, which is typically a shared debt among apartments in the same building.[9]

Comparing to the non-repeated summary statistics in Table C.2, the repeated data seem to be representative for the Oslo housing market, which consists largely of sales of apartments, with a majority being self-owned. The repeated sample has a smaller average size and more apartments, which makes sense because smaller apartments should be sold at a higher frequency, serving as temporary market entrance units.

Note that only the latest list prices are included, and no earlier revisions, which could affect estimation results on list prices since initial list prices may be higher in some cases.[10] Potentially, the estimates could become lower as loss averse sellers should hypothetically put higher list prices than others. Table 2 shows the distribution of repeated sales in the repeated sales data. The fact that many units are sold multiple times such that they have multiple repeated sales is a feature utilized for unit fixed effects, used to deal with unobserved time-invariant heterogeneity in the estimations.

to capture those being close to the limit but not necessarily so. Two different market values are used in the estimations presented below: when hedonic predictions of log selling price are used, the log market value is substituted with the predicted log selling price, and when appraisal values are used, the substitute is the log appraisal value.

[8]See Figure C.2 in Appendix C for histograms of annual observations for both subsamples, and Table C.2 for summary statistics of the non-repeated data and the raw repeated data.

[9]Common debt is usually a result of renovations of shared features of a building, such as the exterior.

[10]Based on data from the second largest Norwegian realtor company, DNB Eiendom, which include list price revisions but no unique identification numbers for housing units, about 76 percent of transactions does not have revisions, while about 16 percent have one revision.

Table 1: Summary statistics

Variable	1st Qu.	Median	Mean	3rd Qu.
(A) *Hedonic subsample (N=32,044, Jan 2005–Dec 2020)*				
List price (MNOK)	2.58	3.37	3.73	4.40
Selling price (MNOK)	2.74	3.50	3.88	4.55
Predicted price at listing (MNOK)	2.69	3.51	3.82	4.53
List-Predicted spread (%)	-9.83	-3.37	-2.71	3.76
Size (m^2)	50	63	68	79
TOM (days)	9	10	19	16
Holding time (weeks)	129	198	222	289
Apartment (%)			92.60	
Self-owner (%)			57.25	
(B) *Appraisal subsample (N=16,111 Jan 2005–Jun 2016)*				
List price (MNOK)	2.10	2.69	3.07	3.63
Selling price (MNOK)	2.27	2.85	3.24	3.82
Appraisal value (MNOK)	2.15	2.72	3.12	3.70
List-Appraisal spread (%)	-3.06	-0.38	-1.78	0.00
List-Predicted spread (%)	-10.77	-4.26	-3.34	3.04
Size (m^2)	50	64	70	82
TOM (days)	9	11	18	14
Holding time (weeks)	117	180	198	258
Apartment (%)			91	
Self-owner (%)			66	

Notes: The table reports summary statistics for the two repeated purchases-to-listings samples from the Oslo housing market. Prices are reported in million Norwegian kroner, and include common debt. The reported predicted price are the exponential of the ones used in the analysis, meaning they should be smaller than if the hedonic specification was in a linear form due to Jensen's inequality for concave functions. Holding time is the number of weeks between previous date of sale and the date of listing. It does not include time from last sale until end of sample, which would have added a truncated duration of ownership of the current owners. TOM is the time-on-market measured as the number of days between the listing and the sale.

2.2 Market characterization and institutional background

The Norwegian housing market can be characterized as transparent. The market is regulated in order for buyers to have as much information as possible about units of interest. When sellers hire realtors,[11] the norm is to hire surveyors to get a technical report of the condition of the unit. This is done before listing, and the report is supplied in the sales-prospectus provided to potential buyers. The idea is to hire a professional surveyor to reduce the risk burden of selling a unit without being fully transparent of potential hard-to-observe qualities, either good or bad. These surveyors are the same that supplied appraisal values until mid-2016.

[11]The Norwegian Real Estate Association reports that the share of market sales which use realtors is 98%.

Table 2: Frequencies of repeated sales

Repeated sales	1	2	3	4	5	6
Hedonic subsample	15,088	5,393	1,576	308	36	5
Appraisal value subsample	10,299	2,312	344	34	4	

Notes: The table presents total number of repeated sales for unique units in the two subsamples. For instance, if a unit is observed sold three times, and the sellers and buyers match between observations, then this unit has two repeated sales. Although the sample are repeated purchases-to-listings each listing results in a sale, therefore these frequencies overlap with purchases-to-listings.

Judged by the short TOM, the Oslo market can be characterized as liquid. The median (mean) TOM in days is only 10 (19) days, suggesting two interesting aspects of the market. First, the TOM is very low compared to other countries. For instance, median TOM in the U.S. housing market is reported to be 69 and 66 days for 2019 and 2020, respectively (Realtor.com, 2022). It is common to conduct public showings about a week after the initial listing, hence, the median suggests that it is relatively common to successfully sell in the days after these showings. Second, some units are harder to sell. Even after dealing with outliers, the distribution is right-skewed.

In short, the sales process goes as follows. A realtor is hired by a seller, while potential buyers do not hire realtors. The realtor does all preparations of paperwork and marketing of the unit, including hiring a surveyor and a photographer. After receiving all that is needed, including the report from the surveyor about the technical condition and a market price estimate (appraisal value), the unit is listed with a list price and a detailed account about the unit. The internet marketplace Finn.no is the most commonly used place for listing real estate. Public showings are conducted and the auction is legally allowed to begin the first workday after the last public showing.[12] The auction is organized as an English auction, in which bids usually are received by the realtor in writing, often electronically, and all submitted bids are legally binding. There are no auctioneer, but the realtor keeps in contact with potential bidders and informs them about incoming bids. The auction can last several hours and ends when a bid is accepted by the seller, which is also legally binding.

Adding to this account of the sales process, one may question whether it is the seller or the realtor that decides the list price.[13] When a seller hires a realtor, the seller makes a decision based on a presentation of a total package presented by the realtor. The package includes an estimate of the total cost of the service to be provided and a rough estimate of the value of

[12] Bids can be received before this, but the expiration is not allowed by law to be shorter than until 12:00 PM at the first workday after the last public showing (Eiendomsmeglingsforskriften, 2007, §6-3). Bids with short expiration can be submitted after this time.

[13] In the Norwegian institutional setting, Anundsen et al. (2022) model the list price decision as the outcome of Nash bargaining between sellers and realtors.

the unit. Total cost includes the commission based on a commission rate (typically 2 percent) times the value estimate. The value can be the reference point for the price expectation of the seller and may be affecting the list price setting. However, if the seller is getting in contact with realtors in the first place, the seller probably already has an idea of what the unit is possibly worth. For markets in which appraisal values were used, such as the Oslo market, the value estimate presented by the realtor was meant to inform the seller about an approximate commission cost, and the surveyor would later come and give the appraisal value which would be a stronger determinant for the list price. One may think of this as the seller updating the expectation multiple times, in vein of Bayesian updating or anchoring-and-adjustment. Even if the seller had some initial expectation, this may shift based on the newly provided information. The appraisal value is the latest price estimate presented to the seller, potentially being the final source of shifting the list price before listing.

3 Identification framework

3.1 Genesove and Mayer (2001) framework

The models applied in this paper are based on the model presented in Genesove and Mayer (2001). Their identification framework captures prospective losses from two sources; aggregate prices and a micro-level purchase-specific term capturing whether the seller paid too much or too little for the unit they now are selling. Adopting mostly the GM notation, the ideal model takes the following form:

$$\begin{aligned} L_{ist} &= \alpha_0 + \alpha_1 \mu_{it} + m_l LOSS^*_{ist} + \epsilon_{it} \\ &= \alpha_0 + \alpha_1 \mu_{it} + m_l \left(P_{is} - \mu_{it}\right)^+ + \epsilon_{it}, \end{aligned} \tag{1}$$

in which L_{ist} denotes the log list price of unit i at the time of listing t. This list price is explained by the log expected market price, μ_{it}, and the nominal prospective loss that the seller faces when listing the unit, $LOSS^*_{ist}$. The prospective loss is defined as the difference between the log selling price when the unit was sold last time, P_{is}, and the log expected market price at the time of listing, truncated from below at zero. Thus, the $LOSS$-variable only takes non-negative values, being positive for prospective losses. Using this specification implies the assumption that sellers' reference points are what they paid for their housing units, so that they evaluate losses and gains in nominal terms from this reference point.

$$L_{ist} = \alpha_0 + \alpha_1 \left(X_i\beta + \delta_t + v_i\right) + m_l \left(\delta_s - \delta_t + w_{is}\right)^+ + \epsilon_{it}, \tag{2}$$

Further, equation (2) gives the reduced form of the ideal model. Here, the log expected market price takes the linear reduced form $\mu_{it} = X_i\beta + \delta_t + v_i$, in which X_i is a vector of the time-invariant attributes, while δ_t is the quarter of listing, and v_i is time-invariant unit-specific unobserved heterogeneity. The log selling price when the seller purchased the unit can be reduced in the same manner, but adding a term for whether the seller paid above, or below, the expected market price, so that $P_{is} = \mu_{is} + w_{is}$, in which $w_{is} > 0$ means that the seller paid above the log expected market price. Finally, ϵ_{it} is a disturbance which is assumed to have conditional mean of zero.

To estimate the relationship, the log expected market price, μ_{it}, is often substituted with the predicted log selling price from a hedonic regression, since the expected price is unobserved. Predictions from a hedonic model only accounts for observed variables, so that $\hat{P}_{it} = X_i\hat{\beta} + \hat{\delta}_t$. This means that both explanatory variables in equation (1) are substituted with proxies. GM discuss implications of substituting estimates for expected prices; the resulting estimate $\hat{m}_l$ could be upward biased. Adding the residual from the selling price prediction of the previous sale, $\epsilon_{is} = v_i + w_{is}$, is argued to give downward bias in $\hat{m}_l$. Some studies (e.g., Beggs and Graddy, 2009; Bokhari and Geltner, 2011; Graddy et al., 2022; Lamorgese and Pellegrino, 2022) utilize this lagged residual as a quality control to account for unobserved heterogeneity. This makes sense when the residual across multiple sales does not show tendencies of reversion, and if the selling prices are likely not influenced by over- or underpayment (w_{is}) compared to the expected market price. The usage of the lagged residual originates from GM, who use it to potentially downward bias the estimate, highlighting the importance of the over- or underpayment in this residual. Furthermore, unobserved attributes and any omitted functional forms of observed and unobserved attributes are assumed to be constant over time, thus being part of v_i. Nonetheless, it is reasonable to expect the true coefficient to be somewhere in the range between the two boundary values, $m_l \in (\hat{m}_l^{LOWER}, \hat{m}_l^{UPPER})$, when estimating the relationship with and without lagged hedonic residual.

3.2 Bokhari and Geltner (2011) extension

Bokhari and Geltner (2011) (hereafter BG) adds to the GM framework by adding the prospective gain as an additional explanatory variable, defined as $GAIN^*_{ist} = (P_{is} - \mu_{it})^-$.[14] There are mainly two reasons for including the gain. First, in prospect theory, loss aversion is the kink in the value function at the reference point (Kahneman & Tversky, 1984, p. 342). By only includ-

[14]Omitting this variable is done deliberately by GM: the sum of the loss and gain nests the residual proxy that is used to downward bias the coefficient estimate of m_l (Genesove & Mayer, 2001, p. 1241). Meaning, $LOSS_{ist} + GAIN_{ist} = \delta_s - \delta_t + v_i + w_{is}$, and the residual control is $v_i + w_{is}$. This is a reasonable concern in light of multicollinearity. However, it would be a greater concern if the loss and gain were added together as a compound of the two, and not included separately as suggested. By separating the two, this probably will result in different coefficients on the two, and the nested control will enter with a discontinuity. BG also argue that adding prospective gain together with the residual, ϵ_{is}, solves the GM identification problem.

ing prospective losses in the model, it is implicitly assumed that the coefficient on prospective gain (m_g) is zero. If this was the case, the estimate of m_l could identify the effect. But sellers facing gains may put lower list prices compared to the situation when they face neither losses nor gains.[15] Hence, the coefficient difference, $m_l - m_g$, is what identifies loss aversion among sellers.

Second, if prospective gain is important for the list price decision, it is an omitted variable contributing with positive bias on the loss coefficient. This is simply because prospective loss and gain correlates positively with each other.[16] A low share of prospective losses compared to gains means the bias from omitting prospective gains is larger, a feature that should be present in rising housing markets.[17]

The feasible model to be estimated which accounts for the prospective gain, without the lagged residual as a control variable, is given in equations (3) and (4). A review of the biases using this specification is presented in Appendix B.1.[18]

$$L_{ist} = \alpha_0 + \alpha_1 \hat{P}_{it} + m_l LOSS_{ist} + m_g GAIN_{ist} + \eta_{it} \tag{3}$$

$$\eta_{it} = \alpha_1(\mu_{is} - \hat{P}_{it}) + m_l \left(LOSS^*_{ist} - LOSS_{ist}\right) + m_g \left(GAIN^*_{ist} - GAIN_{ist}\right) + \epsilon_{it} \tag{4}$$

By adding the prospective gain, it is possible to consider whether there is no behavioral effect ($m_l = m_g = 0$), a pure reference-dependence effect ($m_l = m_g \neq 0$), or a loss aversion effect with, or without, reference-dependence ($m_l > m_g \geq 0$). For the loss aversion effect, the kink at the reference point should manifest in a stronger effect of facing a prospective loss, i.e., $m_l > m_g$. The intuition in this framework is not as straight forward as it may seem. Here, loss aversion is identified if loss averse sellers facing prospective losses actually put higher list prices than they otherwise would. This hinges on the assumption that sellers (unknowingly) believe that putting higher list prices could lead to higher selling prices. Applying the framework means that the "otherwise"-case does not only imply zero prospective loss but potential prospective gain. Using price estimates will, without rounding, give us no cases where there is no prospective losses or gains. And if they are not loss averse but there is an anchoring effect from the purchasing

[15] There can be many reasons for this, such as those facing gains being willing to trade off some gains for a faster sale.

[16] Let X be a random variable, then $X := (X)^+ + (X)^- = X_1 + X_2$. Because $X_1 X_2 = 0$, hence $E(X_1 X_2) = 0$, the asymptotic covariance is $Cov(X_1, X_2) = -E(X_1)E(X_2)$. Prospective gain has negative expectation so that the loss-gain covariance is positive. And from what is commonly known about omitted variable bias, the smaller the variance of the included variable, the stronger the bias.

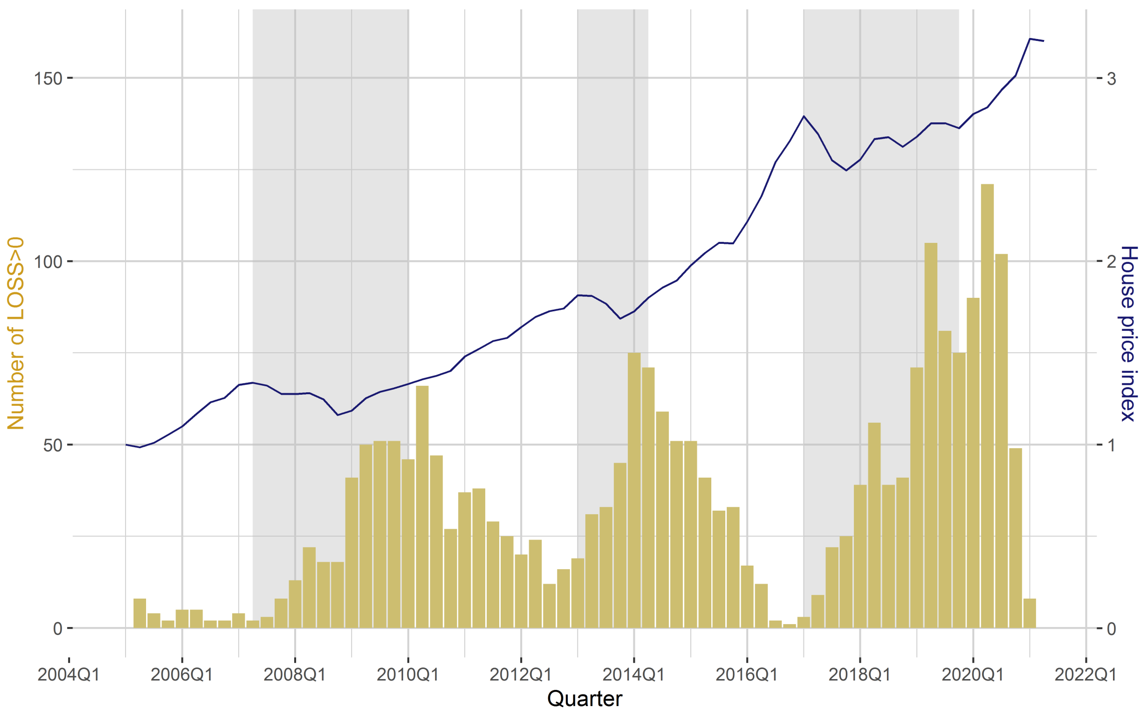
[17] Compared to the Danish replication in Andersen et al. (2022), the relatively larger share of gains versus losses in the Oslo sample can explain the discrepancy in coefficient estimates.

[18] The specification is actually the same as e.g., the right-hand-side in Lamorgese and Pellegrino (2022). They estimate $SB_{it} = \alpha_0 + \alpha_1 \hat{P}_{it} + m_l LOSS_{ist} + m_R R_{ist} + \eta_{it}$ with SB_{it} being the homeowner's stated belief about market price and $R_{ist} = LOSS_{ist} + GAIN_{ist}$. Therefore, the coefficient on prospective loss is the same as $m_l - m_g$ in equation (3). Graddy et al. (2022) also use this specification when estimating loss aversion and reference dependence in the art market.

price, sellers would care about deviations from this reference point. They then put a higher list price if facing prospective losses and a lower list prices if facing prospective gains, with the effect being at the same magnitude for losses and gains. Yet, my main focus is on the difference between the two coefficients.

In order to get a picture of distribution across quarters of the feasible prospective loss, it can be seen from Figure 1 how prospective losses appear in periods after a small price peak. Interestingly, the losses seems to appear at the highest frequency when the index is back at the peak level. Although the main driving force behind the occurrence of prospective losses should be reductions in the price level, several cases with over-payments ($w > 0$) in combination with small changes in aggregate prices may be the reason for the post back-to-peak cases.

Figure 1: Price index and number of prospective losses



Notes: The figure presents a price index based on a hedonic prediction of house prices using year-quarter of sale dummies (not the quarter of listing dummies). The prospective losses are found using a backward-looking hedonic regression approach. The shaded areas starts at peaks and ends when the index is back at the peak-level.

3.3 Using the appraisal as substitute

A recent contribution to the literature dealing with some of the unobserved heterogeneity problem is Clapp and Zhou (2020) and Zhou et al. (2022), showing how normalized assessed value (NAV) substituting the expected market price gives lower estimates of m_l in equation

(3) without the residual control. The problem with using tax-related assessed values is that these assessments are conducted on a 5-year cycle, and, with a fast moving market, there is potentially severe issues with lag in the valuations. However the benefit is that the assessors observe more than what the econometrician observes, so that variation in v_i is reduced. The normalization is done by adding town-year average log selling prices and the deviation between individual and town-year average of log assessed value. By doing this normalization, the NAVs for housing units in each town-year differs only due to the assessed value deviation, which is argued to deal with some of the issues with the lagged nature of assessed values.

In the Norwegian context, the NAV procedure on appraisal values is not necessary. The surveyors are visiting the units and appraisal values are put only a couple of weeks before listings, such that there is no issue with lagged values.[19] By utilizing the idea that the surveyors observe more than the econometrician, the appraised values can be used as substitutes for the expected market price. If we do not invoke the assumption of constant unobserved heterogeneity, the ideal specification becomes:

$$\begin{aligned} L_{ist} &= \alpha_0 + \alpha_1 \mu_{it} + m_l LOSS^*_{ist} + m_g GAIN^*_{ist} + \epsilon_{it} \\ &= \alpha_0 + \alpha_1 \left(X_i\beta + \delta_t + v_{it}\right) + m_l \left(\delta_s - \delta_t + v_{is} - v_{it} + w_{is}\right)^+ \\ &\qquad + m_g \left(\delta_s - \delta_t + v_{is} - v_{it} + w_{is}\right)^- + \epsilon_{it}, \end{aligned} \tag{5}$$

so that the prospective loss and gain depend on changes in the time-effect, the change in unobserved heterogeneity, and whether the seller paid above the expected market price for the unit. Denote the log appraised value at the time of listing as $P^{AV}_{it} = X_i\beta + \delta_t + \tilde{v}_{it}$, with $\tilde{v}_{it}$ capturing the additional heterogeneity observed by the surveyor. The feasible specification and its residual becomes:

$$\begin{aligned} L_{ist} &= \alpha_0 + \alpha_1 P^{AV}_{it} + m_l LOSS^{AV}_{ist} + m_g GAIN^{AV}_{ist} + \eta_{it} \\ &= \alpha_0 + \alpha_1 (X_i\beta + \delta_t + \tilde{v}_{it}) + m_l \left(\delta_s - \delta_t + v_{is} - \tilde{v}_{it} + w_{is}\right)^+ \\ &\qquad + m_g \left(\delta_s - \delta_t + v_{is} - \tilde{v}_{it} + w_{is}\right)^- + \eta_{it} \\ \eta_{it} &= \epsilon_{it} + \alpha_1 \psi_{it} + m_l \left(LOSS^*_{ist} - LOSS^{AV}_{ist}\right) + m_g \left(GAIN^*_{ist} - GAIN^{AV}_{ist}\right). \end{aligned} \tag{6}$$

ψ_{it} is the difference between the actual expected market price and the appraisal value, making it the surveyor mistake, so that the additional information observed by the surveyor ($\tilde{v}_{it}$) is part of v_{it}.[20] This means that the unobserved part is smaller for the surveyor than for the econometrician, so that $E|\psi_{it}| \leq E|v_{it}|$. Also, it is reasonable to believe that surveyors put different weights on the attributes observed by the econometrician and the time-effect,

[19] There are still some lag in the appraisal values, but not of the same order of magnitude as with tax-related (U.S.) assessed values.

[20] ψ_{it} comes from the log difference of the prices: $\mu_{it} - P^{AV}_{it} = v_{it} - \tilde{v}_{it} = \psi_{it}$.

however, deviations in functional form and implicit pricing are nested in $\tilde{v}_{it}$, so that the $X_i\beta$ and δ_t notation remains. The error term, ψ_{it}, does not enter $LOSS_{ist}^{AV}$ or $GAIN_{ist}^{AV}$ directly, but by splitting up the term $v_{is} = \tilde{v}_{is} + \psi_{is}$, it is clear that autocorrelation in surveyor errors could bias estimates of m_l and m_g upwards. The difference between ideal and feasible prospective loss and gain should now be smaller in magnitude than for the hedonic equivalent, as more of the unobserved is now observed. The surveyor, who visits the house and risking legal consequences if doing a poor job, usually observes more of a unit's characteristics, so that it could be reasonable to assume that ψ_{it} has conditional mean zero. An even stronger assumption is simply imposing $\psi_{it} = 0$, making the residual η_{it} collapse to ϵ_{it}, so that the ideal specification is identified.[21]

Finally, adding to the discussion of the identification by estimating equation (3), utilization of the appraisal value highlights another implied assumption when inferring from outcomes. If the price expectation is shared with potential buyers, then buyers will probably be less willing to pay the list price if this is above the price expectation. This hinges on whether the price expectation is common knowledge. As such, whether the true coefficient m_l in equation (5) is positive, and different from m_g, requires that the μ_{it} is available exclusively for the seller. Otherwise, the seller will know that buyers are observing a list price above the market price expectation, potentially making the seller less prone to increase the list price. This may not be the case for the m_g: if the seller expects to gain on a sale, she might put a lower list price to shorten TOM, being more willing to such a trade-off.

3.4 Results

The results of estimating the feasible model of equation (1) are shown in the first two columns of Table 3. I find an upper bound of 1.49 and lower bound of 0.43, in which the former is interpreted as a seller facing an increase of 10 percent in prospective loss is associated with increasing the list price by 14.9 percent, compared to what the seller otherwise would have done. These high estimates can be explained by the relatively few observed prospective losses; not only will sellers facing losses feel like deviants, but if there are omitted variables causing bias, this effect may be stronger, due to low variation in prospective losses in the Oslo sample.[22] Moreover, people facing losses knowing that they are deviating from the (current or historical) average could be more affected by facing losses than if it was more usual to do so. This argument relies on an amplitude effect from regret of paying too much, yet it should be captured through w_{is} taking higher values.

[21] The distribution of prospective appraisal-based losses are presented in Figure C.3.

[22] These are results of replicating the first two columns of Table 2 in Genesove and Mayer (2001) using the Oslo repeated purchase-to-listing data, and controlling for DTV rather than LTV. For the 1990s Boston condominium market, GM found that the effect is between 0.25 and 0.35, while replication in the Danish housing market by Andersen et al. (2022) resulted in an effect between 0.47 and 0.56. Although not stated explicitly, both these markets should have a higher share of positive prospective losses than the Oslo sample. It can also be argued that there are cultural differences that can partly explain the large differing results.

Table 3: Replicating GM and BG extension

	GM		BG	
	(1)	(2)	(3)	(4)
LOSS	1.490***	0.435***	0.924***	0.489***
	(0.102)	(0.078)	(0.075)	(0.077)
GAIN			0.317***	0.068*
			(0.017)	(0.038)
DTV	0.042***	0.027***	0.031***	0.029***
	(0.005)	(0.005)	(0.005)	(0.005)
Predicted base price	1.017***	1.026***		
	(0.012)	(0.009)		
Index	0.443***	0.439***		
	(0.011)	(0.011)		
Predicted price			1.037***	1.032***
			(0.008)	(0.007)
Previous residual		0.519***		0.464***
		(0.017)		(0.047)
log(Holding time)	0.004*	−0.012***	0.062***	0.0001
	(0.002)	(0.002)	(0.006)	(0.008)
Constant	−0.535***	−0.551***	−0.823***	−0.496***
	(0.174)	(0.145)	(0.117)	(0.106)
N	31,966	31,055	32,044	30,450
Adj. R sq.	0.937	0.958	0.953	0.960
LOSS>0 (% of N)	6.657	6.743	6.856	7.087
VIF LOSS	1.054	1.175	1.121	1.178
VIF GAIN			1.871	3.792
F-stat.(LOSS=GAIN)			61.859	56.819
p-value(LOSS=GAIN)			<0.001	<0.001
LOSS-GAIN			0.607	0.421

Notes: The table presents results from replicating the first two columns of Table 2 in Genesove and Mayer (2001), and by adding prospective gains and using a hedonic price rather than a base price and the index, as in Bokhari and Geltner (2011). Note that the GM-replication relies on different predictions than results in the two last columns, see Appendix A.1 and A.2 for more details. This is the reason for the different number of observations in the two model approaches. The dependent variable is log(List price), predictions have log(Selling price) as dependent variable. Holding time is in weeks. Standard errors are calculated using a wild bootstrap (R=1,000) and clustered on list year and 3-digit zip codes. Significance: * p<0.1, ** p<0.05, *** p<0.01.

The two last columns in Table 3 are the results of estimation with the BG extension. Compared to first two columns (GM), estimation of the relationship in equation (3) is done without separating the price predictions into a base price and an index,[23] and using price

[23] Not doing the separation in the GM replication gave almost the same results.

predictions based on the backward-looking approach as explained in Appendix A.1. Some additional information is given in the bottom of this table, namely a F-test of whether the coefficients on loss and gain are equal, with both the F-statistic and the p-value for the test. The difference between them is also given for convenience.

It seems that prospective gain was an omitted variable in the first two columns, as the upper bound is more than halved when including the gain. The difference is the additional effect of facing a loss when setting the list price, meaning that the interpretation is the same as when interpreting the coefficients in the first two columns. Due to the nesting of the lagged residual in the even numbered columns, the variance inflation factor (VIF) is provided. The VIF on prospective gain is 3.79 in column (4), indicating that adding the residual control makes the variance of the gain more inflated. In addition to the direct effect from the residual, there may be an additional effect through the prospective loss. Yet, the relatively small VIFs indicate that using the residual control together with the gain does not impose a threat.[24] Also, the point of adding the residual is to offset the upward bias and, as such, I intentionally include a control that should have common components to the variables of interest.

The results of estimating the relationship in equation (6) are presented in Table 4. In the first column, there is no longer a significant effect, and the coefficient difference is very small. Adding the lagged difference between the log selling price and the log appraisal value as a control variable for unobserved heterogeneity, resembling the residual control in the hedonic-based models, does not affect the outcome. Note that the model explains about 99.6 percent of the variation in the list price. Columns (3) and (4) use the hedonic-based model in equation (3) for the same observations as in the first two columns, showing an effect at the same order of magnitude as for the full sample. The rest of the sample period is covered in the last two columns, giving smaller estimates than the pre-cutoff period. The lower estimates in the later period probably is due to autocorrelation being less important in this period, because the shorter time period means lower frequency of multiple observation of the same units.

The results from estimating the appraisal-based model (6) suggest no loss aversion effect on list prices. Yet, the coefficient on prospective gain is significantly positive, with a probably explanation being that these sellers are more prone to trade off some of the selling price for a faster sale. There is a large gap between the two model outcomes, both in size and significance, which in light of the reduced-form investigation may come from the unobserved heterogeneity. I investigate this in more detail in the next section.

[24]Typical rule of thumb thresholds for multicollinearity are VIF above 5 or 10.

Table 4: Appraisal values as expected selling price

	(1)	(2)	(3)	(4)	(5)	(6)
LOSS	0.016	0.010	0.964***	0.609***	0.770***	0.398***
	(0.043)	(0.043)	(0.050)	(0.042)	(0.136)	(0.089)
GAIN	0.022***	0.021***	0.413***	0.181***	0.330***	0.066
	(0.003)	(0.003)	(0.019)	(0.032)	(0.030)	(0.052)
DTV	−0.003***	−0.003***	0.037***	0.035***	0.041***	0.037***
	(0.0005)	(0.001)	(0.006)	(0.006)	(0.005)	(0.007)
log(Appraisal value)	1.002***	1.003***				
	(0.002)	(0.002)				
Prev. log(SP)-log(AV)		0.002*				
		(0.001)				
Predicted Price			1.027***	1.023***	0.997***	1.012***
			(0.009)	(0.009)	(0.012)	(0.011)
Previous Residual				0.385***		0.492***
				(0.035)		(0.063)
log(Holding time)	0.005***	0.005***	0.055***	0.008	0.075***	0.001
	(0.001)	(0.001)	(0.005)	(0.005)	(0.008)	(0.015)
Constant	−0.075***	−0.082***	−0.636***	−0.385***	−0.262	−0.189
	(0.026)	(0.027)	(0.138)	(0.131)	(0.201)	(0.172)
Substitute for μ_{it}	P_{it}^{AV}	P_{it}^{AV}	$\hat{P}_{it}$	$\hat{P}_{it}$	$\hat{P}_{it}$	$\hat{P}_{it}$
Period	05Q1-16Q2	05Q1-16Q2	05Q1-16Q2	05Q1-16Q2	16Q3-20Q4	16Q3-20Q4
N	15,884	13,063	15,884	13,063	15,063	14,871
Adj. R sq.	0.996	0.996	0.950	0.956	0.929	0.943
LOSS>0 (% of N)	3.349	3.728	8.474	9.025	6.227	6.220
VIF LOSS	1.053	1.061	1.122	1.270	1.126	1.159
VIF GAIN	1.598	1.603	1.563	3.911	2.071	4.370
F-stat.(LOSS=GAIN)	0.020	0.078	112.345	138.147	7.661	30.009
p-value(LOSS=GAIN)	0.887	0.780	<0.001	<0.001	0.006	<0.001
LOSS-GAIN	-0.006	-0.012	0.550	0.429	0.440	0.332

Notes: Columns (1) and (2) use the appraisal values as substitutes for price expectations, using the appraisal subsample, while (3) and (4) use hedonic predictions as substitutes estimated using the same subsample. Columns (5) and (6) use post appraisal value cut-off observations from the hedonic subsample, meaning from 2016 Q3 to 2020 Q4. The dependent variable is log(List price), predictions have log(Selling price) as dependent variable. Holding time is in weeks. The market value in DTV is log of appraisal value in the appraisal-based models, while it is the hedonic prediction of log selling price in the hedonic-based models. Standard errors are calculated using a wild bootstrap (R=1,000) and clustered on list year and 3-digit zip codes. Significance: * p<0.1, ** p<0.05, *** p<0.01.

4 Understanding the gap

4.1 Assessing unobserved heterogeneity

4.1.1 Constant and varying unobserved heterogeneity

In what follows, I assess different sources of the gap between the hedonic-based and the appraisal-based estimation results. There are a couple of sources that can explain this gap.

Because more of the unobserved heterogeneity should be captured by using appraisal values, I start by looking into the assumption of constant unobserved heterogeneity.

To see how the assumption affects interpretation of the reduced-form results, I take a closer look at the part of the residuals originating from mismeasurement of prospective loss (or gain). The three different cases for $\Delta\ell = LOSS^*_{ist} - LOSS_{ist}$ to be considered are:

$$\Delta\ell = \begin{cases} (\delta_s - \delta_t + w_{is})^+ - (\delta_s - \delta_t + v_i + w_{is})^+ & \text{if } v_{is} = v_{it} & \text{(i)} \\ (\delta_s - \delta_t + v_{is} - v_{it} + w_{is})^+ - (\delta_s - \delta_t + v_{is} + w_{is})^+ & \text{if } v_{is} \neq v_{it} & \text{(ii)} \\ (\delta_s - \delta_t + v_{is} - v_{it} + w_{is})^+ - (\delta_s - \delta_t + v_{is} - \tilde{v}_{it} + w_{is})^+ & \text{if } v_{is} \neq v_{it} \text{ and } P^{AV}_{it} \text{ as } \hat{\mu}_{it}. & \text{(iii)} \end{cases}$$

By not imposing constant unobserved heterogeneity, moving from (i) to (ii), I get an additional source of losses, namely changes in unobserved heterogeneity. Examples of time-varying unobserved heterogeneity are deterioration, or renovation, of the unit, noisy neighbors, or densification worsening the view, which is not captured at the aggregate level. Furthermore, keeping the change in aggregate price level constant, a totally renovated apartment should increase the probability of facing a gain while a heavily decayed unit should increase the probability of facing a loss. I do not capture this change in the observed term but only the unobserved quality level at the previous sale.

In case (i), the unobserved heterogeneity makes the observed prospective loss include more noise than the unobserved, so that in an isolated case and disregarding the non-linearity of the terms, it is reasonable to expect this giving attenuation. Case (ii) has less terms in the observed compared to the unobserved prospective loss, so that the mismeasurement gives less variation in the observed loss. In case (iii), I still have less variation in the observed loss, but this should be much closer to the true loss than in the other cases.

The issue when not imposing constant unobserved heterogeneity is not the same as in the (classical) measurement error case. When considering measurement error, one usually think of this as additional noise or missing data, but now there is less information in the observed variable than in the unobserved variable. This is related to Berkson measurement error (Berkson, 1950). In a recent paper considering consequences of Berkson error, Haber et al. (2021) show how two types of Berkson error could lead to biases, so that in the worst case scenario one could get spurious results.[25] They also show that Berkson error could lead to opposite signs on coefficients. However, in case when an explanatory variable suffers from Berkson error in form of random noise, one should not worry about this, as it results in attenuation.[26] Berkson error in the model framework is discussed in more detail in Section 4.2.

[25] Two types are non-differential and differential Berkson errors. In the former, the residual from predicting P_{it} does not correlate with explanatory variables in the main specification, while in the latter they do.

[26] This can easily be seen from a simple measurement error example. Let $y = \beta x + \epsilon$ be the causal model, which we estimate as $y = \beta\tilde{x} + \tilde{\epsilon}$, with $\tilde{x} = x - u$ and $\tilde{\epsilon} = \epsilon + \beta u$. Then $\hat{\beta} \xrightarrow{p} \beta\sigma^2_x/(\sigma^2_x + \sigma^2_u)$, in which σ denotes the standard deviation.

On the other hand, when using appraisal values, the unobserved heterogeneity should be smaller, not only because the surveyor observes the time-invariant but also the time-varying unobserved heterogeneity. If treating appraisal values as estimates, and the hedonic-based model suffers from Berkson error, I should be more worried about hedonic predictions than appraisal values. Assuming constant v_i makes us disregard a possible cause of why some sellers face losses, which again can affect interpretation of how the measurement error in prospective variables affect estimates.

4.1.2 Unit-fixed effects

A feature of the data that can bring us closer to a better estimate of the potential effect of loss aversion on list prices is the repeatedness of the transactions. Although the Oslo market is relatively small compared to other markets, there are still multiple repeated repeat purchases-to-listings in the data, as presented in Table 2. I use this feature to estimate housing unit fixed effects for balanced panels of these units. The two models in equations (3) and (6) are estimated for two panels each, namely panels of two-times and three-times repeated purchases-to-listings. Only units observed exactly with two (three) repeated purchases-to-listings are included, so that this also serves as a robustness check. Both pooling and unit fixed effects (hereafter FE) models are estimated for each balanced panel.

In Table 5 the pure hedonic-based model (3) and the pure appraisal-based model (6) are estimated for two-times repeated observations, making estimation equivalent to a first differences. For the hedonic unit FE estimates, the effect is smaller and more in line with GMs results, but the residual control does not bias the estimate downward. The reason for this may be the demeaning of the residual control within each housing unit, so that the first observation weights its non-lagged and lagged residual control by one half each. Yet, the smaller estimate indicates that there are unobserved constant heterogeneity affecting the estimates. Repeating the same exercise for the appraisal-based model still gives small and insignificant effect. The pooling estimates on these observations are all over in line with my previous results, see Table C.4 in the Appendix. Unit FE estimations on a balanced panel of three-times repeated purchases-to-listings give even smaller estimates, as presented in Table C.5 in the Appendix. However, the sample size is small especially for the appraisal-based variants, so that there are few cases of positive prospective losses.

These results, together with the appraisal-based estimates showing no effect in Table 4, may indicate that the significant effect comes from unobserved heterogeneity. The unit fixed effects does not capture time-varying unobserved heterogeneity, which could be the reason why results in columns (1) and (2) still show significant effects. Adding to this notion, I estimate a model with aggregate prospective terms, meaning $LOSS_{ist} = (\delta_s - \delta_t)^+$ and the same for gains. The results are presented in Table C.6 in the Appendix, showing that there are some effects

Table 5: Unit fixed effect for two-times repeated purchases-to-listings

	(1)	(2)	(3)	(4)
LOSS	0.423***	0.488***	−0.082	0.048
	(0.049)	(0.053)	(0.088)	(0.091)
GAIN	0.106***	0.151***	0.019***	0.032***
	(0.017)	(0.023)	(0.006)	(0.006)
Substitute for μ_{it}	$\hat{P}_{it}$	$\hat{P}_{it}$	P_{it}^{AV}	P_{it}^{AV}
Residual control	No	Yes	No	Yes
N	10,324	10,324	4,026	4,026
Adj. R sq.	0.937	0.939	0.976	0.977
LOSS>0 (% of N)	7.294	7.294	4.148	4.148
VIF LOSS	1.134	1.156	1.073	1.096
VIF GAIN	2.075	2.969	1.457	1.575
F-stat.(LOSS=GAIN)	35.186	39.697	1.351	0.034
p-value(LOSS=GAIN)	<0.001	<0.001	0.245	0.854
LOSS-GAIN	0.317	0.337	-0.101	0.016

Notes: The table presents results of unit fixed effect using balanced two-times repeated observations subsamples of purchases-to-listings. The dependent variable is log(List price), predictions have log(Selling price) as dependent variable. The log of holding time in weeks, DTV, the constant term for the pooling estimates, the predicted price, the log appraisal value, and the residual control (lagged selling price/appraisal value difference) are omitted from the table. Standard errors are calculated using a wild bootstrap (R=1,000) and clustered on list year and 3-digit zip codes. Significance: * p<0.1, ** p<0.05, *** p<0.01.

of aggregate price levels, but these results disappear when the outside price is the appraisal value rather than the hedonic price prediction. I note that the price index, which is constructed from a linear hedonic model, could make the main model suffer from Berkson residuals so that adding the lagged residual from the backward-looking predictions biases the estimated effect upwards.

These results ultimately show that when dealing with constant unobserved heterogeneity, the effect is smaller, suggesting unobserved heterogeneity could be a crucial factor needed to be dealt with when estimating these models. And even the effect of aggregate loss and gain seems to disappear when the main list price determinant is the appraisal value.

4.1.3 Time-varying unobserved heterogeneity

In order to establish whether there is a problem caused by unobserved heterogeneity in the hedonic estimations, I add the residual from a hedonic estimation of the appraisal values as an explanatory variable in the hedonic model of the log selling price. This is the same procedure as presented by Anundsen and Røed Larsen (2018, p. 2144). This means including $e_{it}^{AV} = \hat{P}_{it}^{AV} - P_{it}^{AV}$, and then estimating the list price model with predictions $\hat{P}_{it}|_{e_{it}^{AV}} = X_i\hat{\beta} + \hat{\delta}_t + \hat{\beta}_e e_{it}^{AV}$ as substitutes. Effectively, e_{it}^{AV} should be a compound of what the econometrician do not observe but the surveyor does, and, as such, does not include the difference between actual selling price and price expectation (w_{it}). This gives the following feasible model to be estimated:

$$L_{ist} = \alpha_0 + \alpha_1 \hat{P}_{it}|_{e_{it}^{AV}} + m_l(P_{is} - \hat{P}_{it}|_{e_{it}^{AV}})^+ + m_g(P_{is} - \hat{P}_{it}|_{e_{it}^{AV}})^- + \eta_{it}. \tag{7}$$

By doing this three-step procedure, I ensure that if the residuals from the appraisal value estimation are irrelevant for the selling prices, they would not add more information to the predictions thus not affecting the list price estimates.

The results from estimating the relation is presented in Table 6. In columns (1) and (2) the loss aversion effect is somewhat smaller compared to the baseline hedonic-based estimates for the same sample period (see Table 4). Using unit fixed effects with these alternative predictions in columns (3) and (4) yields even smaller estimates.[27] This indicates that the appraisal value residual adds more information to the predictions, so that prospective loss and gain takes account for more of the time-varying unobserved heterogeneity.

4.1.4 Choice of dependent variable

As seen above, the appraisal-based model estimation gave insignificant results. This gives rise to the question about whether the hedonic-based results would be different if the dependent variable in the hedonic price model was the appraisal value. Modelling price expectations on selling prices implicitly assumes that the expectations follow the same movements and distributional properties of those prices. In markets where experts and their opinions are valued, the price expectations could be affected by these third-party actors. In the Norwegian setting, people listen to realtors and surveyors and anchor to their suggestions of list price setting. Moreover, if potential buyers observe the appraisal value as well, this may constrain sellers wanting to put list prices above appraisal values to not do so.[28] Thus, the appraisal value may be the better option.

By using the same hedonic specification as for the predictions of selling price, I assess whether there is something else going on than the choice of dependent variable that drives the gap. Formally, the feasible list price model to estimate is

$$L_{ist} = \alpha_0 + \alpha_1 \hat{P}_{it}^{AV} + m_l(P_{is} - \hat{P}_{it}^{AV})^+ + m_g(P_{is} - \hat{P}_{it}^{AV})^- + \eta_{it}, \tag{8}$$

[27] Pooling results on the same observations as in columns (3) and (4) gave estimates of 0.54 and 0.47 respectively, both significant at the 1 percent level.

[28] There might also be anchoring effects of sales that are close in distance in multiple dimensions, such as in time, space, and in characteristics of the housing unit.

Table 6: Unobserved heterogeneity through appraisal value residuals

	Eq. (7)		Eq. (7), unit FE		Eq. (8)	
	(1)	(2)	(3)	(4)	(5)	(6)
LOSS	0.491***	0.480***	0.314***	0.267***	0.889***	0.039***
	(0.083)	(0.082)	(0.086)	(0.085)	(0.035)	(0.009)
GAIN	0.071***	0.100***	0.054***	0.076***	0.396***	0.019***
	(0.012)	(0.017)	(0.007)	(0.011)	(0.019)	(0.003)
Residual control	No	Yes	No	Yes	No	Yes
N	15,153	11,936	4,264	3,132	15,949	15,949
Adj. R sq.	0.990	0.991	0.966	0.962	0.950	0.996
LOSS>0 (% of N)	2.831	3.050	3.612	4.119	12.283	12.283
VIF LOSS	1.044	1.055	1.090	1.116	1.146	1.272
VIF GAIN	1.617	1.694	1.521	1.711	1.573	2.131
F-stat.(LOSS=GAIN)	22.574	18.122	8.784	4.865	157.259	4.739
p-value(LOSS=GAIN)	<0.001	<0.001	0.003	0.027	<0.001	0.030
LOSS-GAIN	0.419	0.380	0.259	0.191	0.493	0.020

Notes: The table presents results using hedonic predictions with appraisal value residuals as a control variable, and using hedonic predictions of appraisal values as substitutes. The unit fixed effects use a balanced two-times repeat purchases-to-listings subsample. The dependent variable is log(List price). The log of holding time in weeks, DTV, price prediction, residual control, and the constant term are included control variables omitted from the table. Note that the unit fixed effects are conducted using demeaning, making the share of positive losses potentially misleading. Standard errors are calculated using a wild bootstrap (R=1,000) and clustered on list year and 3-digit zip codes. Significance: * p<0.1, ** p<0.05, *** p<0.01.

in which $\hat{P}_{it}^{AV}$ is the fitted value of log appraisal value. The results are presented in columns (5) and (6) in Table 6. Column (5) shows that the choice of dependent variable in this case does not matter for the estimates. In order to bias the estimates downward in column (6) the non-lagged residual is used as a control variable. This is done because the list price is decided upon after receiving the appraisal value. This residual is the same as used in the hedonic predictions in the first two columns, so that it captures what the surveyor observes but not the econometrician, making it a noisy proxy for both time-invariant and time-varying unobserved heterogeneity. Adding this makes the effect almost disappear, yet being significant at the 5 percent level. The two last columns are crucial in order to get insight into the bias that arises when estimating the relationship. While there is a strong upward bias when not including the residual control, adding the residual leaves a very small effect.[29]

[29] In equation (B.7) in the Appendix, adding the non-lagged residual means that I (approximately) eliminate $\alpha_1 v_{it}$.

4.2 Differential Berkson error

To get a better idea of the bias that are present when estimating the relationship in equation (3), I investigate the properties of *differential Berkson error*. The measurement error is differential when the residual from the prediction of expected market price is correlated with the dependent variable (Haber et al., 2021, p. 865). In my model, this means that the residuals from the hedonic prediction are correlated with the prospective loss and gain, or other control variables which also affect the list price. It is clear from the decomposition in Appendix B.1 that the residual $v_{it} + w_{it}$ from predicting $\hat{P}_{it}$ should be correlated with both $LOSS_{ist}$ and $GAIN_{ist}$ due to the part $v_{is} + w_{is}$. By letting the part of the residual w_{is}, w_{it} be identical and independently distributed, the correlation should come from a common time-invariant part of v_{is} and v_{it}.[30] Further, $LOSS_{ist}$ and $GAIN_{ist}$ suffer from differential Berkson error because they are constructed partly from the Berkson model of expected market price.

The reduced-form framework as presented in Appendix B.1 is a simple way of partly determining potential biases. Potential omitted variables in the list price model that correlate with the Berkson residual could complicate inference. This is why it is fruitful to investigate the biases more rigorously with the Haber-results. Assume that I estimate the list price model by following the GM approach of using $LOSS_{ist}$ alone (omitting prospective gains). For simplicity, leave out the subscripts. Assume that I observe $\hat{P}$ instead of μ, in which $\mu = \hat{P} + e$, and let $LOSS$ be the mismeasured $LOSS^*$. I let $LOSS$ be the prospective loss in the causal relationship, which is a simplification explained in further detail in Appendix B.2. The causal relationship is given by $L = \lambda_0 + \lambda_1 \mu + \lambda_l LOSS + \lambda_\pi \pi + \tilde{\eta}$, with $\tilde{\eta}$ being noise with standard normal distribution.

Denote the covariance between μ and prospective loss as $Cov(\mu, LOSS) = \sigma_{\mu,l}$, the variance as $Var(LOSS) = \sigma_l^2$, and assume $\sigma_{e,l} \neq 0$ (> 0), $\sigma_{\mu,l} \neq 0$ (< 0). Let neither of $\{LOSS, \mu\}$ correlate with the omitted variable(s) in the list price model. Assuming no correlation means that the true α_1 is estimated even when the causal relationship between list price and the other variables is not perfectly modelled. Meaning, I assume that there is no omitted variable bias in estimating λ_1, so that $E(\alpha_1) = \lambda_1$.

Further, omit one variable π when estimating the model. Let the list price residual $\eta = \lambda_\pi \pi + \tilde{\eta}$ with $\sigma_{\pi,e} \neq 0$ and $\sigma_{\tilde{\eta},e} = 0$, but for simplicity keep assuming $\sigma_{\pi,\mu} = \sigma_{\pi,l} = 0$. What I ultimately am left with is two sources of which the Berkson error, e, can affect the estimate of m_l: through $\hat{P}$ and through the omitted variable π. Then, it can be showed, see Appendix B.2, that the bias of estimating the relationship $L = \alpha_0 + \alpha_1 \hat{P} + m_l LOSS + \eta$ has the following

[30] For instance, letting $v_{it} = \nu_{it} + \omega_i$ with $\nu_{it} \overset{\text{iid}}{\sim} N(\mu_\nu, \sigma_\nu^2)$, in which the time-invariant part is ω_i.

form:[31]

$$E\left(\hat{m}_l(\hat{P}) - \hat{m}_l(\mu)\right) = \lambda_\pi \frac{\sigma_{\pi,e}(\sigma_{\mu,l} - \sigma_{e,l})}{\zeta} + \alpha_1 \frac{\sigma_{e,l}}{\sigma_l^2} \frac{(\sigma_\mu^2 - \sigma_e^2)\sigma_l^2}{\zeta}, \tag{9}$$

in which

$$\zeta = (\sigma_\mu^2 - \sigma_e^2)\sigma_l^2 - (\sigma_{\mu,l} - \sigma_{e,l})^2.$$

λ_π is the true coefficient on the omitted variable π. The bias consists of two parts, the first which is the bias from the correlation between the unobserved variable π in the list price model and the Berkson residual. The second is the bias from the correlation between the prospective loss variable and the Berkson residual. If these correlations are zero there is no bias. Also, the second part will disappear if the price prediction did not affect the list price ($\alpha_1 = 0$), or if the expected market price was perfectly observed ($\sigma_e^2 = 0$ giving $\sigma_{e,l} = 0$). Without an omitted variable correlating with the Berkson residual, there would still be bias. By construction, $\sigma_\mu^2 = \sigma_{\hat{P}}^2 + \sigma_e^2$, implying $\sigma_\mu^2 > \sigma_e^2$ if some variation in μ is accounted for in $\hat{P}$. Thus, the denominator is non-negative if there is a correlation between the prediction and the prospective loss, $\zeta \geq 0$.[32]

The sign on the second part depends on the covariance between the Berkson error, e, and $LOSS$, and the denominator, ζ, of the last fraction which is non-negative. Because the expected market price enters $LOSS$ with a negative sign, I likely have $\sigma_{\mu,l} < 0$, while recalling that $\sigma_{e,l} > 0$ due to the common time-invariant component, ω_i. Further, note that the difference between these are the covariance between the prediction and the loss, $\sigma_{\hat{P},l} \leq 0$. Therefore, the second part is likely to contribute with a downward bias in the estimate of m_l.

Considering the first part of equation (9), in general, one can expect omitted variables in the list price model to correlate with the residual in the price prediction because there could be common factors not observed that determine both. Even if these are not correlated with any other covariates in the list price model, the bias still enters with an unknown sign. If $\sigma_{\hat{P},l} < 0$ and $sign(\lambda_\pi) = sign(\sigma_{\pi,e})$, this bias is negative. But there could be unobserved heterogeneity, so that $sign(\lambda_\pi) \neq sign(\sigma_{\pi,e})$, which would yield a positive bias. This bias remains even when there is no correlation with the prospective loss and the Berkson error.

In order to say something more about the unobserved heterogeneity, Table C.3 in the Appendix shows the shares of observations with having a positive or negative sign in the periods $\{s, t\}$, split into those not facing and those facing an appraisal-based prospective loss. For those with positive loss, there is a higher share of under-valuation by the hedonic model in both periods. There is also a higher share of under-valuation in the first period and over-valuation in the second period for the positive losses. Whether under-valuation comes from positive unobserved heterogeneity or a random over-payment is hard to pinpoint. Investigating

[31]For assumptions regarding the predictions of $\hat{P}$, confer with Haber et al. (2021) Section 2.

[32]Note that $\sigma_{\hat{P}}^2 = \sigma_\mu^2 - \sigma_e^2$ and $\sigma_{\hat{P},l} = \sigma_{\mu,l} - \sigma_{e,l}$, so that $\zeta = \sigma_{\hat{P}}^2\sigma_l^2 - \sigma_{\hat{P},l}^2 \geq 0$.

this by simply regressing an indicator of positive loss on indicators of whether the sign on the residuals are positive, results in the average marginal effects presented in Table 7. On average, an under-valuation in s increases the probability of the appraisal-based loss being positive by 6.5 percent, while under-valuation in t decreases the probability by 1.6 percent. On the other hand, the hedonic-based prospective loss has a stronger effect from the first residual but a opposite sign from the second. Disregarding w_{is}, the latter could indicate a larger common time-invariant part, ω_i, positively determining the loss. The different signs of the former could indicate that some of the unobserved heterogeneity is accounted for.

Table 7: AME for indicator of positive appraisal-based loss on hedonic model residual signs

	(A) $\mathbb{1}\{LOSS_{ist}^{AV} > 0\}$			(B) $\mathbb{1}\{LOSS_{ist} > 0\}$		
	AME	SE	p-value	AME	SE	p-value
$\mathbb{1}\{e_{is} > 0\}$	0.065	0.007	$<$0.001	0.184	0.008	$<$0.001
$\mathbb{1}\{e_{it} > 0\}$	-0.016	0.004	$<$0.001	0.080	0.005	$<$0.001

Notes: The table reports the AME for logit estimation for an indicator for whether the seller faces a positive loss on indicators for the signs of the residuals, including an interaction term. In the prospective loss, μ_{it} is substituted with P_{it}^{AV} in panel A and with $\hat{P}_{it}$ in panel B. Standard errors are heteroskedasticity-robust. N=14,544 in panel A and N=30,138 in panel B.

In this highly simplified exercise, by assuming the prospective terms are correctly specified and assuming several zero correlations, having a control variable with Berkson measurement error and an omitted variable correlating with this error may bias the estimate. The two terms in equation (9) are seemingly independent of λ_l, so even if the true effect is zero ($\lambda_l = 0$), I can still get significant estimates.[33] There would still be bias even if there was no correlation between loss and the true market price μ. It all boils down to what I may consider to be a spillover effect. Further, by letting the measurement error in $\hat{P}$ be present in the loss, the total effect would be much harder to interpret.

Adding the residual from the hedonic price prediction, $v_{is} + w_{is}$, complicates interpretation. The bias expression now becomes even larger as the residual likely correlates with the other variables including the omitted variable π, so that there is no obvious way to interpret the sign on the bias expression (see Appendix B.2 for the full expression). Previous studies, such as GM, show that including the residual gives lower estimates than an estimation without the residuals, but whether a model with residuals suffers from upward- or downward bias is not clear. This is especially the case when accounting for correlated unobservables in the list price model and the hedonic model.

Applying the Berkson angle to the first two columns in Table 6, the Berkson bias is smaller

[33] The coefficient that partly determines the size of the bias is the coefficient on expected market price, which should be close to 1.

when the residual contains less factors correlating with the list price. Utilizing more information in the predictions therefore mitigate the bias. For the two last columns, the strong effect found by using fitted appraisal values iterates the point made by Haber et al. (2021), namely that using predictions instead of observed variables may inflate coefficient estimates of less important covariates.

4.2.1 Establishing the source of the biases

Recall specification (5). For convenience, I refer to the substitute of μ_{it} that is not part of the prospective terms as the outside price, while the substitute in the prospective terms is referred to as the inside price:

$$L_{ist} = \alpha_0 + \alpha_1 \underbrace{\mu_{it}}_{\text{outside price}} + m_l(P_{is} - \underbrace{\mu_{it}}_{\text{inside price}})^+ + m_g(P_{is} - \underbrace{\mu_{it}}_{\text{inside price}})^- + \epsilon_{it}. \tag{10}$$

In order to establish whether the bias comes from measurement error of the prospective terms themselves, or as a *spillover effect* from the outside price, I switch between the hedonic log selling price predictions ($\hat{P}_{it}$), the log appraisal values (P_{it}^{AV}), and the hedonic log appraisal value estimates ($\hat{P}_{it}^{AV}$) as substitutes for the outside and inside prices. This breaks up the common source of measurement error between the main list price determinant and the prospective terms, so that these measurement error are no longer the same.[34]

Table 8 shows results from estimating the main model with different substitutes for the outside and inside prices. The choice of control variables depend on what the outside price is. For instance, if the outside price is substituted with the hedonic prediction of log selling price, the classic GM residual control ($v_{if} + w_{if}$) is used, as in Table 3. This is done to counter the issue of unobserved quality being omitted (Genesove & Mayer, 2001, p. 1240). The other downward-biasing controls are as in Table 6.

Most importantly, the table shows that even with appraisal-based prospective loss and gain, using hedonic predictions as substitute for the outside price, there is a large significant effect in the upper bounds. Specifically, the hedonic predictions of selling price gives the strongest effect, while the appraisal value predictions gets lower estimates and has a insignificant lower bound. Yet, when using appraisal values as the outside price, while having hedonic-based prospective terms, the effect is very small and insignificant. The difference in how the hedonic selling prices and the hedonic appraisal values affect the estimates indicates that there is something more in the selling price residuals that leads to stronger bias. In light of the institutional setting and the fitted appraisal values results in Table 6, which also suffer from differential Berkson error, using the selling price as the dependent variable in the hedonic model gives a stronger upward

[34]The procedure relates to the interpretation of potential biases as presented in equation (9), in which I investigated the spillover effect of having measurement error in the outside price and an omitted variable.

Table 8: Mixing price substitutes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
LOSS	−0.005	−0.007	0.728***	−0.085	0.008	0.008	0.252	0.028
	(0.009)	(0.010)	(0.242)	(0.344)	(0.008)	(0.006)	(0.170)	(0.042)
GAIN	−0.004	−0.005	−0.134***	−0.487***	0.004*	0.003	−0.131***	0.020***
	(0.003)	(0.003)	(0.016)	(0.031)	(0.002)	(0.002)	(0.010)	(0.003)
Outside price	P_{it}^{AV}	P_{it}^{AV}	$\hat{P}_{it}$	$\hat{P}_{it}$	P_{it}^{AV}	P_{it}^{AV}	$\hat{P}_{it}^{AV}$	$\hat{P}_{it}^{AV}$
Inside price	$\hat{P}_{it}$	$\hat{P}_{it}$	P_{it}^{AV}	P_{it}^{AV}	$\hat{P}_{it}^{AV}$	$\hat{P}_{it}^{AV}$	P_{it}^{AV}	P_{it}^{AV}
Residual control	No	Yes	No	Yes	No	Yes	No	Yes
N	15,884	14,185	15,884	14,573	15,949	14,240	15,949	15,949
Adj. R sq.	0.996	0.996	0.916	0.970	0.996	0.996	0.921	0.996
LOSS>0 (% of N)	8.474	8.530	3.349	3.603	12.283	12.556	3.373	3.373
VIF LOSS	1.125	1.126	1.054	1.062	1.157	1.161	1.054	1.054
VIF GAIN	1.527	1.571	1.576	1.832	1.540	1.590	1.573	1.616
F-stat.(LOSS=GAIN)	0.034	0.054	13.360	1.511	0.197	0.432	5.072	0.036
p-value(LOSS=GAIN)	0.854	0.817	<0.001	0.219	0.657	0.511	0.024	0.849
LOSS-GAIN	-0.001	-0.002	0.863	0.402	0.004	0.005	0.383	0.008

Notes: The table presents results of mixing the substitutes of outside and inside prices. The dependent variable is log(List price), predictions have log(Selling price) or log(Appraisal value) as dependent variable. The first four columns use hedonic predictions of log selling prices, while the last four columns use hedonic fitted values of appraisal values. The log of holding time in weeks, DTV, the constant term, the outside price, and the residual control are omitted from the table. Standard errors are calculated using a wild bootstrap (R=1,000) and clustered on list year and 3-digit zip codes. Significance: * p<0.1, ** p<0.05, *** p<0.01.

bias.

These results suggest that the spillover effect from the main determinant of the list price is what drives the wedge between the hedonic-based and appraisal-based estimates. Thus, in order to identify loss aversion, the choice of substitutes in the prospective terms is not what drives the majority of the bias, but the choice of substitute for the main list price determinant.[35]

4.2.2 Sequentially adding information and noise

As established in Table 6, there is information in appraisal values that I do not capture by using predicted variables, which could be beneficial in my list price modelling. Rather than using the hedonic appraisal value residuals as a control variable in the hedonic prediction of selling prices, I follow the intuition from the evidence of the spillover effect by using the price predictions and weight in these residuals. By doing this, I sequentially add more information into the outside price, which should decrease the spillover effect, if any, from the Berkson error. Define a weight $\omega \in [0, 1]$ and a new compound price $\tilde{P}_{it} = \hat{P}_{it} + \omega e_{it}^{AV}$, in which $e_{it}^{AV} = P_{it}^{AV} - \hat{P}_{it}^{AV}$. I estimate

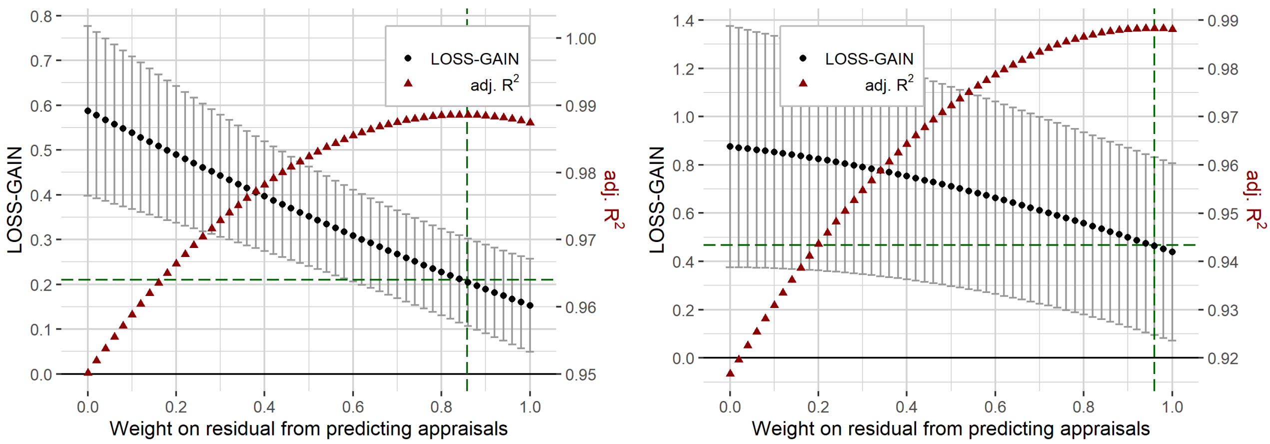
[35] This is at least the case for the sample containing relatively few positive prospective losses. The situation might be different if a larger share of listings have prospective loss.

the following specification for different values of ω:

$$L_{ist} = \alpha_0 + \alpha_1 \tilde{P}_{it} + m_l (P_{is} - \mu_{it})^+ + m_g (P_{is} - \mu_{it})^- + \eta_{it}. \tag{11}$$

I consider both the hedonic- and appraisal-based specifications. Results from estimating the relationship with my usual controls (DTV, log of holding time, a constant term) but without the residual control, are presented in Figure 2.

Figure 2: Effects of weighting in the appraisal value residual



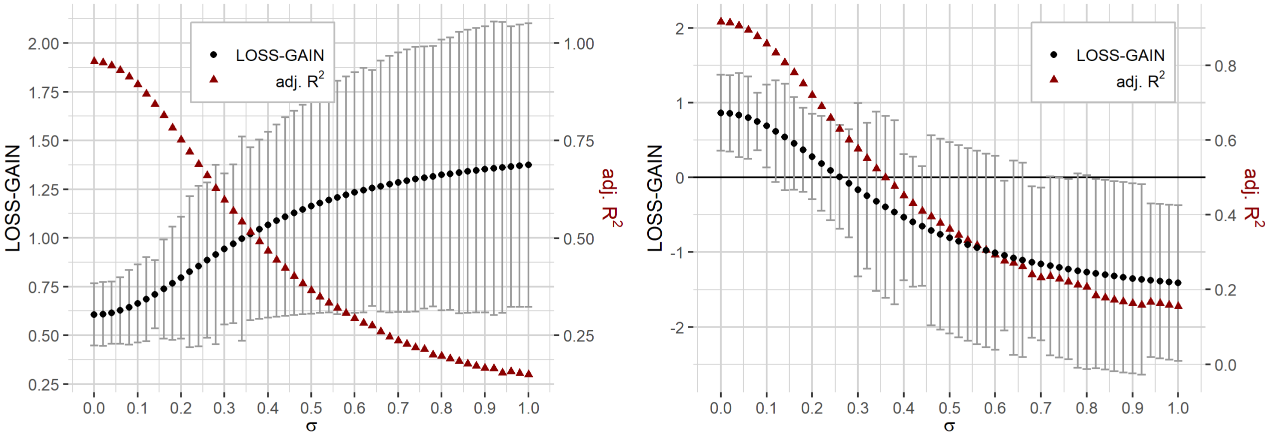
(A) Hedonic-based LOSS/GAIN (B) Appraisal-based LOSS/GAIN

Notes: The figure presents the difference between prospective loss and gain, a 95 percent confidence interval, and the adjusted R^2 for different weights, ω, in the compound price $\tilde{P}_{it} = \hat{P}_{it} + \omega e_{it}^{AV}$, in which $e_{it}^{AV} = P_{it}^{AV} - \hat{P}_{it}^{AV}$. Panel A shows the hedonic-based loss and gain difference, meaning using the hedonic price prediction as the inside price substitute. Panel B show the appraisal-based loss and gain difference. The green dashed lines represent the coefficient on the residual (x-axis) and the effect (left y-axis) when estimating a model keeping the residual as a separate explanatory variable. Standard errors are clustered on list year and 3-digit zip codes.

This procedure ensures that I account for different degrees of missing information. The coefficient on the outside price, which is now the compound price, is close to one. Therefore, adding the residual into this price ensures that the residual is weighted by approximately ω in the list price model. When adding the residual as a separate explanatory variable, the weight would be the coefficient, which is represented in the figure with the green dashed lines. As is clear from both panels, the estimated effect becomes smaller when more of the unobserved heterogeneity is included in the compound price. The effect is stronger for the hedonic-based loss and gain in panel A than panel B, yet putting $\omega = 1$ gives a significant effect.

In the same fashion of investigating the spillover effect, I add more noise. The noisy outside price substitute takes the form $\tilde{P}_{it} = \hat{P}_{it} + \xi$, with $\xi \sim N(0, \sigma^2)$. I estimate the relationship in equation (11) for a range of $\sigma \in [0, 1]$. Because the predicted price is in log scale, I restrict to a maximum of $\sigma = 1$, so that even a $\xi \sim N(0, 1)$ adds relatively much noise to the predictions.

Figure 3: Effects of adding noise, without lagged residual



(A) Hedonic-based LOSS-GAIN (B) Appraisal-based LOSS-GAIN

Notes: The figure presents the difference between prospective loss and gain, a 95 percent confidence interval, and the adjusted R^2 when adding noise $\xi \sim N(0, \sigma^2)$ with different standard deviations σ to the predicted price $\hat{P}_{it}$. For each $\sigma > 0$, the procedure of drawing ξ and estimating the coefficient difference is repeated 1,001 times and the median coefficient difference between loss and gain, with the corresponding confidence interval, is chosen to be plotted. This is done because the loss-gain coefficient distribution becomes normal when adding normally distributed noise. Panel A shows the hedonic-based loss and gain difference, meaning using the hedonic price prediction as the inside price substitute. Panel B show the appraisal-based loss and gain difference. Standard errors are clustered on list year and 3-digit zip codes.

Figure 3 tells two different stories.[36] When substituting the inside price with hedonic predictions, adding more noise to the hedonic outside substitute increases the estimated effect while also increasing the confidence interval. But when substituting the inside price with appraisal values, the effect becomes smaller: starting off positively significant and ending up negatively significant. What I implicitly do is to add more random noise to the Berkson residual. The same parts correlating with omitted variables and the different losses and gains are still in the residuals, but now there are more noise which obviously affect the outcomes. The spillover effect is particularly damaging to the hedonic-based models, indicating that a misspecified hedonic model could lead to stronger estimated effects, even if the error is not differential.[37]

In light of these findings, it may be relevant to ask why I should not estimate the relationship without the outside price substitute. This will lead to a classical omitted variable bias, and as such would be counter intuitive. With the institutional background of sellers being presented with appraisal values, the main take-home message is that using hedonic predictions in the list

[36]Figure C.4 in the Appendix adds the lagged residual in order to account for unobserved heterogeneity and potentially downward bias the estimates, showing the same pattern as in Figure 3.

[37]The reduced-form presentation of the model as presented in Appendix B.1 is not able to explain these results. I.e., in equation (B.8), the new residual becomes $u_{it} - \alpha_1 \xi$, in which ξ is independent and identically distributed.

price modelling could be misleading for inference, and that prediction-based models in general are more sensitive to misspecification.

5 Robustness

5.1 Explanatory power of predictions and appraisal values

A key concern about the choice of price expectation substitutes is how well the different substitutes explain the list price, and whether there is evidence of bunching, especially between the list price and appraisal value. Both hedonic predictions and appraisal values have high explanatory power on the list price. The additional variation explained by the prospective terms and control variables are limited. When comparing with list prices and selling prices, hedonic predictions show approximately normally distributed spreads, while the appraisal value spreads have strong bunching at zero. There are (almost) no positive spreads for the list price to appraisal values spread, which together with the strong zero bunching suggests that appraisal values may be affecting the list price choice (see Figure C.5 and Figure C.6).[38] Even though predictions are explaining log selling prices well, appraisal values are even better predictors. I interpret these findings as being consistent with the proposal of appraisal values being the preferred predictors of list prices (see Table C.7 and Table C.8).

5.2 Endowment effect or unobserved heterogeneity

Another core concern about the loss aversion identification is time-varying unobserved heterogeneity in the market. Graddy et al. (2022) study loss aversion and anchoring in the art market, and consider two subsamples, defined by different lengths of holding time, in order to identify the endowment effect. The endowment effect is identified if sellers are more loss averse when holding time is longer (Strahilevitz & Loewenstein, 1998), which they find evidence for.

When doing a similar exercise for the housing market, longer holding times should result in higher probability of time-varying unobserved heterogeneity being present in the prospective terms. If the estimates of hedonic-based models are biased due to unobserved heterogeneity, the estimated effect should be higher for longer holding time. The results are consistent with this, suggesting that there are time-varying unobserved heterogeneity that the surveyors might account for in their appraisal values (see Table C.9).[39]

[38] The spreads in Figure C.5 are trimmed on the 1st and 99th percentiles in order to get a cleaner visualization. There are 26 cases in the sample that have list price above appraisal value.

[39] The difference between lagged and non-lagged hedonic residual for the two subsamples show a larger empirical variance for the long holding time subsample, indicating more unobserved heterogeneity for this subsample. Note that the probability of facing a loss is lower when holding time increases, which is also present in the subsample for the longer holding times. The appraisal-based model did not get a significant effect for short holding time. But for long holding time the effect was negative and significant at the 5 percent level.

5.3 Surveyors being loss averse on sellers' behalf

A simple test of how the hedonic-based model performs is to check whether the significant effect is maintained when the dependent variable is the appraisal value. Surveyors are certified professionals, who likely would be offended if accusing them of adjusting their appraisal values according to sellers' preferences, which goes against the surveyors' own code of conduct (Norsk takst, 2022). Yet, there might be some surveyors that are biased towards the sellers' preferences, making it possible that appraisal values exhibit some of the loss aversion of the sellers. When substituting hedonic predictions for expected price, the results suggest that surveyors suffer from loss aversion at the same extent as sellers. The estimated effect is actually very close to the list price model as presented in Table 4 columns (3) and (4), indicating that the Berkson errors are biasing the estimates (see Table C.10).

5.4 No trimming

To address whether there are issues with the data trimming that creates the gap between the hedonic-based and the appraisal-based estimates, I estimate the main models using a non-trimmed data. The only observations that I remove are the top influencers based on Cook's distance in the baseline hedonic-based and appraisal-based model estimations. The results are on the same level as presented earlier, meaning that the gap remains, suggesting that there are no issues with the trimming (see Table C.11 and Figure C.7).

5.5 Hockey stick

Prospect theory implies a kink at the transition point from prospective losses to gains, when comparing to the list price premium, meaning the list price to price expectation spread. By letting the prospective terms being measured together continuously, captured by a reference dependence variable instead of splitting it at zero, a hockey stick pattern should emerge with a kink at zero. While the hedonic-based prospective terms give a hockey stick pattern, the appraisal-based prospective terms does not (see Figure C.8). Yet, the fitted appraisal-based relationship shows a hockey stick pattern. It looks like there are no clear cutoffs at zero for the prediction-based variables, so that in the hedonic-case, when including the quadratic and cubic functional forms of the prospective gain, I find that the coefficient on the prospective loss becomes insignificant. Together, this suggests that the bias from Berkson error in prediction-based models gives a reference dependence effect but no loss aversion effect when controlling for other functional forms. Even when disregarding the observed appraisal values, the modelling of the loss aversion effect with different slopes above and below the zero cutoff is ultimately coercing simple linear fits, while the relation is better modelled as a quadratic or cubic of a continuous reference dependence variable. (see Table C.12, in which the last columns are with the reference dependence variable instead of prospective gain).

6 Conclusion

Using repeated purchases-to-listings data from the Oslo housing market, this paper has shown that sellers may not be loss averse to the degree found in other housing markets. When replicating Genesove and Mayer (2001), the estimated effects of loss aversion are much higher than what they found in the Boston condominium market in the 1990s. There are several possible reasons for this large gap, yet a simple addition that reduces the gap is to add prospective gains to the model, as in Bokhari and Geltner (2011). Adding the prospective gain should reduce omitted variable bias.

Adding to the current literature, I investigate how an observable substitute for sellers' price expectations affects estimates. By substituting price expectations with appraisal values instead of predictions of selling prices, the effect disappears.

To explain the gap between the hedonic-based and the appraisal-based estimates, potential sources of the difference between the two substitutes are investigated. First, as previous studies also discuss (e.g., Genesove and Mayer, 2001), the hedonic predictions suffer from unobserved heterogeneity, which introduces biases. Second, when modelling the price expectations of sellers, the choice of dependent variable depends on the institutional setting, which in the Norwegian context could be appraisal values. Third, because predictions will not explain all variation in the dependent variable, there is a possibility that the residual from the price expectation model correlate with observables and unobservables in the list price model. Thus, the hedonic-based model suffer from differential Berkson error (Berkson, 1950; Haber et al., 2021). The potential biases are evaluated empirically by including more information in the hedonic predictions, by estimating the model using fitted values of appraisal values, by mixing between substitutes in the model, and by adding more noise to the predictions.

I find that sellers are less loss averse in the Oslo market than what is found in previous studies. A feasible explanation for this is the Norwegian institutional setting, in which sellers are supplied with third-party price estimates (appraisal values), making both sellers and buyers more informed, ultimately shifting price expectations and making the appraisal values the upper bound of list prices. If the model with hedonic substitutes was consistent in estimating the effect, estimation should have yielded results that mimic the appraisal-based model outcomes. This calls for more research of the effect when dealing with these unobserved factors, and on whether Norwegian sellers facing losses get higher selling prices and longer TOM.

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A More on the data and hedonic regressions

A.1 On the main hedonic predictions

The hedonic predictions used in this paper takes a backward-looking procedure. This is done in order to mimic how sellers are informed about the selling prices; sellers are not able to look into the future. In each period (year-quarter) I use transactions from the earlier periods including the final period to fit a hedonic model. This model is then used to predict selling prices for listings happening in that last period. Inclusion of the last period is done deliberately to estimate an implicit price for the time-effect in that last period. If fitting the model on data with the second-to-last period as the final period and predicting prices for the consecutive period, the predictions would naturally tend be too low, given that the market is rising in the sample period.[40]

The specification for the hedonic model use log selling price as the dependent variable. Omitting subscripts, the model has the following specification:

$$\begin{aligned} log(P) = {} & \beta_0 + \beta_1 size + \beta_2 size^2 + \beta_3 \mathbb{1}\{\text{apartment}\} + \beta_4 \mathbb{1}\{\text{apartment}\} \cdot size \\ & + \beta_5 \mathbb{1}\{\text{apartment}\} \cdot size^2 + \beta_6 \mathbb{1}\{\text{built 1900-1949}\} + \beta_7 \mathbb{1}\{\text{built 1950-1979}\} \\ & + \beta_8 \mathbb{1}\{\text{built 1980-1999}\} + \beta_9 \mathbb{1}\{\text{built 2000-}\} \\ & + \beta_{10} \mathbb{1}\{\text{lot size} \geq 1000m^2\} + \beta_{11} \mathbb{1}\{\text{lot size} \geq 1000m^2\} \cdot \mathbb{1}\{\text{apartment}\} \\ & + \beta_{12} \mathbb{1}\{\text{self-owner}\} + \beta_{13} \mathbb{1}\{\text{self-owner}\} \cdot \mathbb{1}\{\text{apartment}\} \\ & + \sum_k \gamma_k \mathbb{1}\{\text{Post code} = k\} + \sum_{t=2003Q2}^{T} \delta_t \mathbb{1}\{\text{Quarter sold} = t\} + e, \end{aligned} \tag{A.1}$$

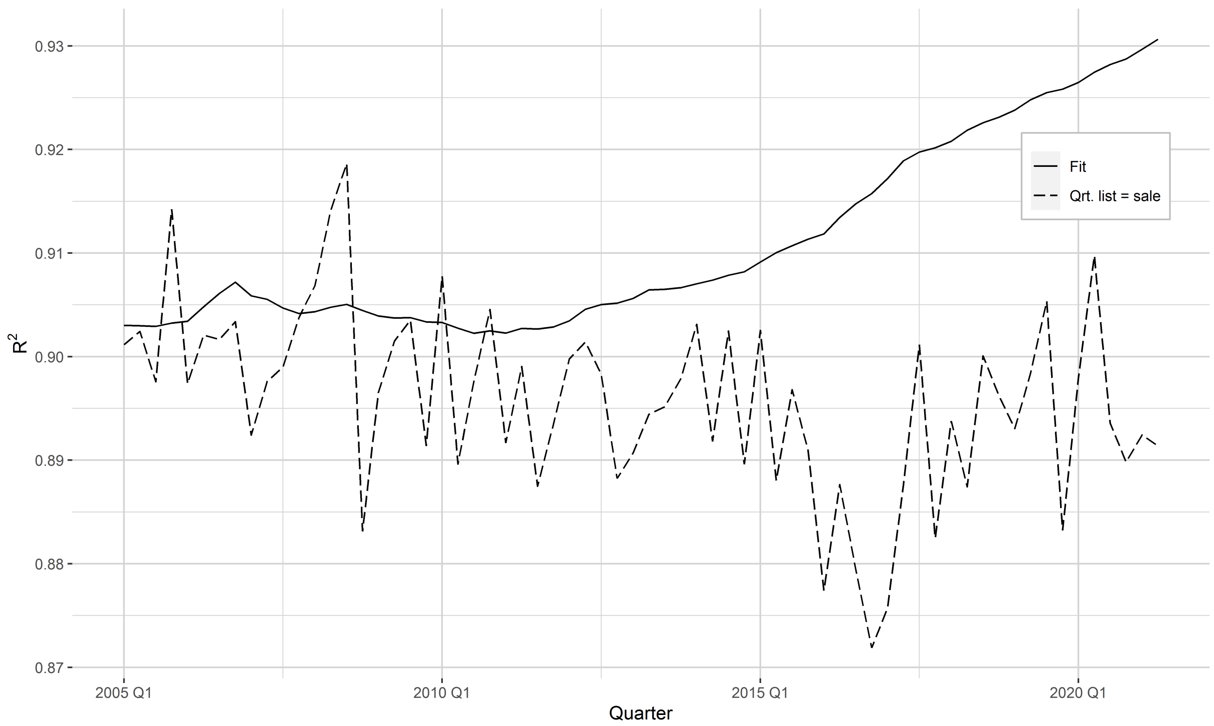
estimated with $T = 2005$ Q1 as the first period to predict. Thus, the first hedonic model fit is the one that use transactions for $t \leq 2005$ Q1 in the estimation. For the year-quarter dummies, 2003 Q1 is the omitted period.[41] To establish how well the model fits the data, I evaluate the model fit using R^2 when predicting log selling prices for the sales happening in the same period as they are listed. Notably, the majority of the transactions happens in the listing period. Figure A.1 shows R^2 for the model fits and the predictions when list and selling quarter is the same.

Although the R^2 curve for the fitted models suffers from the non-adjustment of inclusion of more variables, the share of the sample that is used to evaluate predictions becomes smaller when the sample size increases. This is why the list equals selling period curve is slightly trending downwards.

[40] A work-around could be to estimate an AR-model for the index of each hedonic fit, and adjust predictions according to the AR-predictions of the consecutive period.

[41] A postal code is also omitted to avoid multicollinearity.

Figure A.1: R^2 for backward-looking hedonic estimates



Notes: The figure presents the R^2 for the model fits and the predictions when list and selling quarter are the same.

A.2 On the other predictions

I use other fitted values in the paper in addition to the backward-looking predictions. All these use the same explanatory variables as in equation (A.1) with some changes, and not using the backward-looking approach but with pooling OLS. First, the GM replication use the specification but with listing quarter dummies in place for selling quarter dummies, corresponding to what GM does. The index used as a control variable in Table 3 is based on the dummy coefficients from estimating this model. Second, the index presented in Figure 1 and Figure C.3 are from the same hedonic specification as the backward-looking model but using a pooling approach. Third, the fitted appraisal values use log appraisal value as dependent variable with listing dummies, because appraisal values are presented to sellers prior to listing. Fourth, the predictions adding the appraisal value residuals use the residuals from the fitted appraisal values as explanatory variable with the same specification but with selling year-quarter dummies, and then predicted for listing year-quarters.

B Additional Derivations

B.1 Review of biases including the prospective gain

Let's first have a look at the model specification (3). The reduced form of the ideal specification is

$$\begin{aligned} L_{ist} = \alpha_0 + \alpha_1 \left(X_i \beta + \delta_t + v_i \right) + m_l \left(\delta_s - \delta_t + w_{is} \right)^+ \\ + m_g \left(\delta_s - \delta_t + w_{is} \right)^- + \epsilon_{it}. \end{aligned} \tag{B.1}$$

The feasible specification without adding the residual control is

$$\begin{aligned} L_{ist} = \alpha_0 + \alpha_1 \left(X_i \beta + \delta_t \right) + m_l \left(\delta_s - \delta_t + v_i + w_{is} \right)^+ \\ + m_g \left(\delta_s - \delta_t + v_i + w_{is} \right)^- + \eta_{it}, \end{aligned} \tag{B.2}$$

with the residual

$$\begin{aligned} \eta_{it} &= \alpha_1 v_i + m_l (LOSS^* - LOSS) + m_g (GAIN^* - GAIN) + \epsilon_{it} \\ &= \alpha_1 v_i + m_l \left((\delta_s - \delta_t + w_{is})^+ - (\delta_s - \delta_t + v_i + w_{is})^+ \right) \\ &\quad + m_g \left((\delta_s - \delta_t + w_{is})^- - (\delta_s - \delta_t + v_i + w_{is})^- \right) + \epsilon_{it}. \end{aligned} \tag{B.3}$$

Keeping the assumption of $v_{is} = v_{it} = v_i$ we see that the first part of the residual is contributing with a positive bias in the estimates, while the second part comes from the additional noise from the unobserved heterogeneity. It can be argued that the differences between the ideal and feasible loss and gain are an error-in-variable issue, but as we see from equation (B.2) there should be a negative correlation between the price prediction and the prospective loss and gain due to δ_t. There are other things happening here so that claiming classical measurement error leading to attenuation can be a far reach. We can expect that α_1 is close to 1 giving a relatively strong positive bias, so that the total effect of estimating the model may yield upward biased estimates.

Including the residual from the hedonic estimation of the previous log selling price, while still assuming $v_{is} = v_{it} = v_i$, gives the reduced form:

$$\begin{aligned} L_{ist} = \alpha_0 + \alpha_1 \left(X_i \beta + \delta_t \right) + \alpha_1 \left(v_i + w_{is} \right) \\ + m_l \left(\delta_s - \delta_t + v_i + w_{is} \right)^+ + m_g \left(\delta_s - \delta_t + v_i + w_{is} \right)^- + u_{it}, \end{aligned} \tag{B.4}$$

and the residual

$$u_{it} = -\alpha_1 w_{is} + m_l \left(LOSS^*_{ist} - LOSS_{ist} \right) + m_g \left(GAIN^*_{ist} - GAIN_{ist} \right) + \epsilon_{it}. \tag{B.5}$$

The residual again shows two sources of potential bias in m_l and m_g. The effect of including the residual control is that u_{it} include $-\alpha_1 w_{is}$ which should contribute with a downward bias. The second part of u_{it} is as before, but we also see that w_{is} is included in the feasible loss and gain and the residual control. Naturally, the residual control should correlate positively with loss and gain, so that there might be direct effects on m_l and m_g from this, and indirectly from the $-\alpha_1 w_{is}$ in u_{it} through the residual control. In total, we may get downward biased estimates.

Finally, by not invoking constant unobserved heterogeneity, while the ideal model is as presented in equation (5), the feasible model becomes

$$L_{ist} = \alpha_0 + \alpha_1 \left(X_i\beta + \delta_t\right) + m_l \left(\delta_s - \delta_t + v_{is} + w_{is}\right)^+ + m_g \left(\delta_s - \delta_t + v_{is} + w_{is}\right)^- + \eta_{it}, \quad \text{(B.6)}$$

with the residual

$$\eta_{it} = \alpha_1 v_{it} + m_l(LOSS^* - LOSS) + m_g(GAIN^* - GAIN) + \epsilon_{it}. \quad \text{(B.7)}$$

This should again yield upward biased estimates. To downward bias the estimates, again add the lagged residual, so that the reduced-form of the residual becomes

$$u_{it} = \alpha_1(v_{it} - v_{is}) - \alpha_1 w_{is} + m_l(LOSS^* - LOSS) + m_g(GAIN^* - GAIN) + \epsilon_{it}, \quad \text{(B.8)}$$

so that the change in unobserved heterogeneity is part of the residual. The estimates of interest is likely to be downward bias from the terms in the residual, while the correlation between explanatory variables can lead to upward bias in the estimates. With time-varying unobserved heterogeneity, the downward biasing effect may be smaller than with time-invariant unobserved heterogeneity, because the unobserved heterogeneity at time t does not disappear from the residual (B.8). Therefore, it is not certain that the lower bound is actually a lower bound.

B.2 Differential Berkson Error in Loss Aversion Modelling

B.2.1 Baseline

In what follows, the general form of the Berkson bias is given, as presented by Haber et al. (2021). Leaving out subscripts $\{i, s, t\}$, let the causal relationship be

$$L = \lambda_0 + \lambda_1\mu + \lambda_l LOSS + \lambda_\pi \pi + \epsilon, \quad \text{(B.9)}$$

while the model we actually estimate is

$$L = \alpha_0 + \alpha_1\mu + m_l LOSS + \eta, \quad \text{(B.10)}$$

but with substituting $\hat{P}$ for μ. The Berkson model is $\mu = \hat{P} + e$ with e as the Berkson residual. Note that the causal relationship includes the prospective loss as we observe it and not as the ideal version, this is done deliberately so that we include the mismeasured LOSS that has v_{is} in it.[42] By result 4.1 in Haber et al. (2021), the bias in $\hat{m}$ from estimating B.10 with $\hat{P}$ instead of μ is

$$
\begin{aligned}
E\left(\hat{m}_l(\hat{P}) - \hat{m}_l(\mu)\right) &= A^{-1}B \times \left(-(\sigma_{\mu,l} - \sigma_{e,l})\sigma_l^{-2}\right) + \alpha_1 \sigma_{e,l}\sigma_l^{-2} \\
A &= \sigma_\mu^2 - \sigma_e^2 - (\sigma_{\mu,l} - \sigma_{e,l})^2 \sigma_l^{-2} \\
B &= (\alpha_1 - \lambda_1)\sigma_e^2 + (m_l - \lambda_l)\sigma_{e,l} - \lambda_\pi \sigma_{\pi,e} - \alpha_1 \sigma_{e,l}\sigma_l^{-2}(\sigma_{\mu,l} - \sigma_{e,l}).
\end{aligned} \tag{B.11}
$$

The notation $\hat{m}_l(\hat{P})$ means that we estimate equation (B.10) with $\hat{P}$ while $\hat{m}_l(\mu)$ means the estimate if we estimated the relationship with μ. Also, the subscript l denotes the LOSS, so that $Var(LOSS) = \sigma_l^2$ and so on. We have the following useful relations:

$$
\begin{aligned}
\alpha_1 - \lambda_1 &= \lambda_\pi \frac{\sigma_{\pi,\mu|l}}{\sigma^2_{\mu|l}} = \lambda_\pi \frac{\sigma_{\pi,\mu}\sigma_l^2 - \sigma_{\pi,l}\sigma_{\mu,l}}{\sigma_\mu^2\sigma_l^2 - \sigma_{\mu,l}^2} \\
m_l - \lambda_l &= \lambda_\pi \frac{\sigma_{\pi,l|\mu}}{\sigma^2_{l|\mu}} = \lambda_\pi \frac{\sigma_{\pi,l}\sigma_\mu^2 - \sigma_{\pi,\mu}\sigma_{\mu,l}}{\sigma_\mu^2\sigma_l^2 - \sigma_{\mu,l}^2}.
\end{aligned}
$$

These means that the estimates using equation (B.10) with μ only differs if there is no omitted variable bias. Assume that $\sigma_{\pi,\mu} = \sigma_{\pi,l} = 0$, so that we get $\alpha_1 = \lambda_1$ and $m_l - \lambda_l$. Using this in equation (B.11) the bias now becomes

$$
\begin{aligned}
E\left(\hat{m}_l(\hat{P}) - \hat{m}_l(\mu)\right) &= \lambda_\pi \frac{\sigma_{\pi,e}(\sigma_{\mu,l} - \sigma_{e,l})}{(\sigma_\mu^2 - \sigma_e^2)\sigma_l^2 - (\sigma_{\mu,l} - \sigma_{e,l})^2} \\
&\quad + \alpha_1 \frac{\sigma_{e,l}}{\sigma_l^2} \frac{(\sigma_\mu^2 - \sigma_e^2)\sigma_l^2}{(\sigma_\mu^2 - \sigma_e^2)\sigma_l^2 - (\sigma_{\mu,l} - \sigma_{e,l})^2}.
\end{aligned} \tag{B.12}
$$

The first part of the expression is the bias from the correlation between the Berkson error and the unobserved variable, and the second part is from the correlation between the Berkson error and prospective loss.

B.2.2 Adding hedonic residual

The expression in equation (B.11) is the single variable reduction of a more general expression for the bias, meaning that there is only one variable in addition to the mismeasured one included in the estimated model (B.10). If we were to add the hedonic residual $\epsilon_{is} = v_{is} + w_{is}$, here denoted just ε, from the hedonic price estimation of the previous sale, there will now be two

[42] v_{is} is why the Berkson error is said to be of type *differential*.

additional explanatory variables in the model. The bias expression of estimating the model but with $\boldsymbol{z'} = (l, \varepsilon)$ and $\beta_z' = (m_l, \beta_\varepsilon)$, while keeping to one omitted variable and maintaining the assumptions for the expression (B.11) and denoting the covariance matrix as Σ, is now

$$\begin{aligned} E\left(\hat{\beta}_z(\hat{P}) - \hat{\beta}_z(\mu)\right) = &\left[\sigma_\mu^2 - \sigma_e^2 - (\Sigma_{\mu,z} - \Sigma_{e,z})\Sigma_{z,z}^{-1}(\Sigma_{z,\mu} - \Sigma_{z,e})\right]^{-1} \\ &\left[-\lambda_\pi \sigma_{\pi,e} - \alpha_1 \Sigma_{e,z}\Sigma_{z,z}^{-1}(\Sigma_{z,\mu} - \Sigma_{z,e})\right] \\ &\left(-(\Sigma_{\mu,z} - \Sigma_{e,z})\Sigma_{z,z}^{-1}\right) + \alpha_1 \Sigma_{e,z}\Sigma_{z,z}^{-1}. \end{aligned}$$

We can look at the bias expression for $\hat{m}_l$ by solving the matrix form of the expression above, while noting that $C \geq 0$:

$$\begin{aligned} &E\left(\hat{m}_l(\hat{P}) - \hat{m}_l(\mu)\right) = C^{-1}\left[\alpha_1(\sigma_{e,l}\sigma_\varepsilon^2 - \sigma_{e,\varepsilon}\sigma_{l,\varepsilon}) + DE^{-1}\left((\sigma_{\mu,l} - \sigma_{e,l})\sigma_\varepsilon^2 - (\sigma_{\mu,\varepsilon} - \sigma_{e,\varepsilon})\sigma_{l,\varepsilon}\right)\right] \\ &C = \sigma_l^2\sigma_\varepsilon^2 - \sigma_{l,\varepsilon}^2 = \sigma_{l,\varepsilon}^2\left(\frac{1}{\rho_{l,\varepsilon}^2} - 1\right) \quad \text{if} \quad \rho_{l,\varepsilon} \neq 0 \\ &D = \alpha_1\left(\sigma_{e,l}\sigma_\varepsilon^2(\sigma_{\mu,l} - \sigma_{e,l}) + \sigma_{e,\varepsilon}\sigma_l^2(\sigma_{\mu,\varepsilon} - \sigma_{e,\varepsilon}) + \sigma_{l,\varepsilon}(2\sigma_{e,l}\sigma_{e,\varepsilon} - \sigma_{e,\varepsilon}\sigma_{\mu,l} - \sigma_{e,l}\sigma_{\mu,\varepsilon})\right) \\ &\qquad + \lambda_\pi\sigma_{\pi,e}(\sigma_l^2\sigma_\varepsilon^2 - \sigma_{l,\varepsilon}^2) \\ &E = (\sigma_\mu^2 - \sigma_e^2)(\sigma_l^2\sigma_\varepsilon^2 - \sigma_{l,\varepsilon}^2) - (\sigma_{\mu,l} - \sigma_{e,l})^2\sigma_\varepsilon^2 - (\sigma_{\mu,\varepsilon} - \sigma_{e,\varepsilon})^2\sigma_l^2 + 2(\sigma_{\mu,l} - \sigma_{e,l})(\sigma_{\mu,\varepsilon} - \sigma_{e,\varepsilon})\sigma_{l,\varepsilon}. \end{aligned}$$

B.2.3 Measurement error in prospective loss

Let's consider the case where μ is perfectly measured but $LOSS^*$ is measured as $LOSS$, so that the causal relationship is $L = \lambda_0 + \lambda_1\mu + \lambda_l LOSS^* + \lambda_\pi\pi + \epsilon$ while we estimate $L = \alpha_0 + \alpha_1\mu + m_l LOSS^* + \eta$ with $LOSS$ instead of $LOSS^*$. Denoting $LOSS^* - LOSS = e_l$ the bias expression is

$$E\left(\hat{m}_l(\hat{P}) - \hat{m}_l(\mu)\right) = -\frac{\lambda_\pi\sigma_\mu^2\sigma_{\pi,e_l} + m_l\sigma_{\mu,e_l}(\sigma_{l,\mu} - \sigma_{\mu,e_l})}{(\sigma_l^2 - \sigma_{e_l}^2)\sigma_\mu - (\sigma_{l,\mu} - \sigma_{\mu,e_l})^2},$$

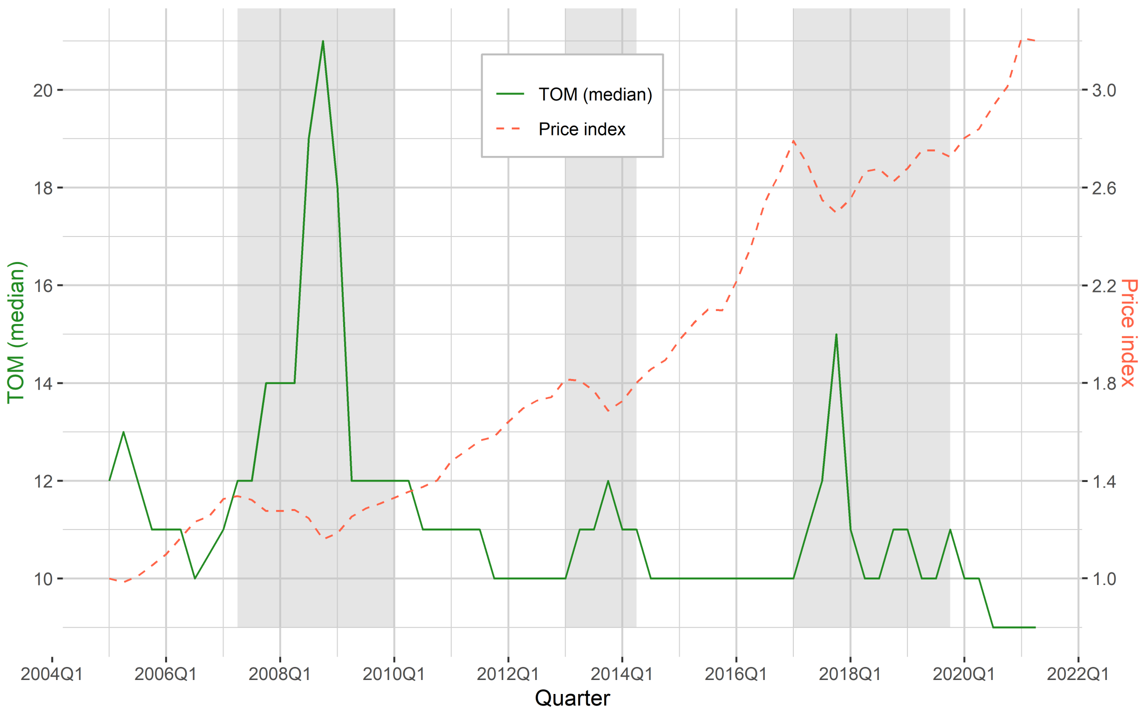
in which the covariance $\sigma_{\mu,e_l} \neq 0$ because

$$e_l = \Delta L = (\delta_s - \delta_t + v_{is} - v_{it} + w_{is})^+ - (\delta_s - \delta_t + v_{is} + w_{is})^+,$$

so that this difference comes from the missing v_{it}, a term that also is included in μ_{it}.

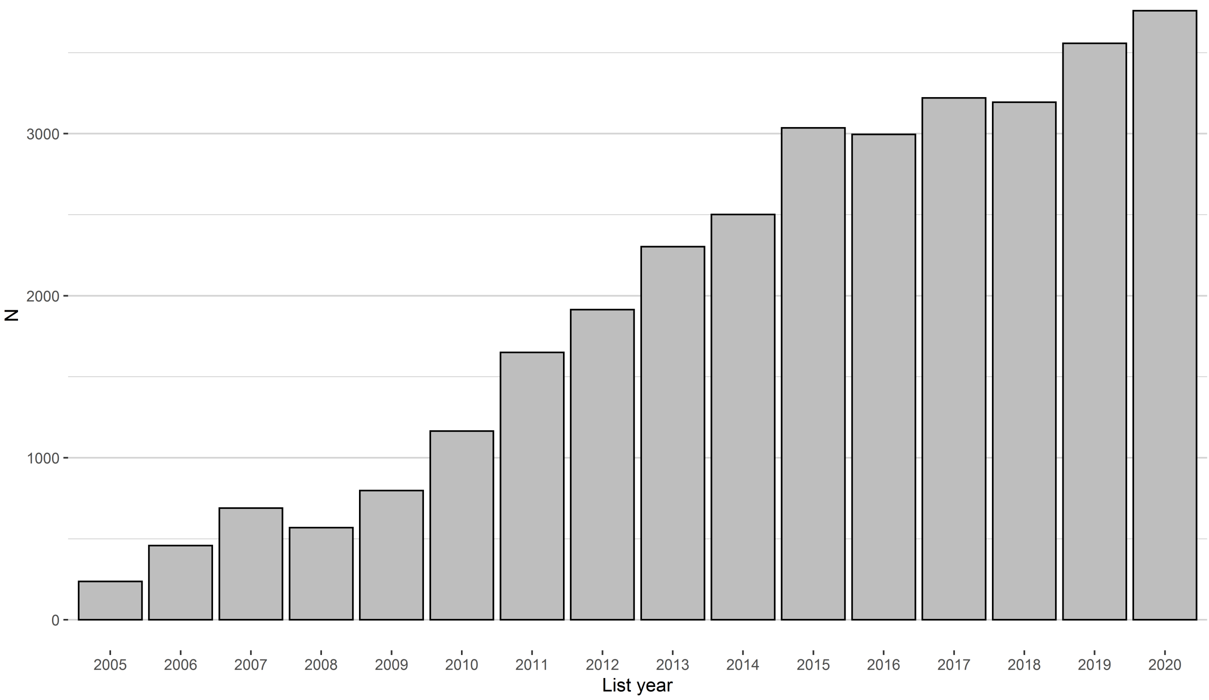
C Additional Tables and Figures

Figure C.1: Price index and median time-on-market for Oslo

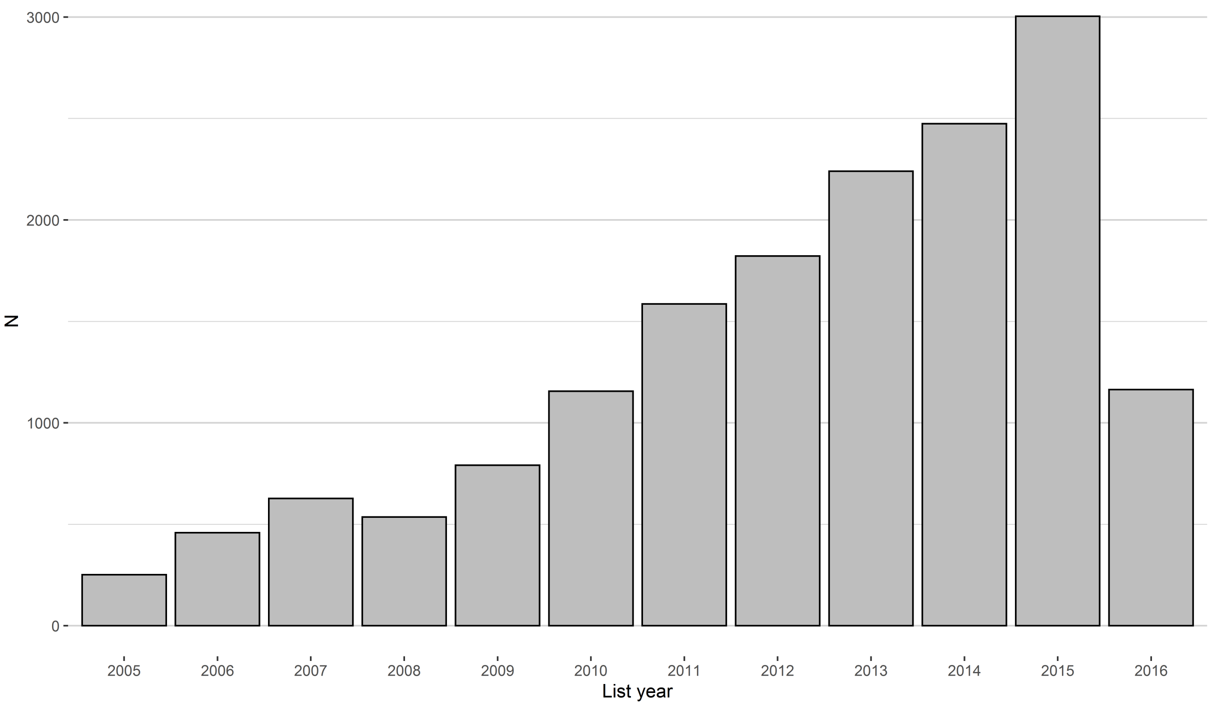


Notes: The figure presents a price index based on a hedonic prediction of house prices using year-by-quarter of sale dummies (not the quarter of listing dummies). Time-on-market are in days. The shaded areas starts at peaks and ends when the index is back at the peak-level.

Figure C.2: Annual observations



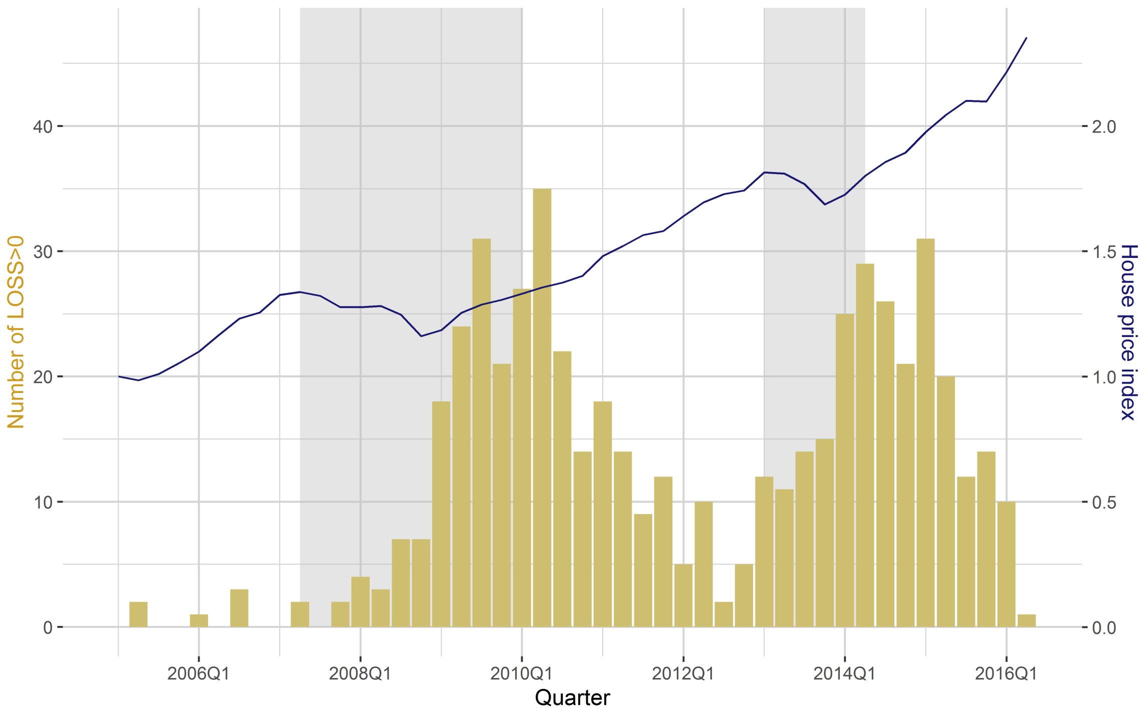
(A) Hedonic subsample



(B) Appraisal subsample

Notes: The figure presents the frequencies of observations for each of the two subsamples of repeated purchases-to-listings. Panel A presents the frequencies for the hedonic subsample, and panel B for the appraisal subsample.

Figure C.3: Price index, uncertainty and number of appraisal-based prospective losses



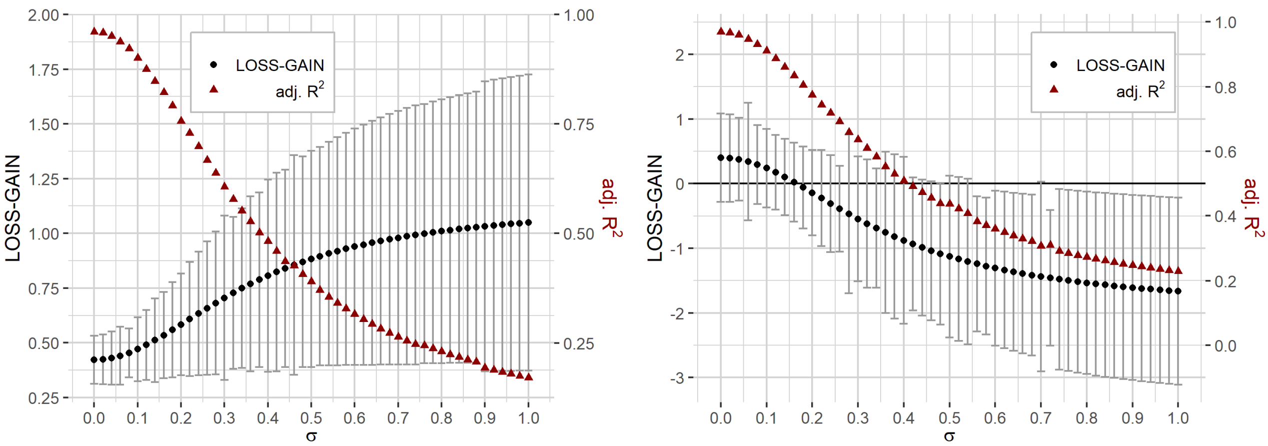
Notes: The figure presents a price index based on a hedonic prediction of house prices using year-by-quarter of sale dummies (not the quarter of listing dummies). The prospective losses are appraisal-based. The shaded areas starts at peaks and ends when the index is back at the peak-level.

Table C.1: Data cleaning

Step	N sellers/buyers	N transactions
Initial	323,261	113,308
Drop co-ops before 2007	321,796	112,756
Remove duplicate rows	321,784	112,756
Remove transactions with missing list price	321,269	112,569
Remove transactions with less than 2 weeks between listings	321,076	112,496
Remove transactions with less than 2 weeks holding time	321,066	112,491
Remove holiday properties	321,020	112,475
To repeated: keep times sold>1	220,163	77,830
To repeated: matched buyers with sellers	194,741	68,472
Removing duplicate sellers and buyers	194,740	68,472
Reducing to one seller and one buyer	134,466	68,472
Reducing to one seller	66,603	66,603
Excluding first sale	41,019	41,019
Restrict to 2005-2020	37,401	37,401
Final trimmed Hedonic subsample	32,044	32,044
Final trimmed Appraisal subsample	16,111	16,111

Notes: The table reports the data cleaning process in detail, reporting numbers for Oslo. The column *N sellers/buyers* is the number of lines in the data, and *N transactions* is the number of unique transactions.

Figure C.4: Effects of adding noise, with lagged residual



(A) Hedonic-based LOSS-GAIN

(B) Appraisal-based LOSS-GAIN

Notes: The figure presents the difference between prospective loss and gain, a 95 percent confidence interval, and the adjusted R^2 when adding noise $\xi \sim N(0, \sigma^2)$ with different standard deviations σ to the predicted price $\hat{P}_{it}$. For each $\sigma > 0$, the procedure of drawing ξ and estimating the coefficient difference is repeated 1,001 times and the median coefficient difference between loss and gain, with the corresponding confidence interval, is chosen to be plotted. This is done because the loss-gain distribution is normal. Panel A shows the hedonic-based loss and gain difference, meaning using the hedonic price prediction as the inside price substitute. Panel B show the appraisal-based loss and gain difference. Standard errors are clustered on list year and 3-digit zip codes.

Table C.2: More summary statistics

Variable	1st Qu.	Median	Mean	3rd Qu.
(A) *Non-repeated data, not trimmed (N=112,475, Dec 1999–Oct 2021)*				
List price (MNOK)	2.20	3.16	3.81	4.49
Selling price (MNOK)	2.35	3.30	3.96	4.65
Appraisal value (MNOK)	1.94	2.56	3.13	3.65
Size (m^2)	51	66	78	90
TOM (days)	9	11	24	19
Apartment (%)			85.68	
Self-owner (%)			59.27	
(B) *Repeated data, not trimmed (N=37,401, Jan 2005–Dec 2020)*				
List price (MNOK)	2.52	3.37	3.89	4.50
Selling price (MNOK)	2.69	3.50	4.04	4.67
Appraisal value (MNOK)	2.14	2.74	3.23	3.78
Size (m^2)	48	63	70	82
TOM (days)	9	10	22	17
Holding time (weeks)	125	197	226	294
Apartment (%)			90.68	
Self-owner (%)			58.92	

Notes: The table reports summary statistics for the non-repeated sample after initial cleaning, and the repeated sample before trimming. Prices are reported in million Norwegian kroner, and include common debt. Holding time is the number of weeks between previous date of sale and the date of listing. TOM is the time-on-market found as the number of days between the listing and the sale.

Table C.3: Residual signs for zero and positive appraisal-based prospective losses

(A) $LOSS^{AV}_{ist} = 0$

		t: -	t: +
s	-	0.353	0.186
s	+	0.099	0.363

(B) $LOSS^{AV}_{ist} > 0$

		t: -	t: +
s	-	0.211	0.032
s	+	0.171	0.585

(C) Shares ($e_{i,\delta\in\{s,t\}} > 0$)

	s	t
$LOSS^{AV}_{ist} = 0$	0.461	0.549
$LOSS^{AV}_{ist} > 0$	0.755	0.617

Notes: The table reports the share of observations with positive or negative sign on the residual from the hedonic estimations. Panel A shows the shares conditional on zero prospective losses, which substitutes μ_{it} with P^{AV}_{it}. Panel B shows the shares conditional on positive prospective losses. Panel C shows the overall shares of positive residuals for the two periods.

Table C.4: Pooling results for two-times repeated purchases-to-listings

	(1)	(2)	(3)	(4)
LOSS	0.918***	0.506***	−0.022	−0.009
	(0.072)	(0.087)	(0.066)	(0.065)
GAIN	0.341***	0.094**	0.031***	0.033***
	(0.021)	(0.041)	(0.005)	(0.005)
Substitute for μ_{it}	$\hat{P}_{it}$	$\hat{P}_{it}$	P_{it}^{AV}	P_{it}^{AV}
Residual control	No	Yes	No	Yes
N	10,324	10,324	4,026	4,026
Adj. R sq.	0.953	0.961	0.995	0.995
LOSS>0 (% of N)	7.594	7.594	4.223	4.223
VIF LOSS	1.135	1.194	1.134	1.076
VIF GAIN	1.768	3.452	1.514	1.732
F-stat.(LOSS=GAIN)	60.842	43.235	0.654	0.413
p-value(LOSS=GAIN)	<0.001	<0.001	0.419	0.520
LOSS-GAIN	0.577	0.412	-0.052	-0.041

Notes: The table presents results of pooling using balanced two-times repeated observations subsamples of purchases-to-listings. The dependent variable is log(List price), predictions have log(Selling price) as dependent variable. The log of holding time in weeks, DTV, the constant term for the pooling estimates, the predicted price, the log appraisal value, and the residual control (lagged selling price/appraisal value difference) are omitted from the table. Standard errors are calculated using a wild bootstrap (R=1,000) and clustered on list year and 3-digit zip codes. Significance: * p<0.1, ** p<0.05, *** p<0.01.

Table C.5: Unit fixed effect of three-times repeated purchases-to-listings

	Pooling		Unit FE		Pooling		Unit FE	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
LOSS	0.719***	0.408***	0.306***	0.350***	−0.0003	0.010	−0.168*	−0.122
	(0.094)	(0.068)	(0.064)	(0.073)	(0.094)	(0.092)	(0.094)	(0.095)
GAIN	0.377***	0.156***	0.140***	0.173***	0.027***	0.029***	0.019***	0.026***
	(0.027)	(0.042)	(0.022)	(0.031)	(0.007)	(0.007)	(0.006)	(0.006)
Substitute for μ_{it}	$\hat{P}_{it}$	$\hat{P}_{it}$	$\hat{P}_{it}$	$\hat{P}_{it}$	P_{it}^{AV}	P_{it}^{AV}	P_{it}^{AV}	P_{it}^{AV}
Residual control	No	Yes	No	Yes	No	Yes	No	Yes
N	4,371	4,371	4,371	4,371	897	897	897	897
Adj. R sq.	0.960	0.965	0.950	0.950	0.996	0.996	0.981	0.981
LOSS>0 (% of N)	8.945	8.945	8.419	8.419	5.463	5.463	5.128	5.128
VIF LOSS	1.153	1.206	1.126	1.150	1.093	1.108	1.075	1.089
VIF GAIN	1.621	3.122	1.851	2.612	1.393	1.586	1.352	1.432
F-stat.(LOSS=GAIN)	11.836	16.235	5.574	6.183	0.080	0.043	3.744	2.260
p-value(LOSS=GAIN)	0.001	<0.001	0.018	0.013	0.778	0.836	0.053	0.133
LOSS-GAIN	0.342	0.252	0.166	0.177	-0.027	-0.020	-0.187	-0.147

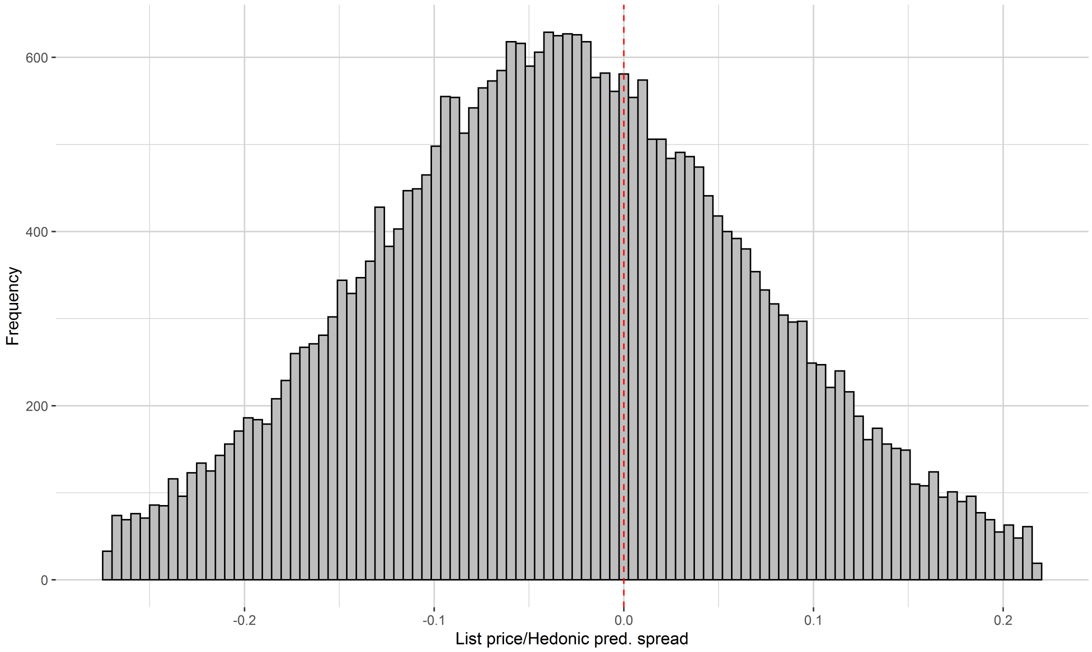
Notes: The table presents results of pooling and unit fixed effect using balanced three-times repeated observations subsamples of purchases-to-listings. Columns (1), (2), (5) and (6) are pooling estimates, and (3), (4), (7) and (8) are unit fixed effects (or first difference). Moreover, (1)-(4) are hedonic-based estimates while (5)-(8) are appraisal-based. The dependent variable is log(List price), predictions have log(Selling price) as dependent variable. The log of holding time in weeks, DTV, the constant term for the pooling estimates, the predicted price, the log appraisal value, and the residual control (lagged selling price/appraisal value difference) are omitted from the table. Standard errors are calculated using a wild bootstrap (R=1,000) and clustered on list year and 3-digit zip codes. Significance: * p<0.1, ** p<0.05, *** p<0.01.

Table C.6: Aggregate prospective terms

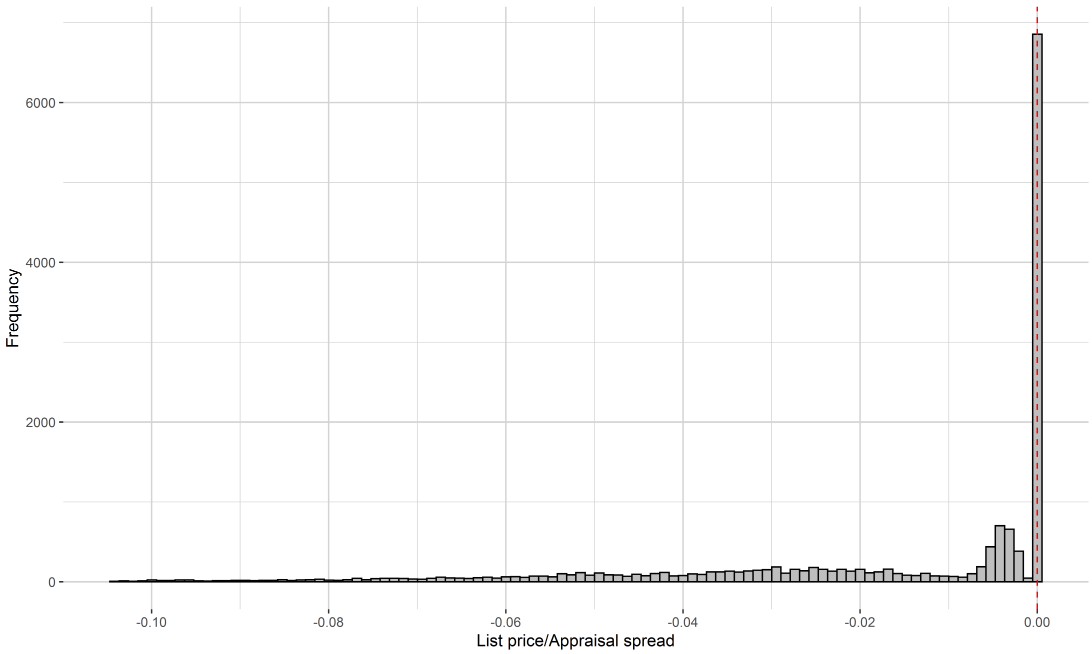
	(1)	(2)	(3)	(4)
LOSS	0.329***	0.507***	−0.091*	−0.098*
	(0.085)	(0.085)	(0.048)	(0.053)
GAIN	0.020	0.024	−0.022***	−0.023***
	(0.018)	(0.018)	(0.005)	(0.005)
Outside price	$\hat{P}_{it}$	$\hat{P}_{it}$	P_{it}^{AV}	P_{it}^{AV}
Residual control	No	Yes	No	Yes
N	31,536	30,450	15,647	13,981
Adj. R sq.	0.935	0.960	0.996	0.996
LOSS>0 (% of N)	2.549	2.631	2.870	2.847
VIF LOSS	1.045	1.047	1.052	1.052
VIF GAIN	2.590	2.594	2.293	2.287
F-stat.(LOSS=GAIN)	14.690	35.979	2.066	2.007
p-value(LOSS=GAIN)	<0.001	<0.001	0.151	0.157
LOSS-GAIN	0.309	0.483	-0.069	-0.075

Notes: The table presents results of aggregated prospective term, meaning $LOSS_{ist} = (\delta_s - \delta_t)^+$ and $GAIN_{ist} = (\delta_s - \delta_t)^-$. Columns (1) and (2) are hedonic-based estimates, and (3) and (4) are appraisal-based estimates. The dependent variable is log(List price), predictions have log(Selling price) as dependent variable. The log of holding time in weeks, DTV, the constant term, the predicted price, the log appraisal value, and the residual control (lagged selling price/appraisal value difference) are omitted from the table. Standard errors are calculated using a wild bootstrap (R=1,000) and clustered on list year and 3-digit zip codes. Significance: * p<0.1, ** p<0.05, *** p<0.01.

Figure C.5: List price spreads



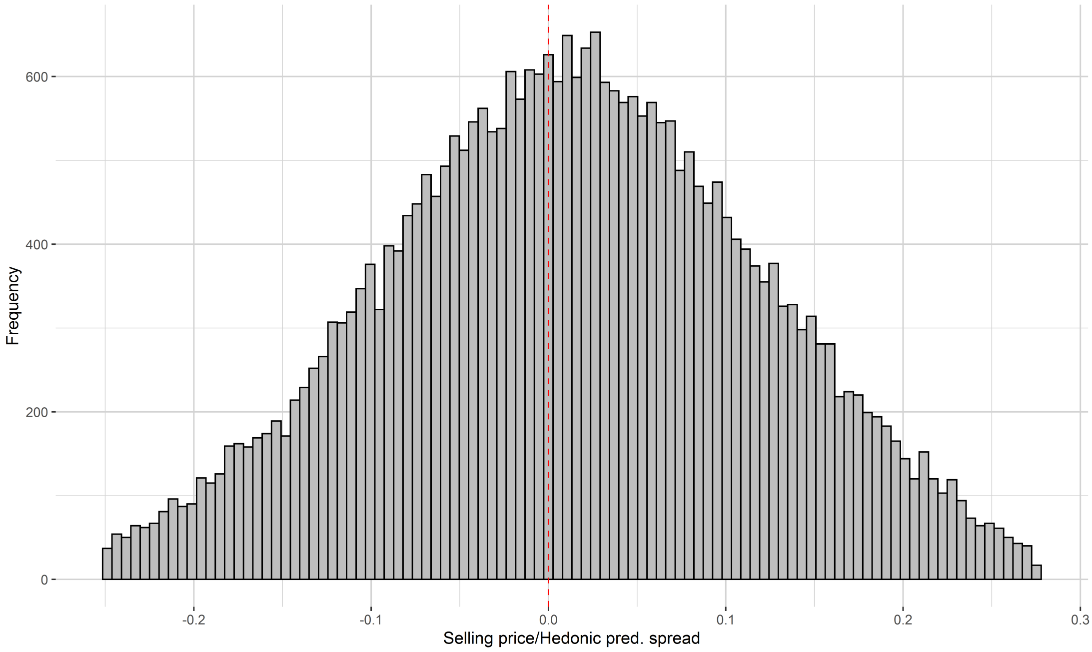
(A) List price/hedonic spread



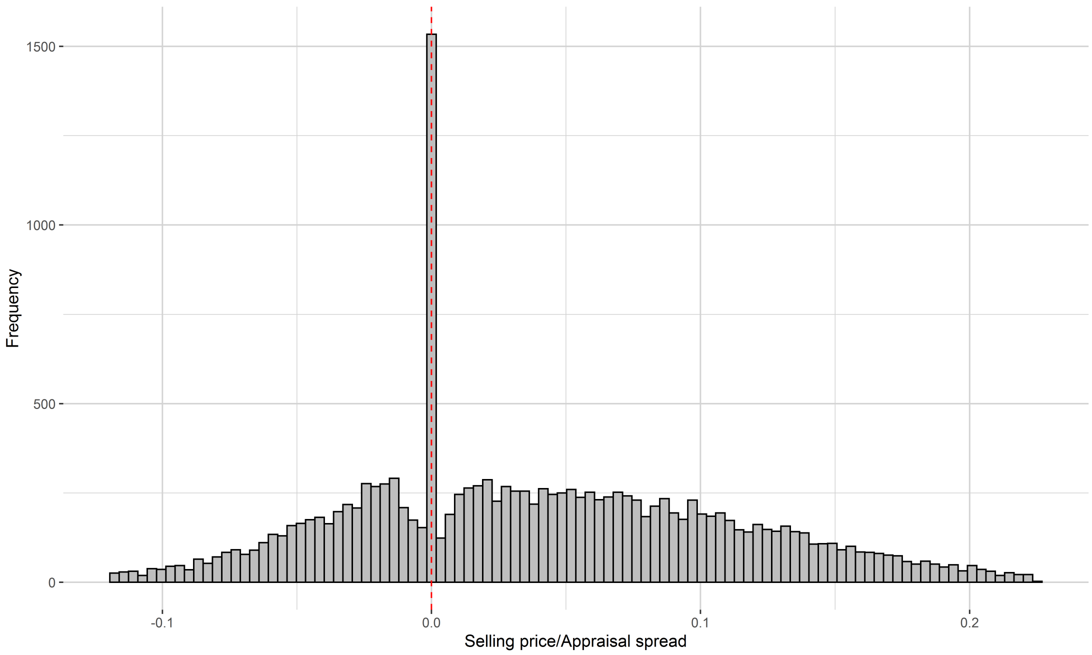
(B) List price/appraisal value spread

Notes: The figure presents the spreads in form of the difference in log terms. Panel A is the list price/hedonic prediction spread from the hedonic prediction repeated purchases-to-listings subsample, and panel B the list price/appraisal value spread from the appraisal repeated purchases-to-listings subsample. For a clean visualization the spreads are trimmed on the 1st and 99th percentiles.

Figure C.6: Selling price spreads



(A) Selling price/hedonic spread



(B) Selling price/appraisal value spread

Notes: The figure presents the spreads in form of the difference in log terms. Panel A is the selling price/hedonic prediction spread from the hedonic prediction repeated purchases-to-listings subsample, and panel B the selling price/appraisal value spread from the appraisal repeated purchases-to-listings subsample. For a clean visualization the spreads are trimmed on the 1st and 99th percentiles.

Table C.7: Results of log list prices on (predicted) log prices

	(1)	(2)	(3)	(4)	(5)
$\hat{P}_{it}$	1.003***				0.048***
	(0.012)				(0.007)
P_{it}^{AV}		1.001***			0.957***
		(0.002)			(0.007)
$\hat{P}_{it}^{AV}$			0.999***		
			(0.010)		
$\hat{P}_{it}\|_{e_{it}^{AV}}$				1.020***	
				(0.007)	
Constant	−0.091	−0.029	0.011	−0.344***	−0.086***
	(0.171)	(0.028)	(0.144)	(0.109)	(0.030)
N	15,506	15,506	15,506	15,506	15,506
Adj. R sq.	0.923	0.996	0.926	0.990	0.996

Notes: The table presents results regressing log(List price) on backward-looking hedonic predictions ($\hat{P}_{it}$), log(Appraisal values) (P_{it}^{AV}), fitted log(Appraisal values) ($\hat{P}_{it}^{AV}$), and cross-sectional hedonic predictions with appraisal value residuals ($\hat{P}_{it}|_{e_{it}^{AV}}$). All estimations use the same subsample. Standard errors are clustered on list year and 3-digit zip codes. Significance: * p<0.1, ** p<0.05, *** p<0.01.

Table C.8: Results of log selling prices on (predicted) log prices

	(1)	(2)	(3)	(4)	(5)
$\hat{P}_{it}$	0.983***				0.156***
	(0.012)				(0.031)
P_{it}^{AV}		0.971***			0.827***
		(0.010)			(0.024)
$\hat{P}_{it}^{AV}$			0.971***		
			(0.014)		
$\hat{P}_{it}\|_{e_{it}^{AV}}$				0.997***	
				(0.007)	
Constant	0.273	0.464***	0.487**	0.049	0.277*
	(0.173)	(0.147)	(0.213)	(0.099)	(0.163)
N	15,506	15,506	15,506	15,506	15,506
Adj. R sq.	0.909	0.963	0.897	0.972	0.965

Notes: The table presents results regressing log(Selling price) on backward-looking hedonic predictions ($\hat{P}_{it}$), log(Appraisal values) (P_{it}^{AV}), fitted log(Appraisal values) ($\hat{P}_{it}^{AV}$), and cross-sectional hedonic predictions with appraisal value residuals ($\hat{P}_{it}|_{e_{it}^{AV}}$). All estimations use the same subsample. Standard errors are clustered on selling year and 3-digit zip codes. Significance: * p<0.1, ** p<0.05, *** p<0.01.

Table C.9: Results from splitting the data into short and long holding time

	Short hold		Long hold	
	(1)	(2)	(3)	(4)
LOSS	0.727***	0.417***	0.809***	0.365***
	(0.060)	(0.066)	(0.158)	(0.119)
GAIN	0.400***	0.171***	0.367***	0.045
	(0.029)	(0.055)	(0.027)	(0.063)
Residual control	No	Yes	No	Yes
N	16,062	15,516	16,034	14,979
Adj. R sq.	0.959	0.965	0.950	0.956
LOSS>0 (% of N)	12.794	13.019	0.823	0.855
VIF LOSS	1.195	1.269	1.026	1.034
VIF GAIN	1.273	2.524	1.777	5.394
F-stat.(LOSS=GAIN)	24.837	32.857	6.651	7.969
p-value(LOSS=GAIN)	<0.001	<0.001	0.010	0.005
LOSS-GAIN	0.327	0.246	0.442	0.320

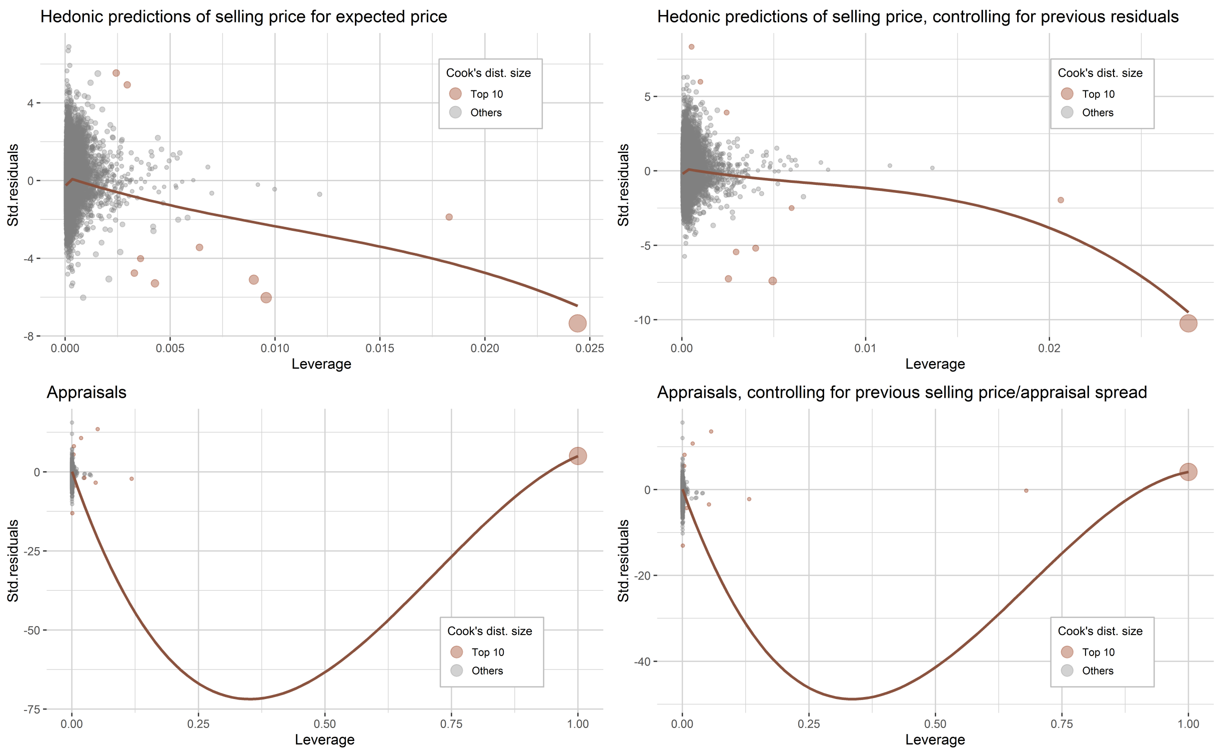
Notes: The table presents results of separating the data into a short and a long holding time subsample, separated based on the median holding time (198 weeks). Columns (1) and (2) are results from the short holding time subsample, and (3) and (4) are from the long holding time subsample. The dependent variable is log(List price), predictions have log(Selling price) as dependent variable. The log of holding time in weeks, DTV, the constant term, the predicted price, and the residual control are omitted from the table. Standard errors are wild bootstrapped (R=1,000) and clustered on list year and 3-digit zip codes. Significance: * p<0.1, ** p<0.05, *** p<0.01.

Table C.10: Results from using log appraisal value as dependent variable

	(1)	(2)
LOSS	0.964***	0.632***
	(0.048)	(0.050)
GAIN	0.415***	0.202***
	(0.019)	(0.036)
Residual control	No	Yes
N	15,901	14,583
Adj. R sq.	0.949	0.955
LOSS>0 (% of N)	8.471	8.969
VIF LOSS	1.122	1.266
VIF GAIN	1.560	3.936
F-stat.(LOSS=GAIN)	124.807	125.893
p-value(LOSS=GAIN)	<0.001	<0.001
LOSS-GAIN	0.550	0.429

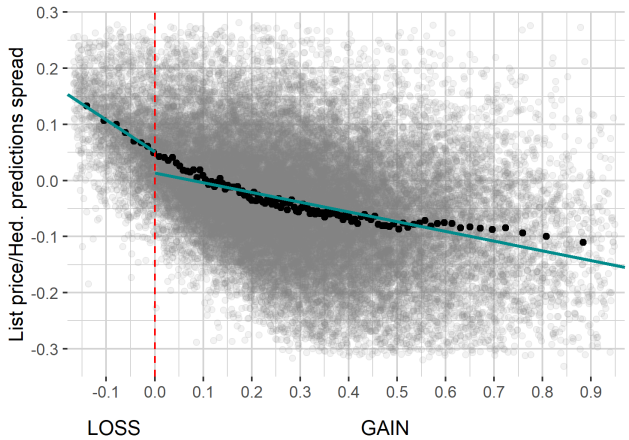
Notes: The table presents results from using log(Appraisal value) as dependent variable, predictions have log(Selling price) as dependent variable. The difference in number of observations of the lower bound estimates presented here compared to Table 4 comes from the balancing not done here. In the baseline lower bound estimation, I require both that the lagged appraisal value and the lagged hedonic residual is available, while the estimations presented here only require the lagged hedonic residuals. The log of holding time in weeks, DTV, the constant term, the predicted price, and the residual control are omitted from the table. Standard errors are wild bootstrapped (R=1,000) and clustered on list year and 3-digit zip codes. Significance: * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Figure C.7: Cook's distance

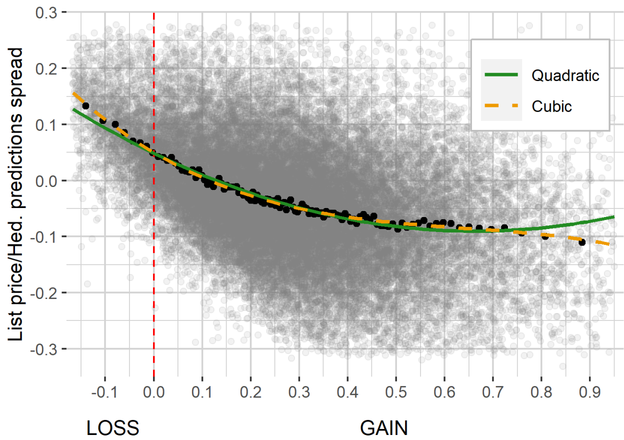


Notes: The figure presents Cook's distance plots for the models estimated in table C.11. The two upper plots are for the hedonic-based models, while the two lower plots are for the appraisal-based models. The y-axis are standardized residuals, and the x-axis is the diagonal of the projection matrix.

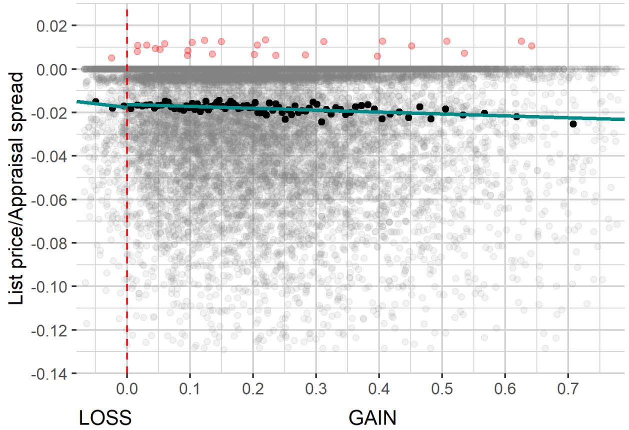
Figure C.8: Hockey stick



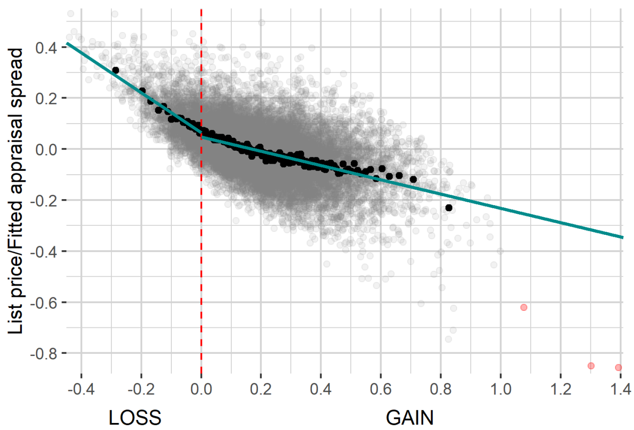
(A) Hedonic LOSS/GAIN



(B) $R = -(LOSS + GAIN)$



(C) Appraisal value LOSS/GAIN



(D) Fitted appraisal value LOSS/GAIN

Notes: The figure presents the unconditional hockey stick pattern between the dependent variable, represented by the list price premium, and the prospective variables. The x-axis is the difference between the price expectation and the previous selling price, $R = -(LOSS + GAIN)$, thus having the opposite sign as in the regressions. Solid black point are the means of the spread within bins of R, so that the hockey stick pattern emerges. Panel A and B show the hedonic-based relationship, with panel B including overall fits showing that using better functional forms makes inclusion of prospective loss as a separate variable irrelevant for the fit. Panel C shows the appraisal-based relationship, with observations having list price above appraisal values being highlighted. Panel D shows the fitted appraisal-based relationship, with in panel D observations having prospective gain above one being highlighted. Highlighted observations are in red.

Table C.11: Results from removing the biggest influencers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
LOSS	0.907***	0.409***	0.046***	0.036**	0.913***	0.408***	0.040*	0.024
	(0.045)	(0.057)	(0.017)	(0.018)	(0.048)	(0.056)	(0.021)	(0.024)
GAIN	0.312***	0.039	0.027***	0.027***	0.313***	0.038	0.026***	0.027***
	(0.017)	(0.032)	(0.003)	(0.004)	(0.017)	(0.032)	(0.003)	(0.004)
Substitute for μ_{it}	$\hat{P}_{it}$	$\hat{P}_{it}$	P_{it}^{AV}	P_{it}^{AV}	$\hat{P}_{it}$	$\hat{P}_{it}$	P_{it}^{AV}	P_{it}^{AV}
Residual control	No	Yes	No	Yes	No	Yes	No	Yes
Removed influencers	Top 5	Top 5	Top 5	Top 5	Top 10	Top 10	Top 10	Top 10
N	34,813	31,803	18,161	16,190	34,808	31,798	18,156	16,185
Adj. R sq.	0.950	0.960	0.995	0.995	0.951	0.960	0.995	0.995
LOSS>0 (% of N)	8.382	8.792	4.240	4.373	8.377	8.787	4.219	4.356
VIF LOSS	1.110	1.249	1.041	1.047	1.110	1.249	1.041	1.056
VIF GAIN	1.780	3.634	1.581	1.628	1.783	3.634	1.581	1.711
F-stat.(LOSS=GAIN)	202.781	118.759	1.529	0.290	174.351	123.607	0.451	0.013
p-value(LOSS=GAIN)	<0.001	<0.001	0.216	0.590	<0.001	<0.001	0.502	0.910
LOSS-GAIN	0.595	0.370	0.019	0.009	0.600	0.369	0.014	-0.003

Notes: The table presents results from non-trimmed subsamples but removing the biggest influencers. Columns (1) to (4) removes the top five influencers, while columns (5) to (8) removes the top ten influencers. The dependent variable is log(List price), predictions have log(Selling price) as dependent variable. The log of holding time in weeks, DTV, the constant term, the predicted price, and the residual control are omitted from the table. Standard errors are calculated using a wild bootstrap (R=1,000) and clustered on list year and 3-digit zip codes. Significance: * p<0.1, ** p<0.05, *** p<0.01.

Table C.12: Hedonic-based model: sensitivity of functional forms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
LOSS	0.649***	0.296***	0.588***	0.255***	0.095	0.042	−0.095	−0.091
	(0.057)	(0.047)	(0.052)	(0.046)	(0.082)	(0.047)	(0.102)	(0.069)
GAIN	0.521***	0.229***	0.605***	0.289***				
	(0.046)	(0.063)	(0.062)	(0.070)				
$GAIN^2$	0.275***	0.213***	0.548***	0.409***				
	(0.051)	(0.042)	(0.134)	(0.090)				
$GAIN^3$			0.227***	0.166***				
			(0.082)	(0.056)				
RF					−0.522***	−0.229***	−0.611***	−0.293***
					(0.046)	(0.063)	(0.064)	(0.070)
RF^2					0.276***	0.214***	0.563***	0.419***
					(0.052)	(0.042)	(0.137)	(0.091)
RF^3							−0.238***	−0.173***
							(0.083)	(0.056)
Substitute for μ_{it}	$\hat{P}_{it}$	$\hat{P}_{it}$	$\hat{P}_{it}$	$\hat{P}_{it}$	$\hat{P}_{it}$	$\hat{P}_{it}$	$\hat{P}_{it}$	$\hat{P}_{it}$
Residual control	No	Yes	No	Yes	No	Yes	No	Yes
N	32,044	30,450	32,044	30,450	32,044	30,450	32,044	30,450
Adj. R sq.	0.954	0.961	0.954	0.961	0.954	0.961	0.954	0.961
LOSS>0 (% of N)	6.856	7.087	6.856	7.087	6.856	7.087	6.856	7.087
F-stat.(LOSS=GAIN)	2.681	2.402	0.037	0.335				
p-value(LOSS=GAIN)	0.102	0.121	0.847	0.563				
LOSS-GAIN	0.128	0.068	-0.017	-0.034				

Notes: The table presents results from including different functional forms of prospective gain and a reference dependence variable $R = LOSS + GAIN$. The dependent variable is log(List price), predictions have log(Selling price) as dependent variable. The log of holding time in weeks, DTV, the constant term, the predicted price, and the residual control are omitted from the table. Standard errors are calculated using a wild bootstrap (R=1,000) and clustered on list year and 3-digit zip codes. Significance: * p<0.1, ** p<0.05, *** p<0.01.

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