Mitigating Omitted Variable Bias in Expected Market Value: An Assessed Value Approach*

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Abstract

We propose a new assessed value approach to control for the amount of persistent unobserved quality. We rely on a well-established two-stage framework developed by Genesove and Mayer (GM, 2001), who test the effect of an expected loss on final transaction prices in the housing market. We show that our assessed value model effectively mitigates the omitted variable bias and produces similar results as GM when the first-stage residual is included. Importantly, our model does not rely on repeat sales and therefore provides a powerful new tool for estimating market value. Results are robust to alternative specifications, to controlling for loan-to-value ratios, to replacing final sale price with listing price, to alternative fixed effects, to subperiods, to different holding periods, to simulated quality, to excluding flippers, and to controlling improvements between sales.

Key Words: Anchoring, Loss Aversion, Repeat Sales, Errors-in-Variables, Unobserved Heterogeneity

JEL codes: C1, E00, R3

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1. Introduction

As properties are infrequently transacted, unobserved quality – defined as the sum of the effects of persistent omitted characteristics on sales prices, i.e., as aggregate valuation of unobserved variables – introduces omitted variable bias (OVB). In this study, we propose a new assessed value approach to control for the amount of persistent unobserved quality. We rely on a well-established two-stage framework developed by Genesove and Mayer, 2001 (hereafter, GM), who test the effect of an expected loss on final transaction prices in the housing market. The GM model has been extensively tested and extended.[1] Our focus on the GM model is motivated by its broad-reaching influence. Asset classes studied with the GM model include art, housing, stocks, bonds, and commercial real estate (e.g., Beggs and Graddy, 2009; Genesove and Mayer, 2001; Malhotra *et al*. 2015; Dougal *et al*., 2015; Bokhari and Geltner, 2011).

The GM literature suggests that anchoring to the purchase price positively influences the market price of a house expected to sell at a loss.[2] Existing studies using the GM model have found sellers obtain a premium (i.e., higher price) relative to expected market value for houses with expected losses. Unobserved quality is particularly important in the GM two-stage model, because the test variable, expected loss, is calculated by comparing the purchase price with expected market value at the second sale. Expected market values are estimated from the first stage using observed hedonic characteristics. Therefore, in the second stage, transactions that appear to have expected losses may in fact simply have high unobserved quality.[3] For example, when the econometrician estimates an expected loss (purchase price is above expected sales price), all or part of the loss may be due to high unobserved quality: i.e., the true expected price is higher than the measured one. This is a likely candidate to explain the premium attributed to anchoring by the

[1] GM's paper aims to measure loss aversion, ignoring other anchoring behaviors such as liquidity constraints, incomplete information or bargaining strategies (e.g., Carrillo, 2013; Head *et al*., 2014; Merlo *et al*., 2015; and Han and Strange, 2014, 2016). For example, a seller with informational, financial or psychological constraints associated with an expected loss may set a high asking price and bargain hard or "fish" for a buyer who will pay more than market value. We thank David Genesove for his constructive comments.

[2] As much of the early literature focuses on loss aversion, we examine the effect of loss. Some studies (e.g. Bokhari and Geltner, 2011) find a seller with a gain may be willing to give up some of the gain to the buyer. Since inclusion of gains in our model would greatly complicate our econometric analysis, we handle gains as a robustness test; results are robust to including gains.

[3] Examples of housing quality typically unobserved by the econometrician include an above (or below) average kitchen or landscaping as well as a view or location on a busy street. Important differences in location are particularly difficult to evaluate with observable variables. We reject the more common term "unobservables" because it misses the fact that unobserved qualities are problematical when they are reflected in market prices (or other dependent variables) but not known to the econometrician.

econometrician.[4] In other words, this "endogeneity bias" that arise from omitted variables would biases the loss premium estimate positively upwards due to the common error components in both the loss estimate and the GM model residual term.

Another source of error-in-variable (EIV) problem for the loss estimate is the "attenuation bias", which bias the loss-aversion premium towards zero due to the variance of the measurement error in the loss estimate. To deal with these two biases, GM examine two versions of specifications in the second stage: without controlling for the first-stage residual (GM-M1), the OVB would dominate; controlling for the first-stage residual (GM-M2), the attenuation bias is more likely to dominate. In other words, GM-M2 produces a conservative lower bound of the loss estimate. Since the loss estimate in the GM model is a nonlinear function of the measurement error, the relative influence of attenuation bias versus the OVB is ultimately an empirical matter. Although it is hardly certain a prior which specification is superior, it is useful to estimate the GM model using alternative market-value specifications to uncover the range of loss premium estimates.

We begin our analysis by fitting anchoring models to a sample of single-family residential transactions in Connecticut. We improve the conventional anchoring model in several ways. Our most important innovation is to use property tax assessed value to control for unobserved quality. The tax assessor is unlikely to be subject to psychological bias or financial or informational constraints associated with a given seller.[5] Moreover, the assessor observes many quality characteristics unobserved by the econometrician (e.g., Clapp and Giaccotto, 1992; Han and Strange, 2016). I.e., assessor data can be used to test the widely used practice of measuring unobserved quality with the residual for the first sale. A feature of our data is that assessed value is predetermined by a 2.5-year average lag, reducing endogeneity concerns. Our assessed value approach is simple to implement. The first step involves estimating town-year averages of the second sale prices. Next, we calculate deviations of assessed value from the town-year averages. Lastly, we construct the normalized assessed value (NAV) by adding the results from the previous two steps to account for the revaluation cycle.

[4] Bayer *et al.* (2020) use three or more repeat pairs to detect unobserved changes in quality between sales. Here we implement a similar method; results suggest that the Connecticut tax assessor observes many quality characteristics unavailable to the econometrician.

[5] The buyer in the first transaction is the seller in the second, raising the possibility of persistent negotiating strength or other owner characteristics influencing both sales. This is different than negotiation related to expected losses at the second sale. We use assessed value to separate quality from owner characteristics.

Using simulations, we show that our NAV model produces better estimates as the conventional hedonic model. Specifically, (1) the maximum R-squared from a regression of second sale price on predicted value using NAV is higher; (2) simulated coefficients on expected loss using NAV produces a conservative bound consistent with effective controls for unobserved quality. Comparing predicted second sales prices from the hedonic model to NAV, our leave-one-out (LOO) validation exercise provides further support for the NAV approach.

We then show that our assessed value model effectively mitigates the OVB and produces similar results as GM-M2. The results are robust to alternative model specification to controlling for improvements between sales, to adding expected gains, to using county fixed effects, to replacing final sale price with listing price, to subperiods, to different holding periods, to variations in supply elasticity and demand growth, and to simulated quality.

Numerous studies rely on repeat sales to control for quality changes by restricting the sample to houses sold at least twice during the sample period. This practice usually causes a large reduction in the sample size. In addition, it has been documented that repeat sale samples might suffer from selection bias.[6] Although we use a repeat sale framework to gauge the effectiveness of our assessed value model in mitigating OVB, our model does not rely on repeat sales and therefore has significant advantages.

To test this conjecture, we apply our model to another well-studied area, the impact of degree of overpricing (DOP), that does not rely on repeat sales. DOP is defined as the ratio of listing price to its expected (true) value, on transaction outcomes. Existing studies find a large and positive relation between DOP and final sale price (Yavas and Yang, 1995; Anglin *et al*., 2003; Knight, 2002; Merlo and Ortalo-Magné, 2004; Rutherford *et al*. 2005). Again, we show that the presence of unobserved quality might create an upward bias of the coefficient estimate of DOP and that the assessed value model effectively produces more conservative estimates of DOP.

Our findings have implications for existing and future research. First, our study has important implications for existing studies on anchoring. Anchoring behavior (e.g., sellers are influenced by the price they paid for the asset) [7] has been widely studied because it opens a window

[6] See, for example, Gatzlaff and Haurin (1997) and Deng and Quigley (2008) for detailed discussions.
[7] More generally, the disposition effect holds that investors are reluctant to sell assets with expected losses and quick to sell with expected gains. One manifestation is anchoring to price paid as a salient reference price, implying negotiated price premiums for sales with expected losses. In a general model by Barberis and Xiong (2012), utility (disutility) is derived in lumps from realizing a gain (loss). Their theory can explain several stylized facts such as the

on ways that rational decisions might be modified by institutional realities and human emotions. Much of the literature focuses on loss aversion (Genesove and Mayer, 2001; Beggs and Graddy, 2009; Ben-David and Hirshleifer, 2012; Bokhari and Geltner, 2011; Andersen *et al.*, 2020) but anchoring behavior provides insights into many other areas such as liquidity constraints (Stein, 1995); asymmetrical, incomplete information (Anenberg, 2016); the behavior of innovators (Rosokha and Younge 2019); forced sales (Campbell *et al*. 2011) and search and bargaining behavior (Han and Strange, 2015). It has stimulated new theories of utility functions (e.g., Barberis and Xiong, 2012).

There is a large literature in anchoring and loss aversion in real estate (e.g., Genesove and Mayer, 2001; Lambson *et al*., 2004; Bokhari and Geltner, 2011; Bucchianeri and Minson, 2013; Andersen *et al.*, 2020). Anchoring is associated with macro-level stylized facts such as volatility in house prices and cyclical transaction volume (Stein, 1995; Han and Strange, 2016; Glaeser and Nathanson, 2016; Zhou *et al.*, 2020).[8] This paper suggests that there are significant premiums on losses when unobserved quality is controlled and mitigated in a rigorous way.

We follow the anchoring literature in which researchers do not use data on time-on-market (TOM) or withdrawals when they implement the GM model. This is a plausible reduced form model because all sellers are responding simultaneously to any time-dependent variables such as demand shocks or changes in financial constraints when they set TOM or make listing or withdrawal decisions, whereas each seller has her own anchor which influences selling decisions. We find indirect evidence for low correlation between TOM and expected losses given our town-year fixed effects, supporting the ability of our model to identify the premium on losses. The premium on losses might be a result of bargaining, but we have a radically different perspective than the search and bargaining literature: ours is based on a reduced-form model that can be estimated without the extensive data requirements of the search literature. Our tests with detailed spatial and time dummy show that the premium on losses can be identified without considering the interaction of the anchor (i.e. price paid) with later events. Using our reduced-form model,

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positive association between price level and transactions volume, suggesting that our assessed value model might be applied here.

[8] Han and Strange (2016) say that "in busts when there are fewer high-type buyers and when high-type buyers value a given house less, the directing effect of the asking price on buyers is stronger. In contrast, in booms when there are more high type buyers and higher type buyers valuing a given house more, a greater reduction in asking price is required to induce a given number of visits (p. 126)."

researchers dealing with listing decisions (delisting, relisting) and TOM, can estimate premiums on losses, then proceed with bargaining models.

More generally, our framework can be applied to many studies relying on the estimation of expected market value using a hedonic model such as the DOP studies. Another potential area for research lies in the relation between local housing market dynamics and its unobserved quality. Using theories from search and bargaining, Bourassa *et al*. (2009) find the effects of unobserved quality (i.e., atypicality) on house price appreciation in weak markets (i.e., markets with declining house prices) are larger than for strong markets. Similarly, Anenberg (2016) separates local markets with declining house prices into deciles: the greater the rate of decline, the higher the ratio of list prices to the expected sales price.[9]

Section 2 summarizes the GM model and explains the NAV model. Section 3 presents the data. Section 4 and 5 discuss results and robustness tests. Section 6 shows another application of our NAV model. Section 7 concludes.

2. Models of Anchoring and Unobserved Quality

In this section, we first summarize Genesove and Mayer (2001)'s (hereafter, GM) approach to estimate the anchoring effect.[10] Then we discuss an assessed value method for controlling unobserved characteristics when estimating anchoring parameters.

2.1 Estimation based on Genesove and Mayer's (2001) Model

The GM model says that owners with an expected loss decide upon a reservation price that exceeds the level they would set in the absence of a loss, and so set a higher asking price and receive a higher transaction price if they do sell. Their framework starts with a standard hedonic model of expected sales prices estimated from all single-family sales, including both single and repeat sales:

$$\mu_{ilt} = \beta X_{il} + v_{il} + FE_{lt} \quad (1)$$

[9] This paper focuses on sales price; our limited access to list price data support conclusions from previous literature that sellers set asking prices based partly on the price they paid (1st sale of a repeat pair). Campbell *et al*. (2011) suggest that asking premiums may vary over time, leading to high rates of forced sales during busts.

[10] The empirical method to test for anchoring is developed by GM and much of the following literature; specifically, most papers test for loss aversion. We take no position on whether the evidence we present is consistent with limited information, financial or liquidity constraints, bargaining or loss aversion. Instead, we focus here on parameter bias.

where μ_{ilt} is the unbiased ("true") expected log of sales price of property *i* at location *l* and time *t* with *t* = *p*, *s*, *o* indexes the time of first (*p*), second (*s*) or only one (*o*) sale of property *i* during our sample, and X_{il} is a vector of time-invariant property and locational characteristics.[11] Here we control for time-vary spatial effects, notably for local public services and taxes, and allow for variation over time with town-year fixed effects, denoted FE_{lt}. It is noted that GM use a time effect (δ_t in their paper) rather than FE_{lt}; our fixed effects generalize time dummies. Town-year interacted fixed effects capture many sources of time-varying unobserved town-level heterogeneity.

The seller observes persistent unobserved quality v_{il} as do buyers who inspect the property; i.e., the subset of potential buyers who make an offer to purchase. v_{il} is the sum of characteristics unobserved by the econometrician but influencing the sales price; v_{il} is the aggregate influence of unobserved characteristics on price, so it enters equation (1) as a separate element of βX_{il}.

Observed sales prices are generated by:

$$P_{ilt} = \mu_{ilt} + w_{ilt} \qquad (2)$$

where P_{ilt} is the natural log of sales price, μ_{ilt} is the true expected sale price defined in equation (1) and w_{ilt} is a zero mean iid term, with variance σ_w^2, generated by random variables influencing the final transaction price.

As the econometrician does not observe v_{il}, she estimates the following hedonic pricing model:

$$P_{ilt} = \beta X_{il} + FE_{lt} + \varepsilon_{ilt}. \qquad (3)$$

Therefore, the disturbance term, ε_{ilt}, in equation (3) contains the persistent unobserved quality characteristic v_{il} as well as random influences, w_{ilt}. i.e.,

$$\varepsilon_{ilt} = v_{il} + w_{ilt}\ . \qquad (4)$$

where w_{ilt} is idiosyncratic to the transaction and captures the overpayment or underpayment by the seller at purchase.[12] We assume zero covariance between w_{ilt} and v_{il}, and w_{ilt} is iid white noise.

[11] As described in the data section, properties with changed characteristics are eliminated from our repeat sales analysis, an improvement over many repeat sales studies. Note that we simplify time notation using for repeat sales using *t*=*p* or *s*.

[12] The w_{ilt} term will not produce bias in the absence of bargaining power which will be addressed in Section 5.3.

Assuming v_{il} as a random coefficient (a random component of the constant term) which is normally distributed with mean zero and variance σ_v^2, the ordinary least squares (OLS) estimates of equation (3) will produce biased estimates of β as well as fixed effects estimates in equation (1) because $Cov(v_{il}, X_{il}) \neq 0$.[13]

The true model for anchoring is motivated by the need to unpack the second sale disturbance term in equation (2), $P_{ils} - \mu_{ils}$, to test anchoring to the price paid:

$$P_{ils} = \gamma \mu_{ils} + \alpha exp\_loss^{*} + w_{ils}, \qquad (5)$$

where μ_{ils} is the true expected log of sales price of property i at time *t*=*s* and FE_{ls} is omitted because it is in μ_{ils}. Based on equations (1)-(4), the true loss, exp_loss^{*}, is equal to town-year specific difference in price trends plus the random noise w_{ilp}, if positive, otherwise zero:

$$exp\_loss^{*} = \left(P_{ilp} - \mu_{ils}\right)^{+} = \left(FE_{lp} - FE_{ls} + w_{ilp}\right)^{+}. \qquad (6)$$

GM's key insight is that the null hypothesis for equation (5) is that $\alpha = 0$, i.e., there is no anchoring. The problem is that unobserved quality, v_{il}, influences both μ_{ils} and exp_loss^{*}. GM propose a two-step step estimation by substituting $\hat{P}_{ils}$ estimated from equation (3) as a proxy for μ_{ils} (hereafter GM-M1).

$$P_{ils} = \gamma' \hat{P}_{ils} + \alpha' exp\_loss + FE_{ls} + \epsilon'_{ils} \qquad (7)$$

where

$$\hat{P}_{ils} = \beta X_{il} + FE_{ls} \qquad (8)$$

$$exp\_loss = \left(P_{ilp} - \hat{P}_{ils}\right)^{+} = \left(FE_{lp} - FE_{ls} + v_{il} + w_{ilp}\right)^{+}. \qquad (9)$$

exp_loss is a proxy for $exp\_loss^{*} = \left(P_{ilp} - \mu_{ils}\right)^{+}$.[14] To partially control for unobserved quality, they add to equation (7) a noisy proxy for unobserved quality, $\hat{\varepsilon}_{ilp} = P_{ilp} - \hat{P}_{ilp} = \left(\widehat{v_{il} + w_{ilp}}\right)$, the residual from equation (3) for the first sale (hereafter GM-M2).

$$P_{ils} = \gamma'' \hat{P}_{ils} + \alpha'' exp\_loss + \lambda \hat{\varepsilon}_{ilp} + FE_{ls} + \epsilon''_{ils}. \qquad (10)$$

[13] This assumption is different from GM, who do assume zero covariance because they assume the first stage parameter estimates are consistent. This might be an implausible assumption about unobserved heterogeneity: i.e., typically omitted variable bias is a concern.

[14] The literature supports anchoring to nominal prices, so we do not deflate prices. See, for example, Brunnermeier and Julliard (2008) and Engelhardt (2003). Other literature includes expected gain, arguing that the difference between coefficients on gain and loss indicates loss aversion (see, for example, Bokhari and Geltner, 2011; Beggs and Graddy, 2009). GM (2001) do not include gain. Our model is easily generalized to include expected gain; here, including gain would merely complicate notation as we develop our econometric analysis.

Because the loss estimate coefficient, α' in GM-M1 (i.e., equation (7)) or α'' in GM-M2 (equation (10)) is a nonlinear function of the measurement error, the relative influence of attenuation bias versus the omitted variable bias is ultimately an empirical matter (see Appendix 1 for detailed explanations). This motivates us to develop an assessed value method to controlling for unobserved characteristics.

2.2 Property Tax Assessed Value Identifies Anchoring and Controls for Unobserved Quality

Our empirical specifications use property tax assessed value to mitigate OVB and to disentangle anchoring from unobserved quality. The important characteristics of assessed value are: 1) the assessor observes many property characteristics unobserved by the econometrician; 2) the tax assessor does not anchor to price paid by any particular seller;[15] 3) assessed values – predetermined by a 2.5 year average lag for the typical sale – help mitigate endogeneity issues.

First, the assessor collects a large amount of data and considers many details unobserved by the econometrician who is simply estimating hedonic valuation models based on a standard hedonic database. Han and Strange (2014, 2016) investigate the impact of listing price on the number of bidders. They suggest that, as the list price is composed of a quality component which is unobserved by the econometrician, regressing the number of bidders on list price is subject to an error-in-variable (EIV) problem. They argue that assessed value contains part of unobserved house characteristics because "assessed value is typically based not only on housing attributes reported in the MLS database but also on the assessor's actual visit of the house and the neighborhood." (p. 125, Han and Strange, 2016) Because the unobserved characteristics would bias the estimates in the manner of an EIV bias, they show (in their Table 5 and 8) that the estimated coefficients of asking price become larger after controlling for property tax assessment.[16]

In Connecticut, the assessor asks to enter the house to verify the interior condition. Although the homeowner is not required to grant access, the assessor considers variables including neighborhood characteristics, house maintenance, construction quality, heating type, and garage

[15] It is possible that the assessor considers price paid as a comparable sale, but this is very different than seller anchoring based on financial constraints, loss aversion or information advantages. Endogeneity enters because anchoring influences both second price and loss; assessed value is free of this channel for endogeneity.
[16] The value added by assessment practices is documented in Clapp and Giaccotto (1992) and Clapp and O'Connor (2008).

type.[17] See Appendix 2 for details on variables available in a typical assessor database in Connecticut.

Second, relative to the seller, the tax assessor is less likely to suffer from psychological bias or financial or informational constraints associated with a given seller. This is important because it substantially reduces endogeneity in GM-M2: the first price influences market value which is used to calculate the expected loss. It is possible that the assessor considers price paid as a comparable sale, but only if the price paid is within 3 years of the sale. A comparable sale is very different than seller anchoring (and bargaining hard) based on financial constraints, loss aversion, or information advantages: assessors do not use models including the loss term such as model (10). It is considered unprofessional for tax assessors to use *any* personal information about sellers or buyers. In fact, assessors should not use or collect any information on individual characteristics or on groups of buyers or sellers. To do so would open the assessor to charges of discrimination or bias in the assessment process.[18] Too much reliance on recent prices is called "sales chasing" by assessors. i.e., assessors make a clear distinction between house value which is based on fundamentals and endures for the 5 years of the assessment and prices which are more volatile (Clapp *et al*. 1994).

Third, a unique feature of our data is that the assessed value is the one in place as of the date of the sale. Each town in Connecticut is required to revalue all property once every 5 years. The 5-year cycle is potentially different for each town, producing an average lag of 2.5 years between the date of revaluation and the sale. Therefore, the value is predetermined by a lag with an average of 2.5 years for most properties, reducing endogeneity concerns.

These three observations lead to the conclusion that, compared with the estimated price using a hedonic model, assessed value reduces endogeneity, better identifies anchoring and controls for unobserved quality. Ideally, we could use log of assessed value, $lnAV$ as a direct substitute for predicted second price, *lnprice2_f* in GM-M1 and -M2, but each town is on a

[17] Rigorous sales ratio standards are used to keep the assessor focused on accurately predicting prices. This practice might differ in other states.

[18] For example, in 2017, the Brighton Park Neighborhood Council and Logan Square Neighborhood Association have filed a lawsuit in circuit court alleging that the office of Cook County Assessor Joseph Berrios conducts assessments that systematically and illegally shift residential property tax burdens from Whites to Hispanics and African-Americans and from the rich to the poor. One defense is that the assessor does not maintain any information on the personal characteristics of the owners. The link to the lawsuit (last access on November 8, 2019): https://static1.squarespace.com/static/5871061e6b8f5b2a8ede8ff5/t/5a329fcaec212d09e4001553/1513267154250/2017.12.14+complaint+and+supporting+documents.pdf

potentially different 5-year revaluation cycle: the assessment in place at the time of sale is determined as of the last revaluation date. To adjust for the revaluation cycle, we normalize $lnAV$ with the following algorithm:

1. Calculate town-year averages of the second sales price, *lnprice2*. I.e., Regress *lnprice2* on town-year fixed effects and calculated the predicted *lnprice2, lnprice2_fty*
2. Calculate deviations of $lnAV$ from town-year averages. I.e., Regress $lnAV$ on town-year fixed effects and calculate the residual, *lnAV_resid*.
3. Calculate $lnAV\_norm$ as *lnprice2_fty* + *lnAV_resid*. I.e., add the results from step 1 to step 2. This works with our identification strategy which comes from variation within town-years, so the only information added is to make the level of $lnAV\_norm_{ils}$ comparable to the average town-year level of the second sales price, as required in order to calculate loss. Therefore, we substitute $lnAV\_norm$ for the predicted second sales price in equations (9) and (10).

The intuition behind normalization is that all the within town-year variation in $lnAV\_norm_{ils}$ comes from $lnAV$ and its level is normalized to the town-year level of sales prices, as required by our identification strategy.

By substituting normalized assessed value (NAV), $lnAV\_norm_{ils}$ for the predicted second price, $\hat{P}_{ils}$ we construct another measure of expected loss, $losslnAV_{ils}$:

$$losslnAV_{ils} = \left(P_{ilp} - lnAV\_norm_{ils}\right)^{+} . \qquad (11)$$

In the GM specification, μ is the true expected log of sales price and $\mu = \hat{P} + v$. In the NAV specification, $\mu = lnAV_{norm} + z$. If z has a sufficiently small variance around zero, the loss coefficient of $losslnAV_{ils}$ should fairly close to the estimate in GM-M2. We therefore compare the following specification with GM-M2:

$$P_{ils} = \gamma^{v} lnAV\_norm_{ils} + \alpha^{v} losslnAV_{ils} + FE_{ls} + \epsilon_{ils}^{v} \qquad (10')$$

The substitution of $lnAV\_norm_{ils}$ for $\hat{P}_{ils}$ is motivated by the characteristics of assessed value discussed earlier in this section. As our assessed value variable is preferred to $\hat{P}_{ils}$ in identifying anchoring and controlling for unobserved quality, we expect $\hat{\alpha}^{v}$ to be close to $\hat{\alpha}''$.

Equation (10') is our preferred model. As a robustness test, we also include $lnA\widehat{V\_resid}_{ilp}$ from the first sale in a similar manner of GM-M2. Although $lnA\widehat{V\_resid}_{ilp}$ is different in nature from $\hat{\varepsilon}_{ilp}$ in equation (10), it partially controls for the persistence of z.[19]

$$P_{ils} = \gamma^v lnAV\_norm_{ils} + \alpha^v losslnAV_{ils} + \lambda lnA\widehat{V\_resid}_{ilp} + FE_{ls} + \epsilon^v_{ils} \quad (10'')$$

3. Data

Our sample contains 548,568 single-family residential transactions between January 1994 and December 2017 in 169 towns in Connecticut.[20] The towns are well distributed throughout the state, with good representation beyond the I-95, I-91 and I-84 corridors. Most importantly, there are many towns far from New York City, a "gateway city" and international financial hub that has grown rapidly over most of the 20 years covered by the study.[21] Our data contain property characteristics and names of buyers and sellers at the time of each sale. This allows us to use a fuzzy logic routine to ensure that the seller in the second transaction was the buyer in the first, as required by anchoring behavior. Our final sample includes 90,345 repeat pairs where the second sale occurred after 1999 to allow the ratio of second sales to all sales to stabilize.[22] Table 1 summarizes sample construction and variable definitions.

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[19] Specifically, *lnAV_resid* is estimated from regressing *lnAV* on town-year fixed effects. Therefore, *lnAV_resid* is a proxy for whether the house is above or below the town-year averages. In contrast, $\hat{\varepsilon}_{ilp}$ is a proxy for unobserved quality as it is the unexplained part from the hedonic model.

[20] Data were collected by town halls monthly from 1994. The immediacy of data collection is important because the characteristics of the house are those in-place at the time of the transaction. Most repeat sales studies (e.g., Anenberg, 2011) have property characteristics at the time of the second sale but not the first, so major structural changes might occur between sales. We eliminate sales with changes in property characteristics. As in Clapp and Salavei (2010) and Clapp *et al*. (2018), our sample is restricted to single-family residential properties with 1) warranty deeds, 2) sale price over $50,000, 3) interior footage over 300sf and lot size between 1,500 sf and 10 acres, 4) more than three rooms and at least one bathroom, 5) structures built between 1901 and 2013, and 6) records of assessed building and land value. We require at least 10 sales in each town-year after 2000 to allow for town-year dummies. These filters eliminate foreclosure sales but not sales below the amount owed on the mortgage.

[21] Connecticut is often described as two states: the wealthy, growing southwestern towns closest to the New York City and the remainder of the state. The term "gateway" is used by commercial real estate investment professionals to describe cities attracting the largest flows of international real estate investment capital.

[22] We keep repeat sale pairs with the minimum holding period of 12 months in order to remove flips. We control for observable quality changes between sales by deleting observations with changes of interior size between sales greater than 5%. We also require the seller of second sale is the same as the buyer of the first. When there is more than one buyer or seller recorded, we ensure that at least one of the sellers/buyers in the second transaction was the buyer/seller in the first. We use matchit in STATA to perform the fuzzy match. The repeat subsample contains somewhat smaller, older houses than one-only sales, as in previous studies. Appendix 3 compares key housing characteristics for one-only sales and repeat sales.

We follow the GM literature by defining *anchor* as the first price less the expected market value at the time of the second sale, $P_{ilp} - \hat{P}_{ils}$. The mean of *anchor* is -.11 (Table 2 Panel A): i.e., the average sale has an expected gain of about 11% in log terms. We define *exp_loss* as *anchor* if *anchor* is positive and zero otherwise: *exp_loss* is defined by equation (9) as equal to $\left(P_{ilp} - \hat{P}_{ils}\right)^{+} = \left(FE_{lp} - FE_{ls} + v_{il} + w_{ilp}\right)^{+}$. About 42 percent of the second sales had an expected loss (see the dummy variable, *exp_lossd*) whereas the rest had an expected gain. *condl_loss* is *exp_loss* conditional on a positive (non-zero) loss. Figure 1 and Table 2 reveal very large expected losses: they average .25 conditional on an expected loss (*condl_loss*) and 50% of losses are between the quartile points of .1 and .34. Figure 1 shows a heavy tail for the upper quartile of the distribution.

An important objective of our work is to determine how much of the measured expected loss is due to unobserved quality. Comparing the two panels in Figure 1 shows that the loss distribution is shrunk towards zero at every percentile point by replacing expected sales price with assessed value in place at the time of the second sale. Table 2 shows that the number (percentage) of sales with losses is reduced from 38,056 (42%) to 33,819 (37%). These numbers are inconsistent with the potential for assessment practices to introduce errors-in-variables.

Our assessed value measure for expected sales price (*lnAVnorm*) has a slightly higher standard deviation than the predicted second price (*lnprice2_hat*), suggesting that it is capturing some additional source of variation such as unobserved quality. Our improved measure of expected loss, *exp_loss_lnAV*, has a lower mean and standard deviation than measured loss (*exp_loss*), suggesting that some variation due to unobserved quality has been eliminated. The conditional distribution (i.e., eliminating zero values), *condl_loss_lnAV* has mean .20 compared to .25 for *exp_loss*, as expected if a substantial part of the loss measured by the econometrician is due to unobserved quality.

The *resid2* variable in Table 2 shows left skewness and a substantially positive mean and median values, .04 and .07. The null hypothesis of no anchoring would require a zero mean iid distribution for *resid2* so the observed distribution supports a need to unpack this variable using anchoring models. The first residual from equation (3), *resid1* (Table 2 Panel A), is roughly symmetrically distributed with mean zero: i.e., it conforms to standard OLS assumptions. The large positive mean (.16) and heavy right skewness of *resid1* conditional on an expected loss, *resid1_condl_loss*, suggest a substantial effect of persistent unobserved quality, as expected from equations (4) and (10).

4. Results

4.1 Results from the GM Model

Table 3 Panel A presents results from estimating the GM models, equations (7) and (10). Given that the loss variables are constructed from a separate regression, the estimates of the asymptotic covariance matrix are corrected using the bootstrap strategy. Appendix 4 shows the first-stage hedonic model estimation. The coefficient on the estimated market value of the second sale, *lnprice2_hat*, is between .95 and .96 for all models, significantly smaller than 1.0; like coefficients estimated by previous research, this supports modeling the second residuals. The expected loss coefficients in Table 3 support the GM model: they are positive, between .21 and .27 for GM-M2, and they explain part of the disturbance term from the first stage regression *resid2* (=*lnprice2* - *lnprice2_hat*) where *lnprice2_hat* is on the right-hand side of the GM specification.

Prior studies use the residual from the hedonic estimate of the value of the first sale, measured by *resid1* (=$P_{ilp} - \hat{P}_{ilp}$), as a proxy for persistent unobserved quality in GM-M2. The estimated coefficient on this variable is between .38 and .41 in models 3-6, suggesting substantial persistence is partially captured by the proxy. The importance of this variable is indicated by comparing results of GM-M1 and GM-M2: the coefficients on the expected loss variable is strongly upward biased when the proxy is omitted. The magnitude of bias is large, similar to findings in previous studies. The negative signs on months between sales are consistent with previous literature.

The signs and significance of the loss coefficients in Table 3 support the possibility of anchoring to a reference point provided by first sales prices. Based on GM assumptions and the preferred baseline model 4, an average sale conditional on an expected loss averaging .25 will obtain a price that is about 5.8% (=exp (0.228*0.25)) above the market for a similar property without loss and of the same observed quality. These magnitudes are robust to different model specifications and they are similar to those found in the previous literature. In Panel B, we replace log of sale price with log of list price as our dependent variable. Despite a smaller sample size because the listing price data is only available up to 2013, our results are highly consistent, supporting directed search models.

In model 5 of Panel A, the quadratic term for expected loss controls nonlinearity. The coefficient is small in economic terms and statistically insignificant. Model 6 of Panel A tests a hypothesis from previous literature that high loan-to-value constrains sellers: they bargain hard if constrained: i.e., high LTV may pick up some of the loss coefficients.[23] The *LTV* coefficient is consistent with prior literature (e.g. e.g., GM, 2001; Engelhardt, 2003; Anenberg, 2011). More important for our purposes is the robustness of the expected loss coefficient: .214 with LTV compared to .228 without. We found similar results for all our models and robustness checks described below. Consequently, our focus on modeling unobserved quality can proceed with model 4 results interpreted as holding at mean values. We therefore refer to model 4 as our preferred baseline GM-M2 model.

4.2 Results from the NAV Model

The purpose of Table 4 is to compare assessed value models with the GM models (in Table 3). Our discussions in Section 2 established some important characteristics of assessed value: 1) the tax assessor does not anchor to the price paid by any particular seller; 2) the assessor observes many property characteristics unobserved by the econometrician; 3) endogeneity is mitigated because assessed value is pre-determined. The comparison of the loss coefficient between GM-M2 and NAV (.228 versus .224) suggests that the expected loss coefficients from our NAV model are comparable to GM-M2 when normalized assessed value (*lnAV_norm*) is substituted for *lnprice2_hat*: this supports unobserved quality and/or endogeneity issues.[24]

[23] The GM literature suggests that loan-to-value is a channel supporting loss behavior. Like GM, about 30% of our sample had current (as of the second sale) loan-to-value ratio greater than .8. We follow the literature (e.g., GM, 2001; Engelhardt, 2003; Anenberg, 2011) and calculate *LTV* as the difference between the loan-to-value ratio and 80%, truncated from below at zero. This truncation only allows LTV to affect prices if it is above 80%. Initial value (i.e., the denominator of LTV) was updated to time of sale with a town-level house price index and the original loan amount was amortized using the 30-year fixed mortgage rate prevailing at time of origination. This approximation and data errors result in some erroneous LTV's; we therefore winsorize *LTV* at the 99.9 percentile; variation in this cutoff does not change results. Results without winsorization are highly consistent.

[24] Can appraisal smoothing (meaning that appraised values in one period are influenced by those in an earlier period rather than responding fully to market changes) explain our results? We cannot think of a model in which smoothing produces downward bias in the coefficients since an x-variable with smaller standard deviation should have a larger coefficient given an otherwise identical data generating process. Smoothing would not change the anchor, which is quite volatile over the cycle and Table 2 descriptive statistics are consistent with reduced unobserved quality, not appraisal smoothing.

In model 4, we further add $resid1\_lnAV$ (i.e., $\widehat{lnAV\_resid}_{ilp}$ from equation (10')) to control for the persistence of z. Again, the loss coefficient is highly similar to that in model 3.[25] Model 5 compared to model 4 shows that the expected loss coefficient is robust to including LTV. We therefore refer to model 3 as our preferred baseline NAV model. Again, results in Panel B using log of list price are consistent: the difference between the loss coefficient in GM-M2 and that in NAV is similar.

4.3 Comparing the GM Model with the NAV Model - Simulation Results

GM suggest that their M1 should be viewed as an upper bound and M2 should provide a lower bound. They propose that a unique intersection of their M1 and M2 identifies the optimal standard deviation of the unobserved quality term in equation (4), i.e., optimal *sigma_v*. Intuitively, a market characterized by a higher level of unobserved quality should have higher *sigma_v*.

To show NAV also produces a conservative bound, we conduct two simulation exercises. Appendix 5 summarizes the simulation procedure. In the first exercise, we search for the optimal *sigma_v* using NAV and compare it with the one identified using hedonic.[26] Intuitively, the persistent unobserved quality should be reflected in the second sales prices because buyers and sellers do observe these characteristics. This implies that the R-squared in the following equation will be maximized at or near the optimal *sigma_v*:

$$P_{ils} = \gamma^{s}(\hat{P}_{ils} + v_{il}^{s}) + w_{ils} \qquad (12)$$

where v_{il}^{s} is simulated unobserved quality based on a grid search over potential values for *sigma_v*. We search a grid from *sigma_v* =0 to *sigma_v* = StdDev($v_{il} + w_{ilt}$): see equations (3) and (4) for the source of these constraints. At each grid value for *sigma_v* we generate v_{il}^{s} from a normal distribution: see details in Appendix 5. By replacing the predicted price with NAV, we have

$$P_{ils} = \gamma^{s\prime}(lnAV\_norm_{ils} + v_{il}^{s}) + w'_{ils}. \qquad (13)$$

If NAV does a better job than hedonic and does capture part of the unobserved quality, we should expect that the maximum R-squared in equation (13) be higher than that in equation (12).

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[25] When we add the same proxy for unobserved quality (i.e., *resid1*) as GM-M2, the loss coefficient estimate reduces to .084.

[26] The term "optimal *sigma_v*" means the one that best fits the observed second price: i.e. the standard deviation of unobserved quality that is consistent with observed market behavior. This is the sense in which we require that the assumptions of the simulation model fit the data.

More importantly, the optimal *sigma_v* identified using equation (13) should be smaller than the one identified using equation (12). The maximum R-squares require that our simulated values match the data; comparison of maximum R-squares and optimal *sigma_v* for hedonic vs. NAV test the ability of each model to control unobserved quality.

Figure 2 shows the R-squared at different grid points of sigma_*v*. Adding simulated unobserved quality (v_{il}^{s}) back into the hedonic model, R-squared using the hedonic model peaks at .834. The NAV model generates a higher maximum R-Squared of .857. The corresponding optimal *sigma_v* of the hedonic model is more than three times larger than NAV (.2 versus .06). Overall, these comparisons demonstrate the advantages of the NAV model in controlling persistent unobserved quality in repeat sales transactions.

To directly compare the GM estimates with our proposed NAV estimates, in the second exercise we show simulated coefficients on expected loss as a function of the mean standard deviation of the unobserved variable, mean of σ_v (*sigma_v*). In Figure 3, we graph coefficients estimated from GM-M1 and -M2 corrected using their equations for bias. We compare these with our NAV model estimates, marked by "NAV". For completeness, we also plot the NAV model with *resid1_lnAV* in Table 4, model 4, marked by "NAV with 1st residual."

In general, the NAV models produce similar patterns as GM-M2: the loss coefficient adjusted for bias is an upward-sloping function of the variance of unobserved quality, *sigma_v*. When the variance of unobserved quality, *sigma_v*, equals zero, our NAV model produces the same estimates as GM-M2 but increases faster when *sigma_v* increases. As shown in Figure 2, the optimal *sigma_v* is .2 using a hedonic model. The corresponding bias-corrected coefficient of GM-M2 (shown in vertical axis) is about .2. Therefore, compared with GM-M2, NAV produces a similar and conservative estimate of about .2 at its optimal *sigma_v* =.06.

4.4 Comparing the GM Model with the NAV Model - Leave-one-out (LOO) Validation

Can tax assessors use the extra information they observe to measure property value more accurately than the econometrician using equation (1)? To directly address this question, we construct a leave-one-out (LOO) validation exercise comparing predicted values from hedonic regression, equation (3), to normalized assessed value. The objective of LOO is to compare the forecasting accuracy of different models. If the NAV model has superior performance over the hedonic model, we should expect that the former generates smaller forecasting error than the latter.

Note that assessed value is at a disadvantage because it lags the date of sale by up to 5 years: any changes to property characteristics or to neighborhood values during the time from assessment to sale will be ignored by assessed value but included in the hedonic which uses all the information up to and including the time of the left-out observation. On the other hand, assessors inspect the property and include many neighborhood and property characteristics unavailable to the econometrician. This implies that our cross-validation exercise is relevant to determining the balance of advantages and disadvantages of the two methods for estimating property value.

Because all the identification in our model comes from variation within town-years, we conduct the validation exercise by town. For hedonic regression we run the following equation using all the observations from the beginning of our sample to through year *t* by leaving out one observation, *i*, in year *t*:[27]

$$P_{it}^{(-i)} = \beta X_i^{(-i)} + FE_t^{(-i)} + \varepsilon_{it}^{(-i)} \quad (14)$$

where FE_t are year dummies. As our analysis is performed by town, we only include year dummies. Then we calculate, for the left-out observation *i*, the predicted value $\hat{P}_{it}{}^{(-i)}$ and its mean square error

$$MSE_{it}^{Hedonic} = (P_{it} - \hat{P}_{it}{}^{(-i)})^2. \quad (15)$$

We repeat the calculation *N* times for all the observations in town *l* in year *t*. Each time we leave out one observation. We calculate

$$CV_{t,(n)}^{Hedonic} = \frac{1}{n}\sum_{i=1}^{n} MSE_{it}^{Hedonic}. \quad (16)$$

The test error, $CV_{t,(n)}^{Hedonic}$, is estimated by averaging the *N* resulting MSE's. The calculation of normalized assessed value is discussed in Section 2. For observation *i* in town *l* in year *t*, we first calculate the expected second sales price by leaving out that observation. i.e., Regress P_{ilt} on year fixed effects and calculated the predicted value $\hat{P}_{ilt}{}^{(-i)}$.

$$P_{it}^{(-i)} = FE_t^{(-i)} + e_{it}^{(-i)} \quad (17)$$

where FE_t are year dummies. Since the analysis is conducted by town, P_{ils} is the same as P_{is}. Next, we calculate deviations of log of assessed value, $lnAV_{it}$, from year averages. I.e., we regress $lnAV_{it}$ on year dummies and obtain the residual, $\hat{\varepsilon}_{it}^{lnav}$.

$$lnAV_{it} = FE_t + \varepsilon_{it}^{lnav}. \quad (18)$$

[27] The town subscript *l* found in earlier equation is dropped in this section.

Lastly, we calculate

$$MSE_{it}^{NAV} = (P_{ilt} - \widehat{lnAV\_norm}_{it}^{(-i)})^2 \qquad (19)$$

where $\widehat{lnAV\_norm}_{it}^{(-i)} = \hat{P}_{it}^{(-i)} + \hat{\varepsilon}_{it}^{lnav}$. The test error, $CV_{t,(n)}^{NAV}$, is estimated by averaging the *N* resulting MSE's,

$$CV_{t,(n)}^{NAV} = \frac{1}{n}\sum_{i=1}^{n} MSE_{it}^{NAV}. \qquad (20)$$

We choose the top ten towns (out of 169 towns) based on their numbers of transactions during our sample period. Transactions in these towns represent 24% of our sample. For each town, we choose one year in the middle of each cycle: 2002 for normal, 2005 for boom, 2010 for bust, and 2015 for recovery. In sum, we calculate 40 MSE pairs, four years for each of the top ten towns, to compare predicted values from hedonic regression and normalized assessed value.

Results of this horse race are summarized in Figure 4. In most town-years, the MSEs using normalized assessed value are consistently smaller than those using hedonic regressions. The results strongly support the superior performance of assessed value.

5. Robustness Tests

5.1 The Effects of Improvements

We use houses sold at least three times to identify changes in quality between sales.[28] Figure 5 gives two examples of a house that sells three times at *t1*, *t2*, and *t3*. The black line represents market price trends or true market value. The blue dots denote residuals estimated from the hedonic model. Panel A shows an example with no improvement and the sale prices strictly follow the market trend. In other words, the residuals are approximately zero. In fact, even if residuals are different from zero, GM attempts to control for this unobserved quality (e.g., nice view) by including the residual from the previous sale as an explanatory variable. For example, if the levels of all three residuals are high, GM's inclusion of the first residual for each pair of sale is intended to control bias in the loss coefficient. In this case, we have persistent unobserved quality: i.e., there are no changes in the residual (a proxy for quality) between sales.

[28] We thank an anonymous referee for this suggestion.

Panel B shows an example where improvements occur between the sale at *t1* and the one at *t2*.[29] When we estimate the first stage hedonic model without observing the improvements, we would find that (1) the residual increases from *t1* to *t2* and (2) the residual at *t3* continues to stay at roughly the same level as *t2*. I.e., we need at least three sales to identify improvements between sales. The observation at *t1* is used to identify the market value of the original house, while the observations at *t2* and *t3* are used to identify the market value for the improved house.

If we are unable to account for this improvement, it might appear that the seller sold the house for above market value due to loss aversion. This would be likely if market prices trended down between the two sales. In fact, the true value above the estimated value is due to improvements. Therefore, we expect that improvements bias loss coefficients in a positive direction, making estimated coefficients too large.

To examine this issue, we re-estimate the GM and NAV models using a subsample of houses sold at least three times during our sample period. This subsample has 110,263 transactions, including 41,818 repeat pairs. We need information on both residual change and residual level from houses sold three times or more as described in Figure 5. To identify an increase in residual as "large" (as shown in Panel B, from *t1* to *t2*), we flag a repeat sale at *t2* with residual increase from the previous sale (*t1* in this example) greater than one standard deviation of residual changes among all the transactions for the year *t2*. To identify whether residual persists at the same level (as shown in Panel B, from *t2* to *t3*), we require the residual for the *t3* sale to be within one standard deviation range from the *t2* residual: the standard deviation is calculated for residuals in all the transactions taking place in the year *t2*. Results are highly similar when we use 0.5 or 1.5 standard deviation.[30]

We utilize these identified improvements in two ways. First, we compare the GM-results with and without improvement. If improvements would bias up our results, we should expect to find a reduced loss coefficient after deleting sales with improvements. Our results in Table 5 are consistent with this expectation: the loss coefficient in model 2 is about 35% smaller than GM-M2 (.156 versus .243). Secondly, we re-estimate the first-stage hedonic regression using all sales and

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[29] We simply this example by showing only one improvement from *t*1 to *t*2. This example easily generalizes to four or more repeat sales. We find relatively few houses in this category, and very few houses experienced two consecutive improvements between sales.

[30] The number of transactions with improvements (out of 110,263 transactions) identified using 0.5-, 1-, and 1.5-standard-deviation is 14,764, 8,047, and 4,663, respectively.

adding a dummy for improvement to estimate the improvement-corrected predicted value of the second sale (*lnprice2_hat_improve*). We then calculate the improvement-corrected expected loss (*exp_loss_improve*) following the same procedure as GM. In model 3, we find the loss coefficient also reduces after correcting for improvement. This reduction in the loss coefficient is likely due to a large coefficient estimate of the improvement dummy in the first stage hedonic model. For example, the coefficient of >3 bathrooms is .18, while the coefficient of improvement dummy in the first stage is .14. As improvements are identified using three or more repeat sales, only 3,932 out of 41,818 (9.4%) transactions involve improvements from the previous sale. Conditional on improvement and positive values for both loss variables, the mean is *exp_loss_improve* is lower than *exp_loss* (.27 versus .39). Consequently, we find that failure to control improvements biases the second stage loss coefficient upward (from .21 to .25), supporting the importance of controlling unobserved quality.

We also calculate NAV results using a subsample of sales with no improvement. As shown in model 5, the assessed loss coefficient is .242, comparable to .253 in our baseline results in model 4. Overall, we conclude from these robustness exercises that our NAV model largely control for endogeneity bias caused by omitted unobserved quality.

5.2 No Fixed Effects in the Second Stage

In equation (3), $\hat{P}_{ils}$ is estimated using observed characteristics and town-year fixed effects (FE_{ls}). In our NAV model, $lnAV\_norm_{ils}$ is estimated, for a given town in a particular year, by adding the deviation of the property's assessed value from the mean assessed value to the mean price. In equations 7 and 10, since town-year effects is already included in the expected value estimates, although in different ways, we re-run our baseline results of Tables 3 and 4 by excluding the FE_{ls} in the second stage. Results in Table 6 suggest that both GM and NAV models produce similar loss coefficients with and without fixed effects in the second stage: the loss coefficient on log of sale price in GM-M2 (NAV) is .228 versus .203 (.224 versus .201).

We find loss coefficients are similar when we include and exclude town-fixed effects in the second stage. Since we know that some omitted variables in our model, such as time-on-market (TOM), are strongly related to the sale price, this finding implies a low correlation between TOM and loss. This low correlation is plausible because anchoring based on historical facts is specific to each individual seller. In other words, the amount paid at the time of purchase is individual-specific whereas TOM is strongly related to current local and macroeconomic conditions common to all who are selling at a given time. This finding is important because it suggests that researchers using our anchoring model do not have to worry about omitted variables related to time-varying local conditions even when their data does not include town-year fixed effects. However, this conclusion may not be true in some other places where buying occurs at about the same time in large numbers.

5.3 County Fixed Effects

Research using spatial identification strategies typically have county or metropolitan fixed effects. We evaluate the generality of our model by substituting county-year for town-year fixed effects in both first and second stages. If our model has general application, then we expect coefficients on expected loss in GM-M2 should increase and those on assessed value expected loss should still be similar to those in GM-M2.

In Table 7, models 1 and 2 reproduce the results using town-year fixed effects. In model 3, the parameter α'' increases substantially from .228 to .362, as expected if town-year fixed effects are important in Connecticut. Compared model 3, assessed values in model 4 produces a similar parameter of .389, providing further evidence that NAV is as effective as GM-M2 in controlling for OVB. Future research can evaluate methods to obtain further reductions in the quality-adjusted coefficients: e.g., knowing that town boundaries are important, one might expect spatial clustering of the estimates of v_{il}, and this can be learned from spatial clustering of first residuals, equation (4) even when town boundaries are not available to the econometrician.

5.4 Subsamples of Demand Growth and Supply Elasticity

A concern is that house prices might rationally depend on expectations about future fundamentals such as income, employment, or new construction. We address this concern by estimating for high- and low-income growth towns, a proxy for change in demand, as well as for high- and low supply elasticity towns.

Table 8 compares results for high-income growth and low-income growth. In high growth towns, the assessed loss coefficient is .384 compared to .134 in low growth towns. We conclude that high growth in demand is required for sellers with losses to obtain premiums over expected sales prices. The conventional method, GM-M2 shows much smaller premium changes with demand growth: .286 for high growth, .200 for low growth, both statistically significant. We conclude that both methods respond to demand growth as expected from theory.

We also estimate separate models for towns with high supply elasticity which should dampen expectations of price change relative to the low supply elasticity sample: Glaeser *et al*. (2008) present evidence that changes in supply will reduce the gap between house prices and fundamentals. To proxy for supply elasticity, we first use decennial census data on percent change in total single-family units from 2000 – 2010. We divide the sample into the 25 towns and 35,386 observations with below-median change (below +5.2%) and the 25 towns and 30,419 observations above median.[31] The low supply elasticity towns had changes roughly uniformly distributed from -3.8% to +5.2%. The high supply elasticity towns were roughly uniformly distributed from +5.2% to +18%; there was one outlier with a change of +26%.

Appendix 6.1 shows that the NAV-based loss coefficient in low elasticity town (.278) coefficient is more than double that in high elasticity town (.179). This is expected since high elasticity is approximated by high growth in the housing stock. New houses will be more similar to each other than older houses, so the effect of unobserved quality is lessened. Similar pattern is found by comparing model (1) with (3) using GM-M2. We conclude that our NAV model for correcting unobserved quality is robust.

As the change in total housing units is likely to be endogenous, we also use the Wharton Residential Land Use Regulation Index (WRLURI). Appendix 6.2. reports the results.[32] The Wharton index does not suffer from endogeneity, but it does not provide much variation in supply elasticity at the town level. Still, results are broadly consistent, as the comparison between low and high elasticity subsamples based on the NAV-based coefficients are qualitatively similar to that based on the GM model coefficients.

5.5 Sub-period Results

Our analysis of sub-periods during the bust and recovery phases after the Global Financial Crisis is motivated by forced sales and periods of market disequilibrium. Campbell *et al*. (2011)

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[31] These are the largest towns where we have data on housing units. Connecticut is a densely populated state where it is generally difficult to obtain permits for new construction, as is true on both US coasts. Some towns are more willing to accommodate growth (and benefit from higher property tax revenue) than others, justifying our proxy. We use the Wharton index as an alternative measure to check results.

[32] The WRIURI is available at http://real-faculty.wharton.upenn.edu/gyourko/land-use-survey/ (last access: December 29, 2018). As it is only available for a cross-section of 66 towns in CT, we aggregate these data to county-level.

and Mian *et al*. (2015) show that forced sales, where a high mortgage loan balance leads to foreclosure, sell at a substantial discount to unforced sales. Coulson and Zabel (2013) review these hedonic price studies related to disequilibrium in the housing market; they classify markets dominated by foreclosures as typically in disequilibrium. These studies motivate us to use subsamples: i.e., we expect greater influence of disequilibrium, mortgage financing and forced sales during the bust.[33]

Table 9 shows results for normal (2000-2003), boom (2004-2006), bust (2007-2012) and recovery (2013-2017) periods. Loss coefficients estimated using both GM-M2 and NAV models in bust and recovery are much smaller than normal and boom. This finding is consistent with bargaining theory which says that negotiating strength of sellers is dependent on market tightness measured by the ratio of buyers to sellers. The bust period was a time of substantially reduced bargaining power, and even the recovery showed small coefficients. We conclude that there is little evidence that forced sales or disequilibrium was important in Connecticut and that loss coefficients respond to economic conditions in the expected way.

In normal and boom periods, a problem is posed by very few transactions with expected losses during these periods: the last row in the table gives the number (percentage) of positive losses in each period. Results show much higher coefficients for assessed value expected losses in normal and boom with few losses compared to the bust and recovery periods. In the normal and boom periods, the assessed value coefficients are higher than GM-M2. We conclude that the assessed value method does not produce reliable estimates due to the few observations on losses available in many town-years. This is a failure peculiar to the anchoring model with its requirement of enough losses: it should not subtract from the general application of the assessed value method to estimating unobserved quality, as demonstrated next.

5.6 Different Holding Periods

Ben-David and Hirshleifer (2012) expect that realization preference will be strongest for short holding periods when the purchase price is likely to be most salient as a reference point. We therefore classify our sample into three terciles of holding period. Table 10 compares results for low (<40 months), mid (41-77 months), and long (>77 months) holding period. As expected, the

[33] Connecticut was never dominated by forced sales, foreclosures or high vacancy as other states were. In terms of Coulson and Zabel (2013), Connecticut looks more like Pennsylvania than like Florida or Nevada.

loss effect is stronger for short holding period. This pattern exists when we examine both GM and NAV results. Results based on GM-M2 suggest that the loss coefficient in houses held for 77 months or more is 33% lower than that in houses held for less than 40 months (.285 versus .428). The reduction on loss effects from short to long holding period is similar using NAV: the loss coefficients reduce from .429 to .226, confirming the robustness of the NAV method.

5.7 The Effects of Flippers

Bayer *et al*. (2020) develop a novel strategy to identify flippers, a set of individuals who resell their properties after a short holding period. This helps decompose the observed price changes into the discount or premium relative to market price at purchase, return during the holding period, and physical improvements made to the property. The physical improvements are highly relevant to our study because flippers may invest or renovate before reselling. Therefore, observed price appreciation is likely due to such improvements rather than anchoring.

In our analyses, we kept only repeat sales were the second sale happened after at least 12 months. Therefore, our results are less likely to driven by flippers because high-volume flippers are more likely to resell homes after a very short period of time. For example, Bayer *et al*. (2020) find that high-volume flippers (defined as the number of flips greater than 10 in their sample period) typically sell 80% of the homes they purchase within the first year.

Nevertheless, we check whether our results are affected by flippers. We follow Bayer *et al*. (2020) and use the names of the buyer and seller to identify flippers as individuals engaged in the buying and selling at least two different properties while holding them for less than two years.[34]

We find a similar pattern as in Bayer *et al*. (2020), although we observe a smaller proportion of flippers as we only focus on single-family housing and Connecticut is less subject to speculative activities compared to Los Angeles. In total, there are 2,736 (out of 90,345) transactions by flippers. We re-ran our baseline analyses by deleting these transactions. Our results, shown in Appendix 7, are robust: changes in coefficients are small.

[34] See Bayer *et al*. (2020) for detailed discussions on the potential bias of using name matches. Bayer *et al*. (2020) also identify flippers using a second home method where the buyer is observed to hold the second property and the additional property is sold within two years. The method we used here is more conservative because the individual must conduct multiple flips in our sample period while the second home method does not require contemporaneous overlap in property holdings.

5.8 Using Gains

A potential concern is that a random error from assessed value could cause an "attenuation bias" which could bias our NAV loss coefficients towards zero. To check this issue, we conduct a falsification test using expected gain. The idea is that, if our finding of a smaller NAV loss coefficient is driven by the attenuation bias, we would expect to find a similar result comparing GM-based and NAV-based gain: i.e., replacing expected loss with expected gain.

In Panel A of Appendix 8, *exp_gain* is equal to the absolute value of *anchor* (i.e. *lnprice1-lnprice2_hat*) if *anchor* is negative (i.e. previous sales price is lower than predicted second price), and 0 otherwise. *gain_lnAV* is defined similarly using *anchor_lnAV*. We use the absolute value of expected gain for ease of interpretation of the expected negative coefficient (gains discount from expected sales price). Comparison of the GM gain coefficients in models 1 and 3 and the NAV gain coefficients in models 2 and 4 suggests that attenuation bias is not likely a concern: given the positive GM coefficients on *exp_gain*, attenuation bias would produce NAV gain coefficients with positive signs but of smaller magnitudes. However, the NAV gain coefficients have opposite signs compared to those on the GM gain. In fact, the negative NAV gain effect is consistent with the predictions from loss aversion models which are based on a kink in the utility function at zero, as marginal gains are valued much less than equivalent losses as documented in Bokhari and Geltner (2011).[35]

More recent studies using the GM framework include both the expected loss and expected gain as regressors. For example, Bokhari and Geltner (2011) incorporate gain as well as loss effects during the global financial crisis. Zhou *et al*. (2020) show that both loss and gain are relevant to the housing cycle. In Panel B of Appendix 8, we add both NAV-based loss and gain. Comparing the loss coefficients in models 1 and 3 with those in our baseline results in Table 4, we find adding the gain variable reduces the GM loss coefficients from .228 to .128 using sale price as the dependent variable and from .319 to .235 using listing price as the dependent variable. Similarly, the NAV loss coefficient is reduced from .224 to .122 and from .357 to .281, respectively. Again, the most noticeable difference is the opposite signs of the gain variables, which provide support to our NAV model. It is consistent with much smaller influence of unobserved quality as the assessors

[35] The incorrect sign on the expected gain variable might be explained by improvements made to houses with low initial unobserved quality: i.e., $\hat{\varepsilon}_{ilp} < 0$. Briefly, these unobserved improvements are positively related to the absolute value of gains and to second price, producing upward bias in the expected gain coefficient. Details are available on request.

are able to account for changes in characteristics influencing sales price but unobserved by the econometrician.

6. An Application of the NAV Model to Control for Unobserved Quality

The application of our NAV model is not restricted to testing anchoring effects and to repeat sale analyses. In this section, we show an application of the NAV model to a well-studied area – the effect of listing price strategy on final transaction price.

Listing price could affect final transaction price in different ways. From behavioral aspects, Bucchianeri and Minson (2013) find that a high asking price set by the seller could impact the buyer's evaluation of house quality. Han and Strange (2016) show that listing price directs buyer search. Other studies look at the impact of degree of overpricing (DOP), defined as the ratio of listing price to its expected (true) value, on transaction outcomes. These studies generally agree that a higher DOP is associated with a longer time-on-market and higher final sale price (Yavas and Yang, 1995; Anglin *et al*., 2003; Knight, 2002; Merlo and Ortalo-Magné, 2004; Rutherford *et al*. 2005).

Like the role of unobserved quality on identifying the anchoring effect, the presence of unobserved quality might upwardly bias DOP coefficient estimates. Whether the listing price is above or below the expected largely depends on the estimation of "true value." Unlike the case of anchoring which compares the purchase price from the first sale with the expected value at the second sale, here we compare the listing price with the concurrent expected price. This means we do not require repeat sales to estimate the effect of DOP on the purchase price.

We estimate four different DOP measures based on (1) predicted sale price from a hedonic model (*DOP_price_hedonic*), (2) predicted listing price from a hedonic model (*DOP_lprice_hedonic*), (3) predicted sale price based on NAV (*DOP_price_NAV*), and (4) predicted listing price based on NAV (*DOP_lprice_NAV*). The procedure of normalizing *lnAV* is the same as described in Section 2 except that for measure (4) we replace the sales price with the list price. Again, we include town-year fixed effects in all model specifications as some omitted variables in our model, such as time-on-market (TOM), are driven by current local and macroeconomic conditions. With town-year fixed effects, our identification derives from within town-year variation among individual sellers.

Table 11 shows the results. Models (1)-(4) are based on repeat sales; models (5)-(8) are based on all transactions including one-only sales to test robustness. The DOP coefficients using NAV (in models (2), (4), (6) and (8)) are about half of the ones with hedonic predictions (in models (1), (3), (5) and (7)). In additional robustness tests we use the full sample to calculate the normalized value, and we control for month, residual and loan-to-value ratio (not shown). As the results are quite robust, we conclude that the NAV model has application to a substantial literature other than the loss premium.

7. Conclusions

We propose an assessed value model as an alternative approach to control for persistent unobserved quality and mitigate omitted variable bias. Property tax assessed values allow us to relax strong assumptions made in the previous literature and to construct quality-adjusted variables for estimation. Our model can be implemented with a standard hedonic dataset where assessed values are available, and it can be applied to many repeat sales models where persistent unobserved heterogeneity might be an issue. Most importantly, our assessed value model does not require repeat sale data and can be applied to many other studies which rely on the estimation of the expected (true) market value.

To demonstrate the effectiveness of our model, we examine the role of unobserved heterogeneity in estimates of anchoring effects. We test the assessed value model and compare to the GM model with over 90,000 repeat pairs in 169 Connecticut towns; data are flooded with town-year fixed effects to identify parameters from within town-year variation. We show that our assessed value model effectively mitigates the omitted variable bias and produces similar results as the GM model that includes the estimated residual from the first sale. Results are robust to alternative model specification using county fixed effects, to controlling loan-to-value ratio, to replacing final sale price with listing price, to simulated unobserved quality, to controls for changes in quality, to subperiods, to excluding flippers, and to variations in supply elasticity and demand growth. We examine the impact of degree of overpricing (DOP) on final transaction price. Again, the presence of unobserved quality is likely to create an upward bias in DOP coefficient estimates. Our NAV model effectively produces more conservative DOP estimates.

A natural future research direction involves the effect on the aggregate housing market cycle associated with anchoring behavior due to changes in unobserved quality. Glaeser and

Nathanson (2016) suggest that anchoring behavior may reduce transaction volume during busts. Zhou *et al*. (2020) document the association between anchoring and house market cycles whereas here we investigate the basic GM model and show how it can be revised to have wider application.[36]

Another potential area for research lies in the relation between local housing market dynamics and its unobserved quality. Using theories from search and bargaining, Bourassa *et al*. (2009) find the effects of unobserved quality (i.e., atypicality) on house price appreciation in weak markets (i.e., markets with declining house prices) are larger than for strong markets. Anenberg (2016) separates local markets with declining house prices into deciles: the greater the rate of decline, the higher the ratio of list prices to expected sales price, suggesting that unobserved quality is more important the greater the price decline.

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[36] Zhou *et al*. (2020) investigate both loss and gain and show the relevance of applying the GM model to the housing cycle. They suggest that the role of loss/gain is determined by the direction of adjustment which comes from the coefficients, the magnitudes and the proportions of loss and gain. As long as the magnitudes and proportions are large, we do not need a large coefficient to get big effects on the cycle. This is because, even with small loss and gain coefficients, the imbalance of proportion between loss and gain could lead to a large impact on aggregate changes in transactions prices.

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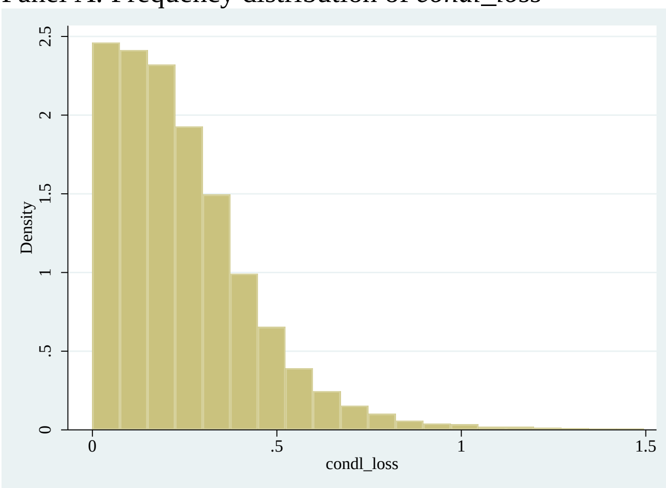
Figure 1: Frequency Distribution of Conditional Expected Losses

Panel A shows the distribution of *condl_loss*, *exp_loss* conditional on a positive loss with zero values set to missing. The right panel shows the distribution of *condl_loss_lnAV*, expected loss conditional on a positive loss based on the assessed value at the time of sale: zero values are set to missing. See Table 1 for variable definitions. These results support the hypothesis that a substantial part of expected losses as measured by the econometrician can be explained by the additional data available to the tax assessor.

Panel A: Frequency distribution of *condl_loss*



Panel B: Frequency distribution of *condl_loss_lnAV*

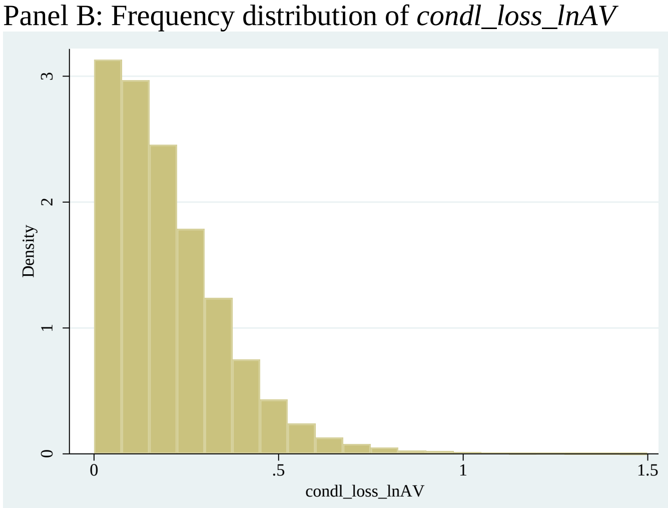


Figure 2: Comparing the GM Model with the NAV Model - Simulation of R-Squared

This figure shows the relationship between the mean standard deviation of the unobserved variable, mean of σ_v (*sigma_v*) and the corresponding R-Squared from a regression of second sale price on predicted value using either a hedonic model (shown as "Hedonic") or NAV (shown as "NAV") and the simulated unobserved quality. The point estimate that produces the maximum R-Squared identifies the "optimal" *sigma_v*.

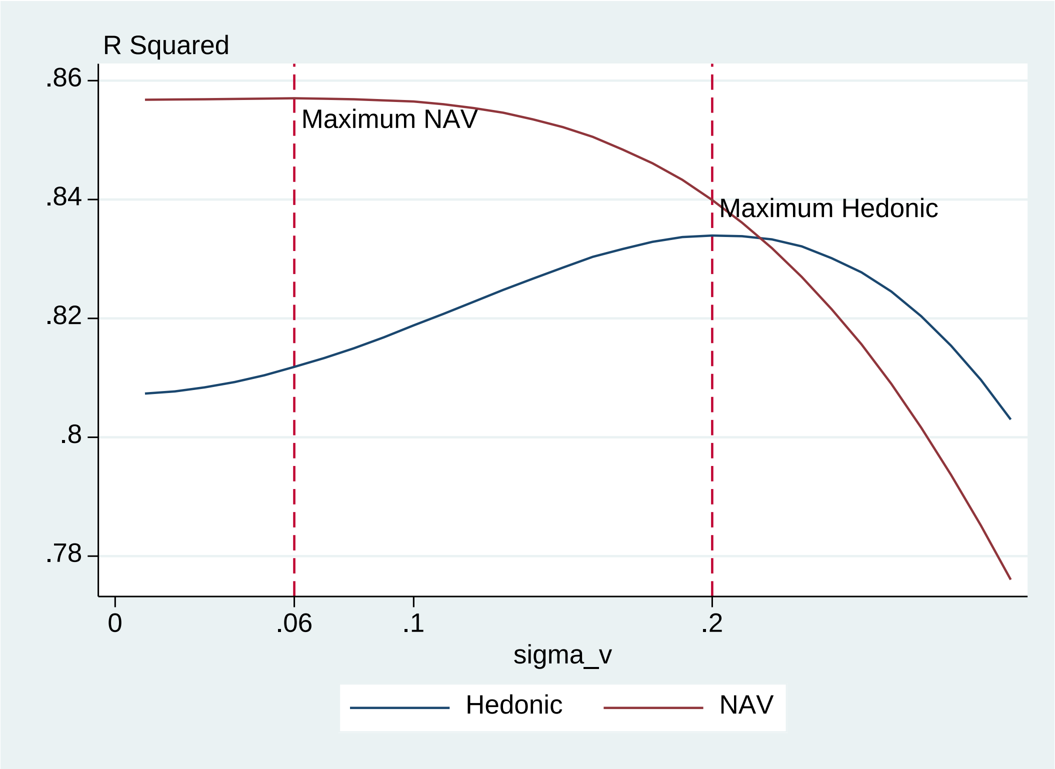


Figure 3: Comparing the GM Model with the NAV Model - Simulation of Coefficients

This figure shows simulated coefficients on expected loss (*exp_loss*) as a function of the mean standard deviation of the unobserved variable, mean of σ_v (*sigma_v*). We graph coefficients estimated from Genesove and Mayer (2001), Models 1 and 2 corrected using their equations for bias. GM's model 1 (GM-M1) is equation (7) in our paper; their equation for the bias in this estimator is our equation (A4). We graph the point estimate in model (2) of Table 3 minus the bias estimate (shown as "GM-M1," the line with squared marker): GM's simulations suggest that this is an upper bound because of omission of the unobserved variable. GM's model 2 (GM-M2) is equation (10) in our paper; their equation for the bias in this estimator is our equation (A7). We graph the M2 point estimate in model (4) of Table 3 minus the bias estimate (shown as "GM M2," the line with diamond marker): GM's simulations suggest that this is a lower bound because of attenuation bias due to measurement error. GM's estimate of the true value of *sigma_v* is the point where their two model estimates are equal. We graph coefficients estimated from our NAV model in equation (7') minus the bias estimate, shown as "NAV", the line with circled marker, and those from equation (10') minus bias, shown as "NAV with 1st residual", the line with triangle marker. The bias in NAV models is estimated in the same way as described in Appendix A1.1 and A1.2 by replacing the predicted value from the hedonic model with NAV.

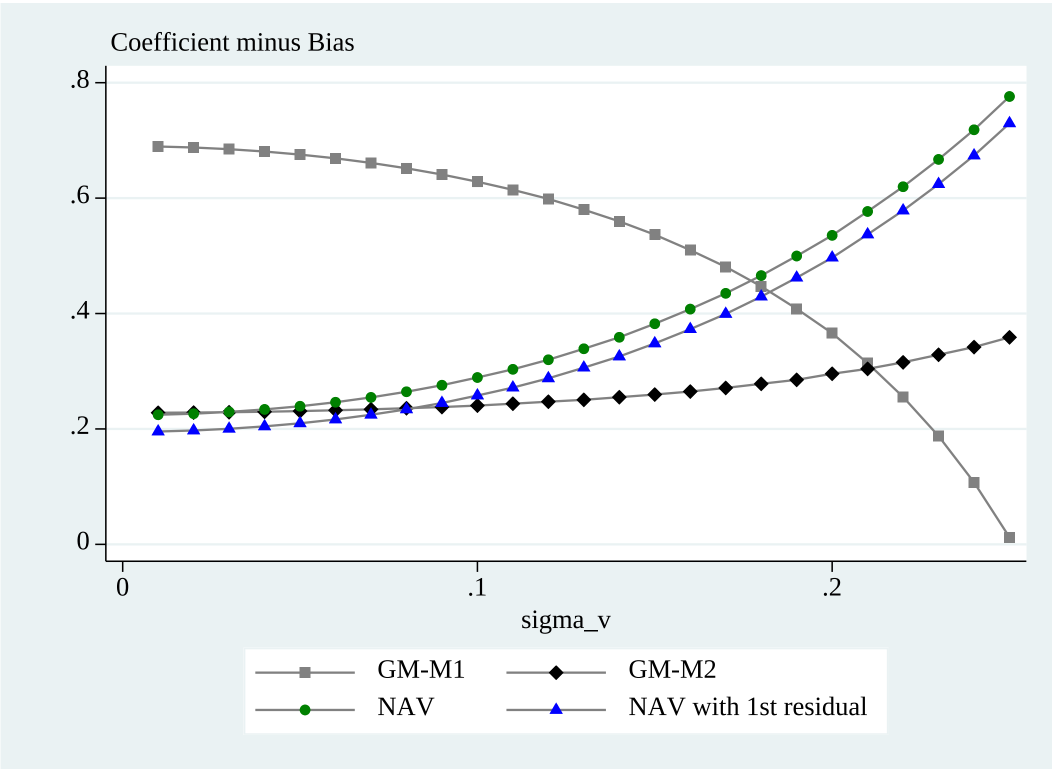


Figure 4. Leave-one-out (LOO) Validation

This figure shows the results of leave-one-out (LOO) validation exercise comparing predicted values from hedonic regression, marked "Hedonic" in blue dot, to normalized assessed value, marketed "lnAV_norm" in red triangle. The validation is performed by town for the top ten towns ranked based on numbers of transitions during our sample period. The horizontal axis is mean squared errors (MSE) of leave-one-out cross-validation (LOOCV). The vertical axis lists the top ten towns in our sample.

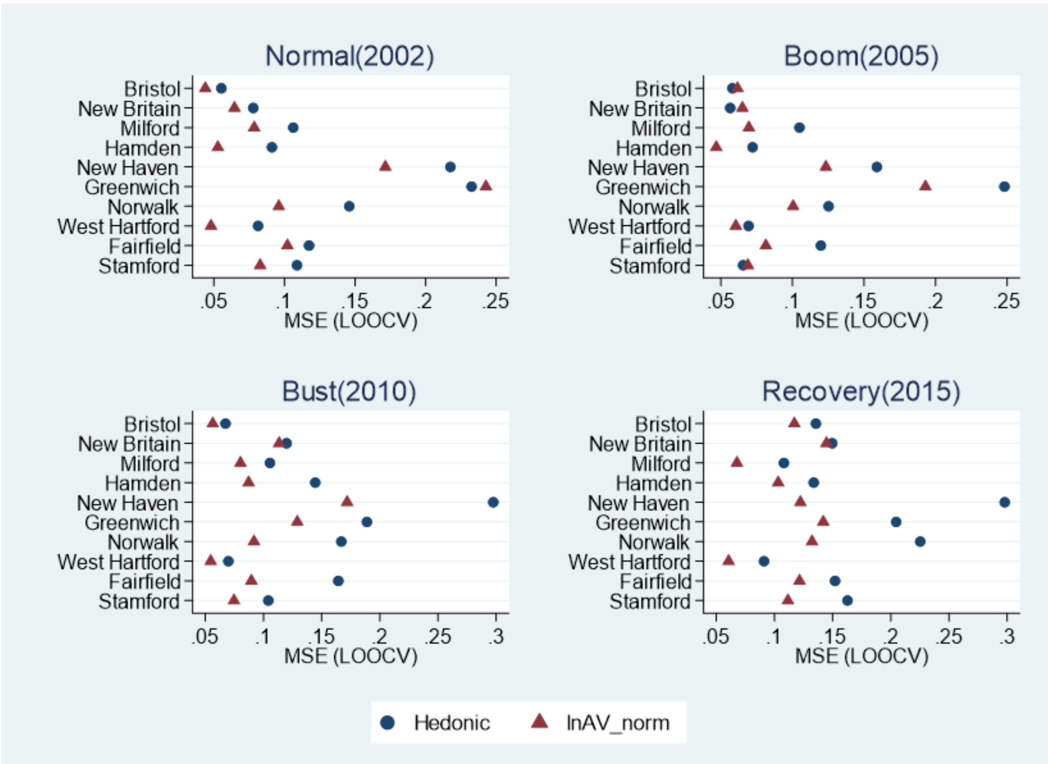
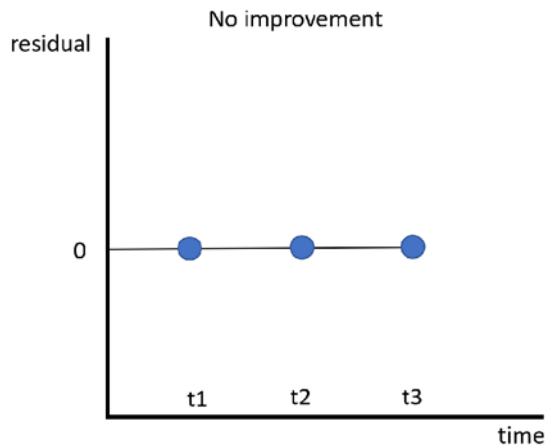


Figure 5: Using Houses Sold More than Three Times to Identify Improvements

Panel A depicts an example in which there is no improvements between sales. Panel B shows an example in which improvements take place between *t*1 and *t*2 but not from *t*2 to *t*3. The black line represents market price trends or true market value. The blue dots denote residuals estimated from the hedonic model.

Panel A: No Improvement



Panel B: Improvements from *t*1 to *t*2

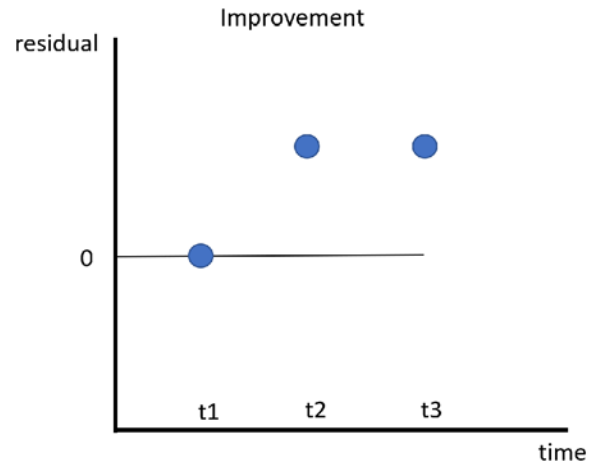


Table 1: Sample Construction and Variable Definitions

This table summarizes sample construction procedure in Panel A and variable names and definitions in Panel B. In Panel B, *_sq* suffix on any variable indicates that the variable is squared: e.g. *resid1_sq* is the square of the first residual. *qual_adj_* prefix on any variable means that the variable is quality-adjusted based on the simulation model, equation (16). For example, *qual_adj_lnprice2_hat* is quality-adjusted *lnprice2_hat*. Variable symbols from equations are shown in column "Equation Variable" if available.

Panel A: Sample Construction

	Observations
Individual residential transactions between 1994 and 2017	1,409,127
Transactions with missing dates	(63)
Transactions with lot size less than 50,000 square feet	(12,764)
Transactions with sale price less than $40,000	(109,625)
Transactions with interior footage less than 300 square feet	(42,874)
Transactions with less than one bedroom	(395,000)
Transactions with structures built earlier than 1799 or after 2018	(66,585)
Transactions with less than 0.5 bathrooms	(9,480)
Transactions with year built later than year sold	(708)
Transactions with property types that are not single-family residential	(150,417)
Transactions without warranty deeds	(67,093)
Transactions with bought and sold on the same date	(5,950)
Final Sample used in the hedonic estimation	**548,568**
Non-repeat Sale	(351,005)
Repeat sales before 2000	(75,469)
Repeat sales in town-year with less than 10 observations	(663)
Repeat sales with holding period less than 12 months	(18,715)
Repeat sales with non-matched buyer and seller	(12,371)
Final Sample of repeat sales	**90,345**

Panel B: Variable Definitions

Variable	**Equation Variable**	**Definition**
lnprice2	P_{ils}	Natural logarithm of the second sales price of a repeat pair.
lnlistprice2		Natural logarithm of the second listing price of a repeat pair.
lnprice2_hat	$\hat{P}_{ils}$	Natural logarithm of the second sales price predicted from a hedonic regression, equation (3): market value at the second sale based on observables available to the econometrician.
lnAV	$lnAV$	Natural logarithm of the assessed value at the time of second sale. Assessed value is estimated by the property tax assessor every 5 years based on observables available to the assessor.
lnAV_norm	$lnAV\_norm$	lnAV normalized for the 5-year assessment cycle. Normalized AV is the assessors estimate of lnprice2_hat.
lnprice2_hat_improve		log of the second sales price predicted by a hedonic regression using all sales and including a dummy for improvement.
lnprice1	P_{ilp}	Natural logarithm of the first sale price of a repeat pair.
anchor	$P_{ilp} - \hat{P}_{ils}$	lnprice1-lnprice2_hat, log of first sales price minus log of market value at the time of the second sale based on observables (predicted price from a standard hedonic regression).
anchor_lnAV		lnprice1-lnAV_norm, log of first sales price minus log of normalized assessed value at the time of the second sale.
anchor_improve		lnprice1-lnprice2_hat_improve
exp_loss	$\left(P_{ilp} - \hat{P}_{ils}\right)^+$	anchor if anchor > 0 (i.e. previous sales > predicted second price), 0 otherwise. It is the owner's expected realized loss based on observables.
exp_loss_sq		exp_loss squared
exp_loss_lnAV	$losslnAV$	anchor_lnAV if anchor_lnAV>0 (i.e. previous sales price > lnAV_norm for the second price), 0 otherwise. It is the owner's expected realized loss based on observables available to the tax assessor.
exp_lossd		A dummy variable equal to 1 if exp_loss>0, 0 otherwise.
exp_loss_improve		anchor_improve if anchor_improve>0, 0 otherwise.
condl_loss		exp_loss conditional on exp_loss>0. Zero values are set to missing.
condl_loss_lnAV		loss_lnAV conditional on loss_lnAV>0. Zero values are set to missing.
exp_gain		The absolute value of anchor if anchor < 0 (i.e. previous sales < predicted second price), 0 otherwise.
exp_gain_lnAV		The absolute value of anchor_lnAV if anchor_lnAV<0, 0 otherwise.
months	$months$	Number of months between sales (holding period) divided by 100.
intersf		Interior size (sq. ft.) of the house.
age		Age of the house, measured as of the previous year of sale.
LTV		The greater of the difference between the ratio of loan to value and 0.8, and zero. The loan-to-value ratio is the amortized mortgage balance at second sale divided by the initial purchase price inflated at a hedonic price index.
resid1	$P_{ilp} - \hat{P}_{ilp}$	Residual from the hedonic regression for the first sales price, $\hat{\varepsilon}_{ilp}$.
resid1_sq		resid1 squared
resid2	$P_{ils} - \hat{P}_{ils}$	Residual from the hedonic regression for the second sales price.
resid1_condl_loss		resid1 conditional on exp_loss>0, otherwise missing.

Table 2: Descriptive Statistics (Repeat Sales Sample, 2000 – 2017)

This table shows descriptive statistics for the variables used in our regression analysis. Observations are repeat sale transactions from 2000-2017. Table 1 summarizes variable definitions.

Variable	N	Mean	Std	Q1	Median	Q3
lnprice2	90,345	12.537	0.705	12.100	12.449	12.899
lnlistprice2	31,838	12.746	0.817	12.254	12.660	13.189
lnprice2_hat	90,345	12.494	0.627	12.051	12.378	12.828
lnAV	89,909	12.040	0.674	11.587	11.952	12.393
lnAV_norm	89,909	12.540	0.671	12.077	12.424	12.886
anchor	90,345	-0.113	0.410	-0.365	-0.079	0.168
anchor_lnAV	89,909	-0.156	0.382	-0.390	-0.116	0.108
exp_loss	90,345	0.105	0.184	0.000	0.000	0.168
exp_loss_lnAV	89,909	0.077	0.148	0.000	0.000	0.108
exp_lossd	90,345	0.421	0.494	0.000	0.000	1.000
condl_loss	38,056	0.250	0.209	0.102	0.208	0.343
condl_loss_lnAV	33,819	0.204	0.178	0.080	0.166	0.285
months (in 00's)	90,345	0.673	0.450	0.329	0.559	0.910
LTV	90,345	0.052	0.162	0.000	0.000	0.038
resid2	90,345	0.044	0.318	-0.087	0.065	0.200
resid1	90,345	-0.004	0.302	-0.130	0.024	0.153
resid1_condl_loss	38,056	0.161	0.226	0.026	0.128	0.248

Table 3: GM Model - OLS Estimates of Coefficients on Expected Loss

This table reports the OLS regression results. Observations are repeat sale transactions from 2000-2017 (2000-2013) in Panel A (Panel B). GM-M1 is our equation (7) and GM-M2 is our equation (10). In Panel A, the dependent variable is *lnprice2*, the logarithm of the second sales price of a repeat pair. In Panel B, the dependent variable is *lnlistprice2*, the logarithm of the second listing price of a repeat pair. *lnprice2_hat* is log of the second sales price predicted by a standard hedonic regression using all sales, the first stage regression. *exp_loss* is equal to *anchor* (i.e. *lnprice1-lnprice2_hat*) if *anchor* is positive (i.e. previous sales price is higher than predicted second price), and 0 otherwise. *months* is the number of months between sales (holding period) divided by 100. *resid1* is the residual from the first stage regression for the first sales price. *exp_loss_sq* is the *exp_loss* squared. *LTV* is the greater of the difference between the ratio of loan to value and 0.8, and zero. See Table 1 for variable definitions. All regressions are estimated with town-year fixed effects. Bootstrap standard errors in parentheses. Standard errors cluster by town are similar due to our large sample size. * p<0.10, ** p<0.05, *** p<0.01.

Panel A: Dependent variable = log of the second sale price (*lnprice2*)

	GM-M1	GM-M1	GM-M2	GM-M2	GM-M2	GM-M2
		Adding months	Adding residual	Adding months & residual	Adding Nonlinear Term	Adding LTV
	lnprice2	*lnprice2*	*lnprice2*	*lnprice2*	*lnprice2*	*lnprice2*
	(1)	(2)	(3)	(4)	(5)	(6)
exp_loss	0.698***	0.690***	0.274***	0.228***	0.268***	0.214***
	(0.012)	(0.011)	(0.012)	(0.011)	(0.025)	(0.013)
lnprice2_hat	0.962***	0.961***	0.952***	0.948***	0.948***	0.949***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
months		-0.033***		-0.076***	-0.075***	-0.074***
		(0.003)		(0.003)	(0.002)	(0.002)
resid1			0.376***	0.399***	0.398***	0.409***
			(0.006)	(0.006)	(0.007)	(0.006)
exp_loss_sq					-0.047	
					(0.036)	
LTV						0.062***
						(0.012)
Constant	0.438***	0.479***	0.619***	0.725***	0.720***	0.705***
	(0.053)	(0.051)	(0.045)	(0.051)	(0.049)	(0.046)
Town-year	Yes	Yes	Yes	Yes	Yes	Yes
Observations	88419	88419	88419	88419	88419	88419
R-squared	0.828	0.829	0.844	0.846	0.846	0.846

Panel B: Dependent variable = log of the listing price of the second sale (*lnlistprice2*)

	GM-M1	GM-M1	GM-M2	GM-M2	GM-M2	GM-M2
		Adding months	Adding residual	Adding months & residual	Adding Nonlinear Term	Adding LTV
	lnlistprice2	*lnlistprice2*	*lnlistprice2*	*lnlistprice2*	*lnlistprice2*	*lnlistprice2*
	(1)	(2)	(3)	(4)	(5)	(6)
exp_loss	0.765***	0.791***	0.345***	0.319***	0.319***	0.265***
	(0.027)	(0.030)	(0.029)	(0.029)	(0.063)	(0.033)
lnprice2_hat	1.017***	1.017***	0.988***	0.987***	0.987***	0.989***
	(0.010)	(0.009)	(0.011)	(0.010)	(0.010)	(0.009)
months		0.041***		-0.027***	-0.027***	-0.017**
		(0.008)		(0.007)	(0.009)	(0.009)
resid1			0.394***	0.403***	0.403***	0.446***
			(0.012)	(0.017)	(0.015)	(0.016)
exp_loss_sq					-0.001	
					(0.083)	
LTV						0.209***
						(0.019)
Constant	-0.168	-0.191*	0.226*	0.251**	0.251*	0.223**
	(0.126)	(0.112)	(0.135)	(0.126)	(0.130)	(0.112)
Town-year	Yes	Yes	Yes	Yes	Yes	Yes
Observations	30808	30808	30808	30808	30808	30808
R-squared	0.715	0.716	0.726	0.726	0.726	0.728

Table 4: GM Model Compared to Assessed Value Losses

This table reports the OLS regression results. Observations are repeat sale transactions from 2000-2017 (2000-2013) in Panel A (Panel B). GM-M1 is our equation (7) and GM-M2 is our equation (10). NAV is our equation (10') and NAV, adding first residual is our equation (10''). In Panel A, the dependent variable is *lnprice2*, the logarithm of the second sales price of a repeat pair. In Panel B, the dependent variable is *lnlistprice2*, the logarithm of the second listing price of a repeat pair. *lnprice2_hat* is log of the second sales price predicted by a standard hedonic regression using all sales, the first stage regression. *lnAV_norm* is normalized log of assessed value at the time of second sale. *exp_loss* is equal to *anchor* (i.e. *lnprice1-lnprice2_hat*) if *anchor* is positive (i.e. previous sales price is higher than predicted second price), and 0 otherwise. *loss_lnAV* is equal to *anchor_lnAV* if *anchor_lnAV* is positive (i.e. previous sales price > *lnAV_norm* for the second price), and 0 otherwise. *months* is the number of months between sales (holding period) divided by 100. *resid1* is the residual from the first stage regression for the first sales price. *LTV* is the greater of the difference between the ratio of loan to value and 0.8, and zero. See Table 1 for variable definitions. All regressions are estimated with town-year fixed effects. Bootstrap standard errors in parentheses. Standard errors cluster by town are similar due to our large sample size. * p<0.10, ** p<0.05, *** p<0.01.

Panel A: Dependent variable = log of the second sale price (*lnprice2*)

	GM-M1	GM-M2	NAV	NAV, adding first residual	NAV, adding LTV
	lnprice2	*lnprice2*	*lnprice2*	*lnprice2*	*lnprice2*
	(1)	(2)	(3)	(4)	(5)
exp_loss	0.690***	0.228***			
	(0.012)	(0.016)			
loss_lnAV			0.224***	0.195***	0.200***
			(0.011)	(0.014)	(0.014)
lnprice2_hat	0.961***	0.948***			
	(0.004)	(0.004)			
lnAV_norm			0.899***	0.726***	0.726***
			(0.003)	(0.008)	(0.007)
months	-0.033***	-0.076***	-0.068***	-0.076***	-0.078***
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
resid1		0.399***			
		(0.006)			
resid1_lnAV				0.194***	0.193***
				(0.008)	(0.007)
LTV					-0.000
					(0.009)
Constant	0.479***	0.725***	1.330***	3.504***	3.510***
	(0.045)	(0.049)	(0.042)	(0.103)	(0.092)
Town-year FE	Yes	Yes	Yes	Yes	Yes
Observations	88419	88419	88419	88419	88419
R-squared	0.829	0.846	0.860	0.862	0.862

Panel B: Dependent variable = log of the listing price of the second sale (*lnlistprice2*)

	GM-M1	GM-M2	NAV	NAV, adding first residual	NAV, adding LTV
	lnlistprice2	*lnlistprice2*	*lnlistprice2*	*lnlistprice2*	*lnlistprice2*
	(1)	(2)	(3)	(4)	(5)
exp_loss	0.791***	0.319***			
	(0.022)	(0.029)			
loss_lnAV			0.357***	0.324***	0.320***
			(0.035)	(0.033)	(0.033)
lnprice2_hat	1.017***	0.987***			
	(0.009)	(0.010)			
lnAV_norm			0.905***	0.733***	0.733***
			(0.010)	(0.015)	(0.018)
months	0.041***	-0.027***	-0.032***	-0.036***	-0.032***
	(0.009)	(0.010)	(0.009)	(0.009)	(0.009)
resid1		0.403***			
		(0.017)			
resid1_lnAV				0.195***	0.196***
				(0.015)	(0.017)
LTV					0.043**
					(0.020)
Constant	-0.191	0.251**	1.284***	3.470***	3.467***
	(0.122)	(0.124)	(0.127)	(0.189)	(0.228)
Town-year FE	Yes	Yes	Yes	Yes	Yes
Observations	30808	30808	30808	30808	30808
R-squared	0.716	0.726	0.735	0.737	0.737

Table 5: The Effects of Improvements on Loss Coefficients

This table reports the results for the effects of improvement on loss coefficients. Observations are houses sold at least three times from 2000-2017. GM-M2 is our equation (10) and NAV is our equation (10'). The dependent variable is *lnprice2*, the logarithm of the second sales price of a repeat pair. *lnprice2_hat* is log of the second sales price predicted by a standard hedonic first stage regression using all sales. *lnprice2_hat_improve* is log of the second sales price predicted by a hedonic regression using all sales and including a dummy for improvement. *lnAV_norm* is normalized log of assessed value at the time of second sale. *exp_loss* is equal to *anchor* (i.e. *lnprice1-lnprice2_hat*) if *anchor* is positive (i.e. previous sales price is higher than predicted second price), and 0 otherwise. *exp_loss_improve* is equal to *anchor_improve* (i.e. *lnprice1-lnprice2_hat_improve*) if *anchor_improve* is positive, and 0 otherwise. *loss_lnAV* is equal to *anchor_lnAV* if *anchor_lnAV* is positive (i.e. previous sales price > *lnAV_norm* for the second price), and 0 otherwise. *months* is the number of months between sales (holding period) divided by 100. *resid1* is the residual from the first stage regression for the first sales price. *resid1_improve* is the residual from the first stage regression including a dummy for improvement for the property. See Table 1 for variable definitions. All regressions are estimated with town-year fixed effects. Bootstrap standard errors in parentheses. Standard errors cluster by town are similar due to our large sample size. * p<0.10, ** p<0.05, *** p<0.01.

	GM-M2	GM-M2, no improvement	GM-M2, improvement corrected	NAV	NAV, no improvement
	lnprice2	*lnprice2*	*lnprice2*	*lnprice2*	*lnprice2*
	(1)	(2)	(3)	(4)	(5)
exp_loss	0.243***	0.156***			
	(0.016)	(0.020)			
exp_loss_improve			0.215***		
			(0.021)		
loss_lnAV				0.253***	0.242***
				(0.022)	(0.022)
lnprice2_hat	0.966***	0.965***			
	(0.006)	(0.006)			
lnprice2_hat_improve			0.977***		
			(0.004)		
lnAV_norm				0.904***	0.908***
				(0.005)	(0.006)
months	-0.117***	-0.125***	-0.110***	-0.110***	-0.107***
	(0.005)	(0.004)	(0.005)	(0.004)	(0.004)
resid1	0.428***	0.508***			
	(0.010)	(0.011)			
resid1_improve			0.449***		
			(0.010)		
Constant	0.490***	0.510***	0.357***	1.268***	1.207***
	(0.076)	(0.077)	(0.056)	(0.067)	(0.071)
Town-year FE	Yes	Yes	Yes	Yes	Yes
Observations	41,159	37,276	41,159	41,159	37,276
R-squared	0.858	0.861	0.861	0.869	0.869

Table 6: Robustness Tests with No Fixed Effects in the Second Stage

This table summarizes the results with no fixed effects in the second stage. Panel A replicates Table 3. Panel B replicates Table 4. Observations are repeat sale transactions from 2000-2017 (2000-2013) in (A) ((B)). In (A), the dependent variable is *lnprice2*, the logarithm of the second sales price of a repeat pair. In (B), the dependent variable is *lnlistprice2*, the logarithm of the second listing price of a repeat pair. GM-M1 is our equation (7) and GM-M2 is our equation (10). NAV is our equation (10'). *exp_loss* is equal to *anchor* (i.e. *lnprice1-lnprice2_hat*) if *anchor* is positive (i.e. previous sales price is higher than predicted second price), and 0 otherwise. *loss_lnAV* is equal to *anchor_lnAV* if *anchor_lnAV* is positive (i.e. previous sales price > *lnAV_norm* for the second price), and 0 otherwise. Control variables are the same as Tables 3 and 4 and suppressed. All regressions are estimated with town-year fixed effects. Bootstrap standard errors in parentheses. Standard errors cluster by town are similar due to our large sample size. * p<0.10, ** p<0.05, *** p<0.01.

Panel A: Table 3 with No Fixed Effects in the Second Stage

	GM-M1	GM-M1	GM-M2	GM-M2	GM-M2	GM-M2
		Adding months	Adding residual	Adding months & residual	Adding Nonlinear Term	Adding LTV
	(1)	(2)	(3)	(4)	(5)	(6)
(A) Dependent variable = log of the second sale price (*lnprice2*)						
exp_loss	0.562***	0.569***	0.201***	0.203***	0.223***	0.191***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.020)	(0.012)
(B) Dependent variable = log of the listing price of the second sale (*lnlistprice2*)						
exp_loss	0.644***	0.643***	0.315***	0.309***	0.303***	0.244***
	(0.020)	(0.018)	(0.020)	(0.024)	(0.038)	(0.026)

Panel B: Table 4 with No Fixed Effects in the Second Stage

	GM-M1	GM-M2	NAV	NAV, adding first residual	NAV, adding LTV
	(1)	(2)	(3)	(4)	(5)
(A) Dependent variable = log of the second sale price (*lnprice2*)					
exp_loss	0.569***	0.203***			
	(0.009)	(0.011)			
loss_lnAV			0.201***	0.207***	0.218***
			(0.011)	(0.011)	(0.009)
(B) Dependent variable = log of the listing price of the second sale (*lnlistprice2*)					
exp_loss	0.643***	0.309***			
	(0.021)	(0.020)			
loss_lnAV			0.384***	0.385***	0.378***
			(0.023)	(0.023)	(0.027)

Table 7: Robustness Tests: Town Fixed Effects versus County Fixed Effects

This table compares the results using town-year fixed effects, in models (1)-(2), with those using county-year fixed effects, in models (3)-(4). GM-M2 is our equation (10) and NAV is our equation (10'). Observations are repeat sale transactions from 2000-2017. The dependent variable is *lnprice2*, the logarithm of the second sales price of a repeat pair. *lnprice2_hat* is log of the second sales price predicted by a standard hedonic regression using all sales, the first stage regression. *lnAV_norm* is normalized log of assessed value at the time of second sale. *exp_loss* is equal to *anchor* (i.e. *lnprice1*-*lnprice2_hat*) if *anchor* is positive (i.e. previous sales price is higher than predicted second price), and 0 otherwise. *loss_lnAV* is equal to *anchor_lnAV* if *anchor_lnAV* is positive (i.e. previous sales price > *lnAV_norm* for the second price), and 0 otherwise. *months* is the number of months between sales (holding period) divided by 100. *resid1* is the residual from the first stage regression for the first sales price. See Table 1 for variable definitions. All regressions are estimated with town-year fixed effects. Bootstrap standard errors in parentheses. Standard errors cluster by town are similar due to our large sample size. * p<0.10, ** p<0.05, *** p<0.01.

	Town-year FEs		**County-year FEs**	
	GM-M2	NAV	GM-M2	NAV
	(1)	(2)	(3)	(4)
exp_loss	0.228***		0.362***	
	(0.011)		(0.009)	
exp_loss_lnAV		0.224***		0.389***
		(0.011)		(0.011)
lnprice2_hat	0.948***		0.949***	
	(0.004)		(0.003)	
lnAV_norm		0.899***		0.952***
		(0.003)		(0.002)
months	-0.076***	-0.068***	-0.067***	-0.059***
	(0.003)	(0.003)	(0.003)	(0.002)
resid1	0.399***		0.588***	
	(0.006)		(0.005)	
Constant	0.725***	1.330***	0.692***	0.607***
	(0.051)	(0.042)	(0.043)	(0.030)
Town-year FE	Yes	Yes	No	No
County-year FE	No	No	Yes	Yes
Observations	88,419	8,8419	88,419	88,419
R-squared	0.846	0.860	0.803	0.826

Table 8: Robustness Tests: High and Low Demand Growth

This table reports the results for low/high income growth towns in our sample. Observations are repeat sale transactions from 2000-2017. GM-M2 is our equation (10) and NAV is our equation (10'). Income growth is measured by the changes in median household income (adjusted for inflation) between year 2000 and year 2010 for 50 largest towns where the data on housing units are available. 25 towns that have lower than median income growth are classified as low demand-growth towns, and 25 towns with higher than median income growth are classified as high demand-growth towns. The dependent variable is *lnprice2*, the logarithm of the second sales price of a repeat pair. *lnprice2_hat* is log of the second sales price predicted by a standard hedonic regression using all sales, the first stage regression. *lnAV_norm* is normalized log of assessed value at the time of second sale. *exp_loss* is equal to *anchor* (i.e. *lnprice1-lnprice2_hat*) if *anchor* is positive (i.e. previous sales price is higher than predicted second price), and 0 otherwise. *loss_lnAV* is equal to *anchor_lnAV* if *anchor_lnAV* is positive (i.e. previous sales price > *lnAV_norm* for the second price), and 0 otherwise. *months* is the number of months between sales (holding period) divided by 100. *resid1* is the residual from the first stage regression for the first sales price. See Table 1 for variable definitions. All regressions are estimated with town-year fixed effects. Bootstrap standard errors in parentheses. Standard errors cluster by town are similar due to our large sample size. * p<0.10, ** p<0.05, *** p<0.01.

	Low Demand Growth		**High Demand Growth**	
	GM-M2	NAV	GM-M2	NAV
	(1)	(2)	(3)	(4)
exp_loss	0.200***		0.286***	
	(0.022)		(0.026)	
exp_loss_lnAV		0.134***		0.384***
		(0.019)		(0.030)
lnprice2_hat	0.925***		0.970***	
	(0.008)		(0.006)	
lnAV_norm		0.877***		0.906***
		(0.006)		(0.005)
months	-0.064***	-0.066***	-0.065***	-0.059***
	(0.005)	(0.004)	(0.004)	(0.003)
resid1	0.408***		0.430***	
	(0.009)		(0.010)	
Constant	0.988***	1.566***	0.446***	1.221***
	(0.100)	(0.073)	(0.081)	(0.065)
Town-year FE	Yes	Yes	Yes	Yes
Observations	32,669	33,108	31,496	31,496
R-squared	0.828	0.844	0.883	0.892

Table 9: Robustness to Sub-periods around the Global Financial Crisis (GFC)

This table reports the results for sub-period tests in bust (2007-2012) in models (1)-(2), recovery (2013-2017) in models (3)-(4), normal (2000-2002) in models (5)-(6) and boom (2003-2006) in models (7)-(8). Observations are repeat sale transactions. Models (1), (3), (5) and (7) report the results using GM-M2 and models (2), (4), (6) and (8) report results using NAV. GM-M2 is our equation (10) and NAV is our equation (10'). The last row shows the number and percentage of observations with expected loss greater than 0. The dependent variable is *lnprice2*, the logarithm of the second sales price of a repeat pair. *lnprice2_hat* is log of the second sales price predicted by a standard hedonic regression using all sales, the first stage regression. *lnAV_norm* is normalized log of assessed value at the time of second sale. *exp_loss* is equal to *anchor* (i.e. *lnprice1-lnprice2_hat*) if *anchor* is positive (i.e. previous sales price is higher than predicted second price), and 0 otherwise. *loss_lnAV* is equal to *anchor_lnAV* if *anchor_lnAV* is positive (i.e. previous sales price > *lnAV_norm* for the second price), and 0 otherwise. *months* is the number of months between sales (holding period) divided by 100. *resid1* is the residual from the first stage regression for the first sales price. See Table 1 for variable definitions. All regressions are estimated with town-year fixed effects. Bootstrap standard errors in parentheses. Standard errors cluster by town are similar due to our large sample size. * p<0.10, ** p<0.05, *** p<0.01.

	Bust		**Recovery**		**Normal**		**Boom**	
	GM-M2	NAV	GM-M2	NAV	GM-M2	NAV	GM-M2	NAV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
exp_loss	0.268***		0.270***		0.510***		0.590***	
	(0.020)		(0.017)		(0.075)		(0.074)	
lnAV_norm		0.190***		0.171***		0.959***		0.696***
		(0.027)		(0.011)		(0.094)		(0.109)
lnprice2_hat	0.957***		0.986***		0.902***		0.874***	
	(0.008)		(0.006)		(0.011)		(0.009)	
exp_loss_lnAV		0.911***		0.967***		0.879***		0.780***
		(0.006)		(0.005)		(0.009)		(0.007)
Months	-0.011*	-0.029***	-0.099***	-0.083***	0.020*	-0.005	-0.025***	-0.068***
	(0.006)	(0.005)	(0.003)	(0.003)	(0.011)	(0.013)	(0.007)	(0.006)
resid1	0.385***		0.304***		0.520***		0.405***	
	(0.014)		(0.010)		(0.016)		(0.011)	
Constant	0.544***	1.110***	0.283***	0.466***	1.245***	1.500***	1.644***	2.818***
	(0.100)	(0.072)	(0.074)	(0.067)	(0.142)	(0.109)	(0.113)	(0.092)
Town-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	27,574	27,574	32,523	32,523	11,201	11,201	17,121	17,121
R-squared	0.816	0.830	0.842	0.866	0.886	0.889	0.880	0.885
Obs. (%) with loss > 0	14,053 (50)	14,053 (50)	20,889 (64)	20,889 (64)	834 (8.3)	834 (8.3)	805 (5)	805 (5)

Table 10: Robustness to Different Holding Periods

This table reports the results for sub-sample tests in short holding period in models (1)-(2), mid holding period in models (3)-(4) and long holding period in models (5)-(6). Observations are repeat sale transactions. Models (1), (3), and (5) report the results using GM-M2 and models (2), (4), and (6) report results using NAV. GM-M2 is our equation (10) and NAV is our equation (10'). The dependent variable is *lnprice2*, the logarithm of the second sales price of a repeat pair. *lnprice2_hat* is log of the second sales price predicted by a standard hedonic regression using all sales, the first stage regression. *lnAV_norm* is normalized log of assessed value at the time of second sale. *exp_loss* is equal to *anchor* (i.e. *lnprice1-lnprice2_hat*) if *anchor* is positive (i.e. previous sales price is higher than predicted second price), and 0 otherwise. *loss_lnAV* is equal to *anchor_lnAV* if *anchor_lnAV* is positive (i.e. previous sales price > *lnAV_norm* for the second price), and 0 otherwise. *months* is the number of months between sales (holding period) divided by 100. *resid1* is the residual from the first stage regression for the first sales price. See Table 1 for variable definitions. All regressions are estimated with town-year fixed effects. Bootstrap standard errors in parentheses. Standard errors cluster by town are similar due to our large sample size. * p<0.10, ** p<0.05, *** p<0.01.

	Short Holding Period (Months: ≤ 40)		Mid Holding Period (Months: 40 – 77)		Long Holding Period (Months: > 77)	
	GM-M2	NAV	GM-M2	NAV	GM-M2	NAV
	(1)	(2)	(3)	(4)	(5)	(6)
exp_loss	0.428***		0.346***		0.285***	
	(0.032)		(0.025)		(0.020)	
exp_loss_lnAV		0.429***		0.404***		0.226***
		(0.033)		(0.036)		(0.015)
lnprice2_hat	0.885***		0.960***		1.005***	
	(0.007)		(0.007)		(0.008)	
lnAV_norm		0.832***		0.908***		0.974***
		(0.007)		(0.005)		(0.006)
Months	-0.351***	-0.275***	0.005	-0.015	0.021***	-0.009*
	(0.023)	(0.021)	(0.012)	(0.016)	(0.007)	(0.005)
resid1	0.289***		0.428***		0.473***	
	(0.011)		(0.013)		(0.012)	
Constant	1.568***	2.176***	0.505***	1.135***	-0.117	0.289***
	(0.092)	(0.083)	(0.084)	(0.067)	(0.102)	(0.079)
Town-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	29,939	29,939	29,923	29,923	30,047	30,047
R-squared	0.853	0.862	0.874	0.881	0.850	0.865

Table 11: The Effect of Degree of Overpricing (DOP)

This table reports the OLS regression results. Observations are repeat sale transactions in models (1)-(4) and all transactions in models (5)-(8) from 2000-2013. The dependent variable in models (1)-(4) is *lnprice2*, the logarithm of the sales price of the second sale in a repeat pair. The dependent variable in models (5)-(6) is *lnprice*, the logarithm of the sales price in all sales transactions including repeat and one-only sales. *DOP_price_hedonic* is log of list price minus log of expected sales price predicted by a standard hedonic regression using all sales in the first stage regression. *DOP_price_NAV* is log of list price minus log of normalized assessed value. *DOP_listprice_hedonic* is log of list price minus log of expected listing price predicted by a standard hedonic regression using all sales in the first stage regression. *DOP_listprice_NAV* is log of list price minus log of normalized assessed value which is calculated as described in section 2 except that we substitute listing prices for transactions prices. All regressions are estimated with town-year fixed effects. Bootstrap standard errors in parentheses. Standard errors cluster by town are similar due to our large sample size. * p<0.10, ** p<0.05, *** p<0.01.

	Repeat Sales Transactions				All Transactions			
	lnprice2	*lnprice2*	*lnprice2*	*lnprice2*	*lnprice*	*lnprice*	*lnprice*	*lnprice*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DOP_price_hedonic	0.324***				0.347***			
	(0.024)				(0.011)			
DOP_price_NAV		0.155***				0.165***		
		(0.013)				(0.006)		
DOP_listprice_hedonic			0.304***				0.311***	
			(0.021)				(0.012)	
DOP_listprice_NAV				0.155***				0.165***
				(0.014)				(0.007)
Constant	12.672***	12.698***	12.706***	12.707***	12.644***	12.662***	12.674***	12.675***
	(0.005)	(0.005)	(0.004)	(0.005)	(0.002)	(0.002)	(0.002)	(0.001)
Town-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	31,631	31,631	31,631	31,631	162,480	162,480	162,480	162,480
R-squared	0.751	0.720	0.746	0.720	0.725	0.692	0.717	0.692

Online Appendix

A1. Explaining Bias in Genesove and Mayer (2001)

A1.1 GM-M1 Bias Equations

We present their model here in order to compare bias simulations for the two models. The "true model" for testing anchoring effects is

$$P_{ils} = \gamma \mu_{ils} + \alpha exp\_loss^{*} + FE_{ls} + \epsilon_{ils} \quad \text{(A1)}$$

where ϵ_{ils} is an iid noise term without any unobserved quality. We estimate GM model 1 (GM-M1) as

$$P_{ils} = \gamma' \hat{P}_{ils} + \alpha' exp\_loss + FE_{ls} + \epsilon'_{ils} \quad \text{(A2)}$$

Here ϵ'_{ils} includes unobserved quality omitted from $\hat{P}_{ils}$ which comes from the first stage regression.

In GM model 1, the bias is Eq. (A1) minus (A2)

$$0 = [\gamma \mu_{ils} + \alpha exp\_loss^{*} + FE_{ls} + \epsilon_{ils}] - [\gamma' \hat{P}_{ils} + \alpha' exp\_loss + FE_{ls} + \epsilon'_{ils}]$$

Noted that GM assume that $\gamma = \gamma' = 1$ and $\alpha = \alpha'$. Substitute eq. (3) in the paper into eq. (1) to obtain $\mu_{ils} - \hat{P}_{ils} = v_{il}$. Therefore, $\epsilon'_{ils} = \gamma v_{il} + \alpha(exp\_loss^{*} - exp\_loss) + \epsilon_{ils}$. i.e.,

$$\epsilon'_{ils} = v_i + \alpha \left[\left(FE_{lp} - FE_{ls} + w_{ilp} \right)^{+} - \left(FE_{lp} - FE_{ls} + v_{il} + w_{ilp} \right)^{+} \right] \quad \text{(A3)}$$

Eq. (A3) is the same as GM Eq. (7).

Consider an OLS regression of the second sale price on predicted price and loss, the vector of coefficient estimates equals $(X'X)^{-1}X'P$, where X is an $n \times k$ matrix consisting of *k* independent variables for *n* observations and P is $n \times 1$ vector of observations on the dependent variable. The error-in-variable (EIV) of GM model 1 is $(X'X)^{-1}X'\epsilon$.[37] The ϵ vector is given by (A1); its first term is $B_1^I = (X'X)^{-1}X'v$. Defining $\eta_1 = \left(FE_{lp} - FE_{ls} + w_{ilp} \right)^{+} - \left(FE_{lp} - FE_{ls} + v_{il} + w_{ilp} \right)^{+}$, the second term of Eq. (A3) is $\alpha B_2^I = \alpha (X'X)^{-1}X'\eta_1$

The overall bias is

[37] For example, if $y = X\beta + \varepsilon$ where β is the unknown true coefficient vector and b is the OLS estimate of it. $b = (X'X)^{-1}X'y$. And $b - \beta = (X'X)^{-1}X'y - \beta = (X'X)^{-1}X'(X\beta + \varepsilon) - \beta = (X'X)^{-1}X'\varepsilon$

$$B^{I} = \alpha' - \alpha = B_1^I + \alpha B_2^I = \frac{B_1^I + \alpha' B_2^I}{(1 + B_2^I)} \quad \text{(A4)}$$[38]

A1.2 GM-M2 Bias Equations

GM model 2 (GM-M2) is

$$P_{ils} = \gamma'' \hat{P}_{ils} + \alpha'' exp\_loss + \lambda \varepsilon_{ilp} + FE_{ls} + \epsilon''_{ils} \quad \text{(A5)}$$

where $\varepsilon_{ilp} = v_{il} + w_{ilp}$ is the 1st stage disturbance term from a standard hedonic model, eq. (3) in our paper. The bias is eq. (A1) minus (A5):

$$0 = [\gamma \mu_{ils} + \alpha exp\_loss^* + FE_{ls} + \epsilon_{ils}] - [\gamma'' \hat{P}_{ils} + \alpha'' exp\_loss + \lambda \varepsilon_{ilp} + FE_{ls} + \epsilon''_{ils}]$$

GM assume that $\gamma = \gamma'' = 1$, $\alpha = \alpha''$ and $\lambda = 1$. Therefore,

$$\epsilon''_{ils} = -w_{ilp} + \alpha\left[\left(FE_{lp} - FE_{ls} + w_{ilp}\right)^+ - \left(FE_{lp} - FE_{ls} + v_{il} + w_{ilp}\right)^+\right] \quad \text{(A6)}$$

Note that two unobserved quality variables, v_{il} cancel because of assumptions on parameters. This gives a strong role for EIV, the w_{ilp} term.

Eq. (A6) is the same as GM Eq. (9).

In matrix form, the first term of Eq. (A6) is $B_1^{II} = -(X'X)^{-1}X'w$. Defining $\eta_1 = \left(FE_{lp} - FE_{ls} + w_{ilp}\right)^+ - \left(FE_{lp} - FE_{ls} + v_{il} + w_{ilp}\right)^+$, the second term of Eq. (A6) is $\alpha B_2^{II} = \alpha(X'X)^{-1}X'\eta_1$

Similarly, the overall bias is

$$B^{II} = \alpha'' - \alpha = B_1^{II} + \alpha B_2^{II} = \frac{B_1^{II} + \alpha'' B_2^{II}}{(1 + B_2^{II})} \quad \text{(A7)}$$

Noted that $B_2^I \neq B_2^{II}$ because the set of regressors in the two models differ.

[38] Proof: $\alpha' - \alpha = B_1^I + \alpha B_2^I$. Adding $\alpha^I B_2^I$ on both sides, we have $\alpha' - \alpha + \alpha^I B_2^I = B_1^I + \alpha B_2^I + \alpha' B_2^I$. So $\alpha' + \alpha' B_2^I - \alpha - \alpha B_2^I = B_1^I + \alpha + \alpha' B_2^I$ and $\alpha'(1 + B_2^I) - \alpha(1 + B_2^I) = B_1^I + \alpha' B_2^I$.Then$(1 + B_2^I)(\alpha' - \alpha) = B_1^I + \alpha' B_2^I$ and we have $\alpha' - \alpha = \frac{B_1^I + \alpha' B_2^I}{(1 + B_2^I)}$.

A2. Selected Characteristics Considered in a Typical Assessor Database

Variable	Description
parcelid	A unique identifier. Format: First 3 numbers= Book, Next 2 numbers = Map, Last 3 numbers = Lot, and split (if applies) denoted by a letter (A-Z)
prcl_st	Parcel status: X denotes parcel has since been canceled through either a split or combine.
market	Residential Market Area
nbhd	Residential Neighborhood: If 5 digits long, the first 2 characters are the residential market area. Otherwise, the first character denotes the residential market area.
sprice	Sale price as recorded on the Affidavit of Sale
vl_perpr	Value of personal property if denoted on the Affidavit of Sale
smonth	Sale Month
syear	Sale Year
deedtype	Type of Deed (Warranty Deed)
multprop	Y/N- if multiple parcels involved in the sale
proptype	Property Type as designated on the Affidavit of Sale. A= Vacant Land, B=Single Family Residential, C= Condo/Townhouse, D= 2-4 Plex, E= Apartment Building, F=Commercial/Industrial Use, G= Agricultural, H= Mobile or Manufactured Home, I= Other
fintype	Financing Type
own_cc	Only for residential properties- indicates if the buyer intends to use the property as a primary residence
per_prop	Y/N- if the personal property was involved in the sale. A similar variable for sale of partial interests.
sale_solar_indc	Y/N- solar involved in sale
landsqft	the total amount of land (square feet) in the parcel
std_zne	Assessor's standardized zoning code
corner	The parcel is located on a corner
culdesac	The parcel is located in a culdesac
gated	The parcel is located in a gated community (similar variables for golf course, greenbelt, lake or other water features)
premium	The parcel has a premium view
adj_apt	The parcel is located adjacent to an apartment/multi-family complex
adj_cm	The parcel is located adjacent to commercial/industrial property
trans_ln	The parcel is located adjacent to a transmission line
waterway	The parcel is located adjacent to a waterway
paved	The parcel is accessible via a paved road
ut_none	The parcel has no utilities
ut_elec	The parcel has electricity
ut_water	The parcel has water
ut_well	The parcel has a well
ut_gas	The parcel is connected to gas lines (similar entries are available for sewer and septic)
fld_plan	The parcel is in a flood plain
flt_sub	The parcel is in a substantial noise flight path
r_totimpsqft	The residential square foot of living area in an economic unit. Similar variable for finished basement.
r_iclass	Residential quality class. The scale is 0-7 with 3 being average, 7 being highest
r_wtdyrblt	Residential weighted construction year: a weighted calculation which accounts for the age and square footage of livable additions
r_stories	Residential number of stories (maximum is 4- a basement + three floors)
r_addqual_att	Residential attached addition quality (In comparison to main quality (R_ICLASS), 1=below, 2= comparable, 3= above)
r_carport_att_sqft	Residential attached carport square feet (similar variables for detached carport and for garage space)
r_pool	Residential pool (square feet) or spa.
r_sport_court	Residential sport court (square feet)

Note: In Connecticut "property cards" and GIS systems contain similar detail about property characteristics and its location. For example, see https://westhartfordct.mapgeo.io/datasets/properties?abuttersDistance=300&latlng=41.7626%2C-72.756789&panel=themes&zoom=12 and http://gis.vgsi.com/westhartfordct/ (last accessed 11/09/19).

A3. Comparison between One-Only and Repeat-Sales

This table summary statistics of hedonic characteristics for one-only sales and repeat sales based on a sample of individual transactions from 2000 to 2017. There are in total of 473,099 sales (on 343,728 unique houses) after 2000. Of these 343,728 unique houses, 223,602 were sold only once. The repeat sales sample includes 249,497 (=343,728 – 223,602) transactions, more than 90,345 x 2 because changed repeats are included.

	One-Only				Repeat Sales			
	N	Mean	Std	Median	N	Mean	Std	Median
price	223,602	358,953	493,846	250,000	249,497	383,744	544,014	247,000
price_sf	223,602	180	167	154	249,497	194	176	160
intersf	223,602	1,925	971	1,677	249,497	1,862	971	1,584
lotsize	223,602	38,017	52,020	19,602	249,497	31,255	43,729	15,246
bath2or3	223,602	0.53	0.5	1	249,497	0.49	0.5	0
bath3	223,602	0.09	0.28	0	249,497	0.09	0.28	0
age	223,602	52.21	33.03	49	249,497	54.82	32.15	52

A4. First Stage Hedonic Estimation

This table reports the hedonic regression results based on a sample of individual transactions from 1994 to 2017. The dependent variable is the log transaction price. The following hedonic characteristics are used: interior size, interior size squared, lot size of the property, lot size squared, age of the property, age of the property squared, a dummy variable that is equal to 1 if the number of bathrooms is between 2 and 3 and 0 otherwise, a dummy variable that is equal to 1 if the property has more than 3 bathrooms and 0 otherwise, number of bathrooms. Results are based on equation (3): $P_{ilt} = \beta X_{il} + FE_{lt} + \varepsilon_{ilt}$. Results control for town-year fixed effects. Robust standard errors are clustered at town level. ***, **, * denote for 1%, 5% and 10% significance, respectively.

	Estimation of equation (3)
Interior Size	0.000302925601658***
	(0.000012494034234)
Interior Size Squared	-0.000000012374876***
	(0.000000001120796)
Lot Size	0.000001944329014***
	(0.000000253274582)
Lot Size Squared	-0.000000000003740***
	(0.000000000000591)
2-3 Bathrooms	0.067556781652462***
	(0.006621530500353)
> 3 Bathrooms	0.186844889355204***
	(0.012727501610936)
Age	-0.006159793519940***
	(0.000430248696399)
Age Squared	0.000022258922381***
	(0.000001768893134)
Constant	12.056764379470760***
	(0.035143367988667)
Town-Year FE	Yes
Observations	548,568
Adj. R-squared	0.789

A5. Simulation Framework

For simplicity, we write v_{il} as v and w_{ilp} as w. We assume that v and w are each normally distributed with mean zero and standard deviation of σ_v and σ_w, respectively. i.e., $v \sim N(0, \sigma_v^2)$ and $w \sim N(0, \sigma_w^2)$.

We observe neither v nor w individually. By estimating the first stage price model, we can obtain the combination of the two, i.e. $v + w$. Based on Bayes rule and probability density function of the normal distribution, the conditional distribution of v, conditional on $v + w$ is

$$v|(v+w) \sim N(\frac{(v+\omega)\sigma_v^2}{(\sigma_v^2+\sigma_w^2)}, \frac{\sigma_v^2\sigma_w^2}{(\sigma_v^2+\sigma_w^2)})$$

We illustrate our simulation step as follows:

1. Based on 90,345 observations of repeat sales, the standard deviation of the 1st stage residual, $\hat{\varepsilon}$, is 0.302. This means that $\widehat{\sigma_v^2 + \sigma_w^2} = 0.302^2$ and the estimation range of σ_v is [0, 0.302].
2. In GM model 1, the loss coefficient is .690 in model (2) of Table 3 Panel A.
3. In GM model 2, the loss coefficient is .226 in model (4) of Table 3 Panel A.
4. We draw 100,000 draws from the 90,345 observations with replacement.
5. For each point on a grid of σ_v from zero of 0.302, we draw a random vector of v^s from the above conditional distribution, one v^s for each observation. Since we are able to estimate $\hat{\varepsilon} = (\widehat{v+\omega})$ from the first-stage price regression, knowing $\hat{\varepsilon}$ and v^s, we know w^s, an estimate of the noise term.

   For example, if $\sigma_v = 0$ then $\sigma_w = \sqrt{0.302^2 - \sigma_v^2} = 0.302$. And we draw v^s from a normal distribution with mean of $\frac{(v+w)\sigma_v^2}{(\sigma_v^2+\sigma_w^2)}$ and variance of $\frac{\sigma_v^2\sigma_w^2}{(\sigma_v^2+\sigma_w^2)}$. In this case, $\sigma_v^2 = 0$ and $\sigma_w^2 = 0.302^2$. After we obtain v^s, we can also calculate w^s as $\hat{\varepsilon} - v^s$. We repeat the process using a grid of σ_v from zero to 0.302 with an increment of 0.01.
6. Using the formulas above and in Appendix A1, we calculate B^I as $\frac{B_1^I+\alpha' B_2^I}{(1+B_2^I)}$ where $\widehat{\alpha'} = 0.690$; we calculate B^{II} as $\frac{B_1^{II}+\alpha'' B_2^{II}}{(1+B_2^{II})}$ where $\widehat{\alpha''} = 0.226$.

A6. Subsamples of Supply Elasticity

A6.1 Supply Elasticity based on Percent Change in Housing Units

This table reports the results for low/high supply elasticity towns in our sample. Observations are repeat sale transactions from 2000-2017. Elasticity is measured by percent changes in the number of single-family houses between year 2000 and year 2010 for 50 largest towns where the data on housing units are available. The 25 towns that have lower than median percent changes are classified as low supply elasticity towns, and the 25 above-median towns are classified as high elasticity towns. Regression specifications are the same as Table 6. See Table 1 for variable definitions. All regressions are estimated with town-year fixed effects. Bootstrap standard errors in parentheses. Standard errors cluster by town are similar due to our large sample size. * p<0.10, ** p<0.05, *** p<0.01.

	Low Supply Elasticity		**High Supply Elasticity**	
	GM-M2	NAV	GM-M2	NAV
	(1)	(2)	(3)	(4)
exp_loss	0.238***		0.226***	
	(0.027)		(0.020)	
exp_loss_lnAV		0.278***		0.179***
		(0.022)		(0.022)
lnprice2_hat	0.946***		0.960***	
	(0.006)		(0.007)	
lnAV_norm		0.892***		0.895***
		(0.005)		(0.006)
months	-0.073***	-0.072***	-0.056***	-0.053***
	(0.004)	(0.003)	(0.005)	(0.004)
resid1	0.421***		0.420***	
	(0.011)		(0.011)	
Constant	0.772***	1.418***	0.542***	1.326***
	(0.075)	(0.061)	(0.081)	(0.068)
Town-year FE	Yes	Yes	Yes	Yes
Observations	34347	34347	29818	29818
R-squared	0.892	0.901	0.751	0.773

A6.2 Supply Elasticity based on the Wharton Residential Land Use Regulatory Index

This table reports the results for low/high supply elasticity towns in our sample. Observations are repeat sale transactions from 2000-2017. Supply elasticity is measured by the Wharton Residential Land Use Regulatory Index. 85 towns that have lower than median supply elasticity are classified as low elasticity towns, and the other 84 towns are classified as high elasticity towns. Regression specifications are the same as Table 6. See Table 1 for variable definitions. All regressions are estimated with town-year fixed effects. Bootstrap standard errors in parentheses. Standard errors cluster by town are similar due to our large sample size. * p<0.10, ** p<0.05, *** p<0.01.

	Low Supply Elasticity		**High Supply Elasticity**	
	GM-M2	NAV	GM-M2	NAV
	(1)	(2)	(3)	(4)
exp_loss	0.276***		0.161***	
	(0.015)		(0.019)	
exp_loss_lnAV		0.227***		0.212***
		(0.020)		(0.019)
lnprice2_hat	0.927***		0.983***	
	(0.006)		(0.006)	
lnAV_norm		0.895***		0.903***
		(0.005)		(0.006)
months	0.420***		0.368***	
	(0.010)		(0.008)	
resid1	-0.074***	-0.073***	-0.076***	-0.066***
	(0.004)	(0.004)	(0.004)	(0.003)
Constant	1.007***	1.375***	0.284***	1.217***
	(0.075)	(0.058)	(0.078)	(0.071)
Town-year FE	Yes	Yes	Yes	Yes
Observations	45899	45899	42520	42520
R-squared	0.857	0.871	0.735	0.754

A7. GM Model Compared to Assessed Value Losses, Deleting Flippers

This appendix supplements Table 4 and shows robustness tests deleting flippers. Flippers are identified following Bayer, Geissler, Mangum, and Roberts (2020). Observations are repeat sale transactions from 2000-2017 (2000-2013) in Panel A (Panel B). GM-M1 is our equation (7) and GM-M2 is our equation (10). NAV is our equation (10'). In Panel A, the dependent variable is *lnprice2*, the logarithm of the second sales price of a repeat pair. In Panel B, the dependent variable is *lnlistprice2*, the logarithm of the second listing price of a repeat pair. *lnprice2_hat* is log of the second sales price predicted by a standard hedonic regression using all sales, the first stage regression. *lnAV_norm* is normalized log of assessed value at the time of second sale. *exp_loss* is equal to *anchor* (i.e. *lnprice1-lnprice2_hat*) if *anchor* is positive (i.e. previous sales price is higher than predicted second price), and 0 otherwise. *loss_lnAV* is equal to *anchor_lnAV* if *anchor_lnAV* is positive (i.e. previous sales price > *lnAV_norm* for the second price), and 0 otherwise. *months* is the number of months between sales (holding period) divided by 100. *resid1* is the residual from the first stage regression for the first sales price. *LTV* is the greater of the difference between the ratio of loan to value and 0.8, and zero. See Table 1 for variable definitions. All regressions are estimated with town-year fixed effects. Bootstrap standard errors in parentheses. Standard errors cluster by town are similar due to our large sample size. * p<0.10, ** p<0.05, *** p<0.01.

	GM-M2	NAV	GM-M2	NAV
	lnprice2	*lnprice2*	*lnlistprice2*	*lnlistprice2*
	(1)	(2)	(3)	(4)
exp_loss	0.233***		0.307***	
	(0.013)		(0.035)	
loss_lnAV		0.234***		0.357***
		(0.014)		(0.038)
lnprice2_hat	0.948***		0.985***	
	(0.004)		(0.010)	
lnAV_norm		0.898***		0.902***
		(0.003)		(0.009)
months	0.406***		0.411***	
	(0.006)		(0.019)	
resid1	-0.069***	-0.064***	-0.019*	-0.030***
	(0.003)	(0.002)	(0.010)	(0.009)
Constant	0.718***	1.304***	0.277**	1.297***
	(0.045)	(0.041)	(0.128)	(0.112)
Town-year FE	Yes	Yes	Yes	Yes
Observations	87,188	87,188	30,838	30,838
R-squared	0.849	0.862	0.720	0.728

A8. GM Model Compared to Assessed Value, Using Expected Gains

This appendix shows robustness tests using the absolute value of expected gain: absolute value for ease of interpretation of the expected negative coefficient (gains discount from expected sales price). Panel A replaces expected loss with expected gain. Panel B includes both expected loss and expected gain. Observations are repeat sale transactions from 2000-2017 (2000-2013) in models (1)-(2) ((3)-(4)). GM-M2 is our equation (10). NAV is our equation (10'). In models (1)-(2), the dependent variable is *lnprice2*, the logarithm of the second sales price of a repeat pair. In models (3)-(4), the dependent variable is *lnlistprice2*, the logarithm of the second listing price of a repeat pair. *lnprice2_hat* is log of the second sales price predicted by a standard hedonic regression using all sales, the first stage regression. *lnAV_norm* is normalized log of assessed value at the time of second sale. *exp_gain* is equal to the absolute value of *anchor* (i.e. *lnprice1-lnprice2_hat*) if *anchor* is negative (i.e. previous sales price is lower than predicted second price), and 0 otherwise. *gain_lnAV* is defined similarly using *anchor_lnAV*. *months* is the number of months between sales (holding period) divided by 100. *resid1* is the residual from the first stage regression for the first sales price. See Table 1 for variable definitions. All regressions are estimated with town-year fixed effects. Bootstrap standard errors in parentheses. Standard errors cluster by town are similar due to our large sample size. * p<0.10, ** p<0.05, *** p<0.01.

Panel A: Replacing Expected Loss with Expected Gain

	GM-M2	NAV	GM-M2	NAV
	lnprice2	*lnprice2*	*lnlistprice2*	*lnlistprice2*
	(1)	(2)	(3)	(4)
exp_gain	0.254***		0.229***	
	(0.010)		(0.021)	
gain_lnAV		-0.188***		-0.215***
		(0.004)		(0.014)
lnprice2_hat	0.943***		0.981***	
	(0.004)		(0.010)	
lnAV_norm		0.901***		0.911***
		(0.003)		(0.010)
months	0.647***		0.657***	
	(0.010)		(0.023)	
resid1	-0.139***	-0.042***	-0.154***	0.018**
	(0.003)	(0.002)	(0.011)	(0.009)
Constant	0.797***	1.320***	0.370***	1.228***
	(0.050)	(0.043)	(0.134)	(0.130)
Town-year FE	Yes	Yes	Yes	Yes
Observations	88,419	88,419	30,808	30,808
R-squared	0.847	0.862	0.726	0.736

Panel B: Including both Expected Gain and Expected Loss

	GM-M2	NAV	GM-M2	NAV
	lnprice2	*lnprice2*	*lnlistprice2*	*lnlistprice2*
	(1)	(2)	(3)	(4)
exp_loss	0.128***		0.235***	
	(0.012)		(0.029)	
exp_gain	0.215***		0.124***	
	(0.008)		(0.020)	
loss_lnAV		0.122***		0.281***
		(0.017)		(0.036)
gain_lnAV		-0.171***		-0.193***
		(0.005)		(0.014)
lnprice2_hat	0.944***		0.985***	
	(0.003)		(0.010)	
lnAV_norm		0.904***		0.917***
		(0.004)		(0.009)
months	0.577***		0.513***	
	(0.009)		(0.025)	
resid1	-0.123***	-0.042***	-0.084***	0.034***
	(0.003)	(0.002)	(0.014)	(0.011)
Constant	0.766***	1.266***	0.291**	1.129***
	(0.044)	(0.054)	(0.124)	(0.112)
Town-year FE	Yes	Yes	Yes	Yes
Observations	88,419	88,419	30,808	30,808
R-squared	0.848	0.863	0.727	0.738