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List Prices in the US Housing Market

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Abstract A seller sets the list price based upon their *ex-ante* perception of the trade-off between marketing duration versus transaction price, which depends on the liquidity of the property and the depth of the market. As such, list prices reflect property, market, and seller characteristics. In addition, Genesove and Mayer (2001) and Bokhari and Geltner (2011) use prospect theory to motivate how expected nominal losses and gains from sale can also influence list prices. We consider these multiple factors affecting list prices through a rich dataset from the National Association of Realtors, which contains variables on seller motivations, structure liquidity, and other difficult to observe variables such as seller age, race, and income.

Keywords List prices · Sellers' motivations · Sellers' characteristics · Loss aversion · Urgency · List price reductions

Upon deciding to sell their house, the owner faces the problem of setting the initial asking price. Sellers routinely set list prices higher than expected transaction prices to allow for negotiation with potential buyers. Additionally, sellers need to set higher list prices to obtain higher transaction prices. But owners cannot markup their list prices by too much or they risk materially delaying the sale, especially for more illiquid properties. Therefore, when setting their optimum list price, an owner must balance the potential marginal utility that can come from a higher price versus the marginal disutility of a longer time on market (TOM).

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Sellers will differ in their price-TOM preferences due to their reason(s) for sale, liquidity constraints, and urgency. Sellers also own properties with varying degrees of liquidity across markets with different levels of depth and activity. The resulting list prices therefore reflect seller, property, and market measures. Yet despite their vital role, the literature–largely due to a lack of data–has not shown the impact sellers' motivations and characteristics have on their price-TOM preferences. Accordingly, the principal objective of this paper is a comprehensive empirical investigation of how seller, structural, locational, and transactional characteristics impact the setting of list prices.

We are able to investigate the many facets of strategic price setting through an unusual dataset from the National Association of Realtors (NAR). By design, the NAR collects the information that is important to the setting of list prices. We can therefore examine empirical measures affecting seller utility and property liquidity such as structure quality, structure atypicality, reasons for selling, seller's income, age, and race, the use of an agent, seller's market experience, and transactional considerations like selling to an acquaintance and short sales.

Since purchase prices are available, we also compute the nominal losses and gains sellers will expect from sale. Genesove and Mayer (2001) find that owners who expect losses from sale will set their list prices significantly higher. But this finding has not been tested in conjunction with other possible determinants. Empirical analysis combining the Genesove and Mayer (2001) findings with the considerations mentioned above will yield a more comprehensive picture of seller behavior. For instance, our analysis investigates whether sellers set higher list prices due to loss aversion or if these same sellers exhibit a lack of urgency or even an ambivalence to selling. This ambivalence may be thought of as price fishing. This type of seller has a low liquidity preference and therefore sets a price knowing that it is at the upper end of the expected price distribution. Price fishing should decrease the propensity to sell the property, which we control for in our models. Another possible measure of price fishing is an increase in the number of list price reductions, which we also observe with the NAR sample.

As expected, the results first demonstrate that list prices reflect a number of structural characteristics. Home quality and size correlate positively with list prices. We also observe that sellers with greater incomes set higher asking prices, which suggests two interpretations that move in the same direction. One rationale is that higher list prices are evidence of better quality, condition, and amenities in homes owned by sellers with higher incomes. Another interpretation is reduced liquidity constraints and an ability of these owners to ask higher prices.

Another robust determinant of list prices is expected losses. The results consistently demonstrate that owners who anticipate losses will set higher mean list prices at approximately 40 % of the difference between the expected selling prices and the original purchase prices. Bokhari and Geltner (2011) extend the Genesove and Mayer (2001) model to compute nominal gains. We observe that nominal gains do not change list price levels, which differs from the finding by Bokhari and Geltner (2011) that sellers with nominal gains set lower list prices. We find these results are robust to the additional considerations of market conditions prior to setting the list price and market uncertainty.

Some attributes are notable because they do not impact list prices. Race, most structural atypicalities, selling to an acquaintance, and the use of an agent do not significantly change asking prices. Base models also indicate that urgent owners do not set lower list prices. But when we include the number of expected list price reductions (LPR) before sale, we uncover the result that some urgent sellers reduce their initial asking prices by 2 to 3 %. The combined results therefore indicate that a portion of urgent sellers begin with the lower asking prices but the others set their list prices commensurate with expected market prices and their urgency is reflected in LPR prior to sale.

Our analysis also considers sellers' future expectations of TOM and LPR at the time of listing.[1] The evidence indicates that owners expecting longer marketing periods set higher list prices. Additionally, owners that expect to reduce their list prices more often during the marketing period set higher asking prices.

Overall, our analysis investigates many aspects of strategic pricing and–after controlling for multiple considerations that are not mutually exclusive–presents a number of novel findings. We discuss the specifics of our investigation in the balance of this article. The next section models the seller's perspective when considering the optimal asking price as well as discusses the list price literature.

Theoretical Model and List Price Literature

As an initial motivation, we present a simple partial equilibrium model that illustrates the basic problem facing sellers when setting list prices. A key ingredient of the problem is the illiquidity of real property. We assume a static economy, but allow properties to vary in liquidity specified by a deterministic relation $p(t)$, which shows the potential price an asset can obtain as a function of marketing time t. For liquid assets $p(t)$ has a flat trajectory, but shows a positive slope for illiquid assets. In (1) we require some illiquidity of the asset such that $dp(t)/dt > 0$, but with diminishing marginal effects so that $d^2p(t)/dt^2 < 0$. An individual seller cannot affect the potential price trajectory and conditions on $p(t)$.

$$p(t) > 0, \frac{dp(t)}{dt} > 0, \frac{d^2p(t)}{dt^2} < 0 \tag{1}$$

A seller's utility involves a tradeoff between a possible higher transaction price in the future $p(t)$ versus the preference for a shorter marketing time t as expressed in (2). In addition, Eq. (2) includes r, the personal discount rate. Along a spectrum, individuals with more urgency from either natural inclination or due to exogenous factors (e.g., financial or familial pressures) will have a higher level of r. Alternatively, individuals who mainly focus on the gain from increased exposure of the property over time presumably will have lower levels of r. Whatever the price-liquidity preferences, we assume all individuals have a strictly positive discount rate r as shown in (2).

$$U(t) = b{\cdot}e^{-r{\cdot}t}p(t), \quad r, b > 0 \tag{2}$$

[1] When setting list prices, TOM and LPR are future expected outcomes. Nevertheless, we formally test for possible simultaneity and find expected TOM and LPR are in fact endogenous. We use instrument variables and two stage least squares to treat the endogeneity.

The utility in (2) rises with the discounted price. The seller maximizes their utility $U(t)$ with respect to the marketing time (t), which yields the first order conditions in (3). Assuming an interior solution of $t \in (0, \infty)$, Eq. (4) expresses this as an equimarginal relation. This indicates that the seller will be willing to hold onto the property while it appreciates by an amount greater than their personal discount rate, but will wish to sell when the appreciation declines to their discount rate.

$$\frac{dU(t)}{dt} = e^{-r \cdot t} \frac{dp(t)}{dt} - re^{-r \cdot t} p(t) = 0 \tag{3}$$

$$\frac{dp(t)/dt}{p(t)} = r \tag{4}$$

The second derivative of utility with respect to marketing time appears in (5). The term in brackets will equal 0 at the optimum. The second and third terms in (5) are each negative, and therefore the second derivative of utility with respect to marketing time is negative as noted in (6). Consequently, the interior first order condition solution maximizes utility.

$$\frac{d^2U(t)}{dt^2} = \left[r^2 e^{-r \cdot t} p(t) - re^{-r \cdot t} \frac{dp(t)}{dt} \right] - re^{-r \cdot t} \frac{dp(t)}{dt} + e^{-r \cdot t} \frac{d^2p(t)}{dt^2} \tag{5}$$

$$\frac{d^2U(t)}{dt^2} < 0 \tag{6}$$

To the degree that properties vary in liquidity and sellers vary in their preferences for an early closing, the optimum in (4) means that list prices thus will reflect seller preferences as well as property and market characteristics. This is a focus of our analysis.

As mentioned previously, the above represents a partial equilibrium model and does not derive the function $p(t)$ from more basic relations. In other words, what leads to illiquidity? More sophisticated models come from search theory, which is an extension of the vast job search literature.[2] Search theory is a natural tool because it takes time and effort for sellers to find suitable buyers. Search models illustrate how best to balance the cost of delay against the value of trying again. Mathematically, search models are optimal stopping problems.

A number of search-theoretic models of list prices appear in the real estate literature.[3] These models, such as the Krainer (1999) two-sided model, allow for random arrival rates of buyers along with heterogeneous offer prices in addition to the sellers maximizing expected utility given their discount rates. If buyers arrive at a low rate for

[2] Seminal papers include Stigler (1961); McCall (1970), and Mortensen (1970).

[3] Theoretical studies include Wu and Colwell (1986); Haurin (1988); Quan and Quigley (1991); Salant (1991); Horowitz (1992); Yavaş and Yang (1995); Arnold (1999); Krainer and LeRoy (2002); Haurin et al. (2010); Deng et al. (2012); Stacey (2013), and Albrecht, Gautier, and Vroman (2016).

certain properties, such as those with unusual features, this would make these more illiquid than conventional properties in accessible subdivisions.

In contrast to the theoretical papers, the empirical literature is less evolved. The empirical studies are Haurin (1988); Knight et al. (1994); Anglin et al. (2003); Rutherford et al. (2005), and Deng et al. (2012). Genesove and Mayer (2001) and Bokhari and Geltner (2011) also use a transactions dataset to model nominal losses and gains. Haurin et al. (2010) and Haurin et al. (2013) scale list prices by transaction prices to examine the degree of overpricing. These studies use transaction datasets with data limitations, which we look to address using the sample described in the next section.

Data Sample and Additional Literature

This section details the sample as well as additional relevant literature. The dataset consists of property-level transactions from the annual homebuyer surveys conducted by the NAR from 2010 to 2012. The 2010 survey includes sales from 2009. The setting of list prices extends back to 2007. Figure 1 maps the observations across the contiguous US, which total 3,302 after restricting the sample to single family homes and townhouses.

To assemble the Profile of Home Buyers and Sellers report, the NAR mails out a survey with over 100 questions to a random sample of almost 100,000 recent home buyers. A potential drawback of the data is the low response rate, which is approximately 10 % for our sample period. However, the NAR survey is the only dataset we are aware of that includes the necessary variables to perform a comprehensive list price analysis. Further, the response rates are similar to other surveys, and recent studies by Genesove and Han (2012) and Han and Strange (2014) using the NAR dataset indicate the data are well behaved. For their purposes, Genesove and Han (2012) show that sample selection bias is either not evident or quantitatively unimportant.

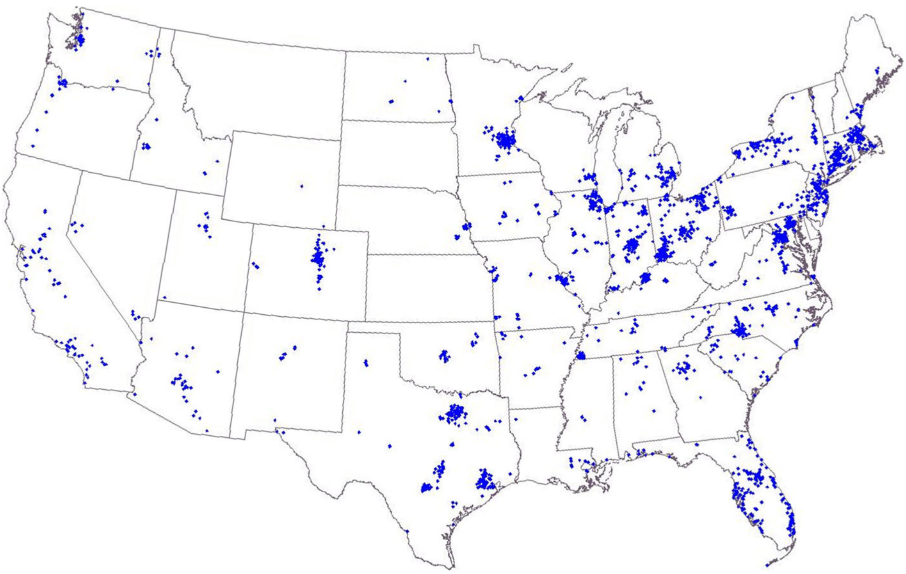

Fig. 1 Observation locations

We restrict our sample to the latest surveys for multiple reasons. One is to control for changes in structural quality, which we discuss further below. The foremost reason is because earlier questionnaires do not provide answers required for a complete analysis. For example, the 2003 survey asks 11 questions about the home structure while the more recent surveys collect 21 attributes. Even the more recent 2009 questionnaire does not ask whether a responder is a first time seller or the number of bedrooms and bathrooms. One of the critical missing questions in earlier surveys is purchase price, which is also lacking in most MLS and public records datasets (although it can be obtained using repeat transactions). Purchase price is necessary to determine expected nominal gains or losses at time of listing as well as to measure structural quality.

We apply two filters to the sample in addition to removing observations with invalid answers or lack of data. There are 19 survey responses that indicate TOM in excess of 4 years. While the market may have been challenging in certain areas during the sample period, we drop these observations to avoid undue influence. To focus on the more-typical housing market, we trim six observations with list prices less than $7,000 and greater than $4.5 M.

Table 1 reports the many sample attributes. The median sold residence is 25 years old with 3 bedrooms, 2 bathrooms, and 2,000 square feet. The median purchase price is $177,000 with a selling price of $220,000. The mean (median) TOM is 19.31 (10) weeks. Sellers' demographics indicate that a majority of the responders are white, speak English, and born in the U.S. While 93 % of the responders identify themselves as white, this is actually less than the almost 96 % in Harding et al. (2003a), who use the American Housing Survey from 1985 to 1993.

As to the many sample attributes that can affect the price-liquidity tradeoff, we group them as sellers' motivations, sellers' characteristics, atypicality, and search costs. We discuss each in the remainder of this section. Regarding sellers' motivations, the first consideration is urgency. To date, the literature has been challenged to measure sellers' urgency levels. There are two general strands of real estate studies.

One strand attempts to measure urgency more directly. There are no studies in this literature that examine list prices. Glower et al. (1998) conduct a telephone survey and ask sellers if they have a move date, a new job, or made an offer on a new home. Springer (1996) and Knight (2002) use keywords like "motivated" and "must sell" in the comments field of MLS datasets to proxy for urgency. Springer (1996) finds that motivated sellers experience a decrease in transaction prices and an increase in the TOM; however, the models do not control for the simultaneity of the two outcomes. Knight (2002) finds an increase in one TOM specification but not in another and no effect on transaction prices. Keyword studies are challenging because the levels of sellers' urgency is hard to measure as entering keywords in MLS comes at little cost. Because they may be used as marketing ploys to generate additional interest, it is not surprising that keyword proxies for urgency are inconsistent determinants.

The other literature strand uses transactional features that should proxy for higher seller urgency. Much of this literature examines the illiquidity costs of distress and focuses on transaction prices.[4] Papers examining short sales, foreclosures, and vacant homes find

[4] See Springer (1996); Harding et al. (2003b); Clauretie and Daneshvary (2011); Goodwin and Johnson (2013), and Aroul and Hansz (2014).

Table 1 Summary statistics

	Mean	Median	Std. Dev.	Minimum	Maximum
Purchase price	222,232.86	177,000.00	190,321.12	10,400.00	3,600,000.00
List price	300,181.28	235,000.00	269,205.36	9,000.00	4,250,000.00
Sale price	277,866.63	220,000.00	230,791.33	9,000.00	3,590,000.00
Overpricing (%)	6.85	4.93	0.15	−3.57	2.34
Time on market (weeks)	19.31	10.00	27.26	0.00	208.00
Home age	32.71	25.00	26.91	1.00	182.00
Square feet	2,202.55	2,000.00	988.80	703.00	9,900.00
Number of bedrooms	3.39	3.00	0.82	1.00	9.00
Number of bathrooms	2.14	2.00	0.80	1.00	6.00
Holding period (years)	10.80	8.00	8.63	0.00	56.00
Townhouse	0.13	0.00	0.34	0.00	1.00
Detached SF	0.87	1.00	0.34	0.00	1.00
Suburb	0.08	0.00	0.27	0.00	1.00
City	0.10	0.00	0.30	0.00	1.00
Small town	0.37	0.00	0.48	0.00	1.00
Resort	0.01	0.00	0.10	0.00	1.00
High urgency	0.17	0.00	0.38	0.00	1.00
Some urgency	0.44	0.00	0.50	0.00	1.00
No urgency	0.39	0.00	0.49	0.00	1.00
First time seller	0.38	0.00	0.48	0.00	1.00
Sellers' ages	49.92	49.00	13.69	22.00	89.00
Number of children	0.85	0.00	1.10	0.00	8.00
African American	0.02	0.00	0.13	0.00	1.00
Asian	0.03	0.00	0.16	0.00	1.00
Caucasian	0.93	1.00	0.25	0.00	1.00
Hispanic	0.02	0.00	0.15	0.00	1.00
English speaking	0.98	1.00	0.12	0.00	1.00
Income to 25 k	0.01	0.00	0.12	0.00	1.00
Income 25–35 k	0.03	0.00	0.17	0.00	1.00
Income 35–45 k	0.04	0.00	0.20	0.00	1.00
Income 45–55 k	0.05	0.00	0.21	0.00	1.00
Income 55–65 k	0.06	0.00	0.23	0.00	1.00
Income 65–75 k	0.07	0.00	0.26	0.00	1.00
Income 75–85 k	0.08	0.00	0.27	0.00	1.00
Income 85–100 k	0.11	0.00	0.32	0.00	1.00
Income 100–125 k	0.18	0.00	0.38	0.00	1.00
Income 125–150 k	0.11	0.00	0.32	0.00	1.00
Income 150–175 k	0.07	0.00	0.25	0.00	1.00
Income 175–200 k	0.05	0.00	0.22	0.00	1.00
Income 200–250 k	0.06	0.00	0.24	0.00	1.00
Income 250–500 k	0.06	0.00	0.24	0.00	1.00
Income 500–1,000 k	0.01	0.00	0.11	0.00	1.00
Income 1,000 k and more $\times 10^{-1}$	0.01	0.00	0.50	0.00	1.00

Table 1 (continued)

	Mean	Median	Std. Dev.	Minimum	Maximum
Short sale	0.03	0.00	0.17	0.00	1.00
Sold to a friend	0.07	0.00	0.25	0.00	1.00
Reason for selling					
Avoid foreclosure	0.04	0.00	0.19	0.00	1.00
Relocation	0.19	0.00	0.39	0.00	1.00
Family change	0.08	0.00	0.27	0.00	1.00
Too expensive	0.03	0.00	0.16	0.00	1.00
New home	0.01	0.00	0.08	0.00	1.00
Old home	0.01	0.00	0.10	0.00	1.00
Small home	0.01	0.00	0.12	0.00	1.00
Large home	0.02	0.00	0.13	0.00	1.00
Many baths	0.01	0.00	0.11	0.00	1.00
Many beds	0.01	0.00	0.10	0.00	1.00
Distance between sale and purchase					
1 to 5 miles	0.24	0.00	0.43	0.00	1.00
6 to 10 miles	0.16	0.00	0.36	0.00	1.00
11 to 15 miles	0.09	0.00	0.28	0.00	1.00
16 to 20 miles	0.07	0.00	0.26	0.00	1.00
21 to 50 miles	0.09	0.00	0.28	0.00	1.00
51 to 100 miles	0.04	0.00	0.19	0.00	1.00
101 to 500 miles	0.10	0.00	0.30	0.00	1.00
501 to 1,000 miles	0.09	0.00	0.29	0.00	1.00
More than 1,000	0.13	0.00	0.33	0.00	1.00
Computed miles	300.42	18.00	506.77	3.00	1,500.00
Year 2009	0.04	0.00	0.19	0.00	1.00
Year 2010	0.23	0.00	0.42	0.00	1.00
Year 2011	0.45	0.00	0.50	0.00	1.00
Year 2012	0.28	0.00	0.45	0.00	1.00
No agent used	0.08	0.00	0.27	0.00	1.00
MLS	0.80	1.00	0.40	0.00	1.00
Open house	0.55	1.00	0.50	0.00	1.00
Internet	0.86	1.00	0.34	0.00	1.00
Magazine	0.20	0.00	0.40	0.00	1.00
Video	0.12	0.00	0.33	0.00	1.00
Television	0.02	0.00	0.15	0.00	1.00
Flyer	0.17	0.00	0.37	0.00	1.00
Print	0.26	0.00	0.44	0.00	1.00
Sign	0.75	1.00	0.44	0.00	1.00
Other websites	0.26	0.00	0.44	0.00	1.00
Social media	0.06	0.00	0.24	0.00	1.00

Number of observations is 3,302

sellers generally experience lower transaction prices. There is no literature on the relation of distress costs and list prices.

Instead of having to proxy, the NAR survey directly records sellers' levels of urgency. Seventeen percent of sellers express high urgency and 44 % indicate some urgency. Thirty-nine percent answer as not being urgent.

Other seller motivations are job relocation, changes in family status, short sales, cash constraints, and avoiding foreclosure. The last two variables are important because they measure liquidity constraints for those sellers that have or are close to having negative equity in their home. Genesove and Mayer (2001) show that the loan-to-value ratio can be predictive of list prices. Note that foreclosure avoidance does not mean the property is in foreclosure but in some stage of default.

A set of additional seller characteristics include the household composition, income, age, race, and market experience. The household composition is partially revealed through the number of children and number of earners. Having school age children can reduce bargaining power during the school year (Harding et al. 2003b). The impact of the number of household earners on list prices is not entirely clear. More earners can increase the likelihood of a job relocation. Alternatively, more earners can soften the impact of the loss of employment by one household member and also may cause the household to be less motivated to sell if another earner holds a high quality job. Additionally, multiple earners should produce higher incomes and wealth *ceteris paribus*, which can lead to higher list prices for more expensive homes.

We are also able to control directly for sellers' income levels. Sellers with higher (lower) incomes should have reduced (increased) cash constraints, which may reduce (increase) their preference for a quicker sale. The NAR reports income within levels. Table 1 shows that income is largely distributed normally with the largest proportion of incomes falling between \$100,000–\$125,000. Our analysis examines each of these categories coded as a binary variable and also a continuous measure of log income using the midpoint of each category with the top-coded upper category set to \$1.5 M. We observe a relation across the income levels so we report the parameter estimates on each binary variable.

Another seller attribute that can impact price setting is market experience. Owners with less experience may set list prices too high initially and then learn about the market value during the marketing period. First time sellers should have limited experience and represent 38 % of the sample. Another characteristic that may proxy for market experience is sellers' ages. Older sellers will have a greater likelihood of having transacted real property previously. Age may also interact with retirement goals. Responders report their ages using 5 year ranges. Similar to income, we model the multiple levels as binary variables as well as a continuous variable using the midpoint of each age range. For greater informational context, we report the multiple ranges in the results.

One factor that can help inexperienced sellers is the employment of an agent. We therefore set a binary variable equal to one if an agent is not part of the transaction when the list price is determined and zero otherwise. Sellers who do not use an agent may also be less urgent, which can increase their list prices. Eight percent of sellers do not use an agent.

The next set of variables measure atypical structural features. Atypicalities do not provide a clear relation with list prices as they exist on a spectrum. Mildly unique features like a gourmet kitchen may be desirable and expected in luxury homes, and sellers can increase their list prices accordingly. But certain atypicalities will only be desirable to the current owner and a very small number of buyers who may or may not be present in the local market (e.g., a soundproofed indoor shooting range).[5] These amenities may not increase marginal values and can even reduce prices. When examining the ratio of list prices scaled by transaction prices, Haurin et al. (2010) find an increase in atypicality increases the degree of overpricing. The authors attribute the higher overpricing to sellers of atypical goods setting relatively higher list prices.

To measure atypicality we construct six new variables as well as look upon others as possible proxies. We follow Harding et al. (2003a) to compute binary variables representing the extreme 1 % of the distribution for various structural features. We define a new home as 2 year old or less while an old home is equal to or greater than 120 years old. A large home is greater than 5,000 square feet and a small home is less than 900 square feet. A home has many bathrooms if there are 5 or more and many bedrooms if 6 or more.

Other variables that may proxy for atypicality in more expensive home are seller income levels and certain advertising. Sellers with higher incomes should own more expensive homes which have a greater propensity to include unique features. Homes that are marketed through magazine and television advertising should also have additional features that justify the time and expense of these unique types of marketing.

Harding et al. (2003b) include the inverse Mills ratio (IMR) as an atypicality measure. The IMR may proxy for atypicality as homes with unique features may have a higher propensity to not sell due to the thinness of the market. The IMR can also measure price fishing and miscalculation. As Quan and Quigley (1991) note, increases in list prices will reduce the pool of potential customers and impact the probability of sale. Owners that are ambivalent to selling and fishing for high transaction prices should have a greater likelihood of not selling. Additionally, owners who miscalculate the market value on the high end of the price distribution may increase the propensity to not sell. We compute the IMR using the traditional Heckman two-step procedure that corrects for sample selection bias and also serves as a potential proxy for these additional pricing motivations. The first-stage model is in Appendix 1.

A final set of variables measure search costs. The first is selling to a friend, relative, or acquaintance. If a familiar buyer is known at the beginning of the marketing period, the seller clearly will experience lower search costs. But it is unclear if this savings will be capitalized into list prices. These transactions are 7 % of the sample. A second set of search variables are the marketing methods.

The dataset also provides a locational measure of search costs. The survey records the ZIP codes of the sold and subsequently purchased properties. Moving a greater distance from their previous residences can increase sellers' costs and motivate them to reduce the list price to effect a sale before moving. We thus include the separation distance between properties as a possible search cost.

Lastly, also using the ZIP codes of the sold properties, we control for 455 locational fixed effects at the three-digit ZIP code level. Fixed effects control for local real estate factors including market liquidity, uncertainty, and thinness. They also control for other

[5] http://www.forbes.com/sites/morganbrennan/2013/01/16/the-most-opulent-and-lavish-amenities-invading-luxury-homes/

general economic characteristics in the local market that impact property prices such as local tax regimes and labor markets.

Empirical Findings

Descriptive Statistics

We begin the empirical analysis by examining univariate statistics of prices, overpricing, and TOM after dividing the sample into transactions that do and do not reduce the list price prior to sale. This inquiry contrasts transactions that should be initially priced close to the expected market value–since there is no need to reduce the list price to affect a sale–to those that should be more overpriced as demonstrated by the LPR.

The Table 2 statistics first illustrate the price-liquidity tradeoff. Column 1 reports transactions that do not reduce their list prices before sale. Consistent with search theory, TOM decreases when list prices are close to the expected transaction prices. The overpricing level for these transactions is a mean of 3.02 % and a median of only 1.77 %. The mean TOM is 5.66 weeks and the median is only 2 weeks. Alternatively, for transactions in column 2 that exhibit a LPR, the percentage of average overpricing is 11.86 with a median of 8.26. The mean TOM is almost 28 weeks and the median is 18 weeks.

In addition to being able to compute the total reduction in list price as the difference between the original asking prices and eventual transaction prices, the NAR dataset provides the number of reductions. We thus investigate whether there is a difference in outcomes for sellers who do not reduce their list prices, those who reduce it once, and those who decrease the price one or more times.

Columns 5–7 in Table 2 details the 798 transactions that exhibit exactly one LPR. Asking prices are higher in column 5 compared to column 1 but, unlike column 2, are

Table 2 Comparing Means and Medians of LPR Subsamples

	No LPR	LPR	*t*-statistic	Non-parametric statistic	Exactly one LPR	*t*-statistic	Non-parametric statistic
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
List prices	279,459 (220,000)	310,245 (244,950)	−3.40**	−4.55**	285,711 (220,000)	−0.58	0.53
Transaction prices	272,936 (215,000)	278,176 (222,000)	−0.67	−1.18	268,249 (210,500)	0.48	−0.53
Overpricing (%)	3.02 (1.77)	11.86 (8.26)	−9.03**	−32.09**	6.91 (4.82)	−2.83**	18.49**
TOM (weeks)	5.66 (2.00)	27.95 (18.00)	−24.94**	−33.76**	14.16 (8.00)	−14.25**	18.83**
Number of observations	1,286	1,922			798		

The table reports the differences between subsamples that have no reductions in list prices, those that have at least one reduction, and a subsample that has exactly one reduction. Median values are in parentheses. The non-parametric test is the Wilcoxon-Mann-Whitley rank sum statistic. ** denotes p-value <0.01

not statistically different. The sellers with higher list prices in column 5 also experience longer TOM but not as much as the owners in column 2. We also note the positive relation between TOM and LPR, a point we consider later using multivariate analysis.

Beyond illustrating the price-TOM tradeoff, the results demonstrate that the outcomes are not always linear. Note the transaction prices across the columns. Relative to the base case in column 1 with the list prices close to the expected transaction prices, the selling prices in column 2 are higher, which is consist with the theory and being on the market sufficiently long to find a buyer with a high enough reservation price. However, the difference in transaction prices between columns 1 and 2 is not statistically different.

In contrast, the mean and median transaction prices in column 5 are not higher but lower than the base column 1 values. Despite being on the market longer, the mean and median transaction prices are lower by approximately $5,000 (although not statistically significant). Of course, there are limitations to univariate statistics, thus the rest of this section investigates multivariate models.

List Prices – Baseline Models

In addition to the many sample attributes, fixed effects by ZIP codes, and the computed measures of home atypicality, the models of the natural log of list prices include expected losses and gains. The calculation of nominal losses and gains are the percent differences sellers will realize between the purchase price and the expected transaction price at the time of listing. A positive value is the percentage loss at the current average market price and is truncated from below at zero. An expected gain is the same difference but a negative amount and truncated above at zero.[6]

Modeling anticipated losses and gains require additional covariates including a measure of quality. Home quality should be a first-order determinant of market value and the setting of list prices. However, it is generally difficult to measure by the researcher and thus not generally included in housing studies. We calculate structure quality as in Genesove and Mayer (2001) and Bokhari and Geltner (2011). The essential component is purchase price. Following the literature, we model a hedonic specification of value at the time of purchase. Quality is measured as the residuals from the hedonic model, which are the portion of the previous sale prices that the hedonic regression did not predict. To the extent these qualities do not change significantly over time, the residuals are a reasonable, if noisy, measure of their impact on future transaction prices. The need to control for time variation in quality is another reason we reduce the sample period to the latest surveys.

The theory in Genesove and Mayer (2001) and Bokhari and Geltner (2011) shows the other empirical variables to complete the model are *Estimated value*, *Holding period*, plus binary variables for the year of listing. *Estimated value* is the predicted

[6] It is more intuitive to code expected gains as positive and losses as negative. However, subsequent interpretation of the gain and loss variables may prove challenging. The data exhibit a positive relation between expected nominal losses and list prices i.e., the greater the expected loss the higher the list price. If expected losses are coded as negative, the positive relation will yield a negative slope coefficient on loss. To avoid confusion caused by the negative parameter estimate being an increase in list prices, we follow the literature in coding the loss and gain variables.

transaction prices at time of listing and comes from a hedonic model of all sold properties. *Holding period* is the number of years since purchase.

The holding period provides a time-series control but may also measure two other pricing considerations. It can control for the time component of home quality. Owners have a tendency to clean and update their property leading up to a sale. There thus may be an inverse relation between the holding period and home quality due to deferred maintenance. To the extent structural quality correlates with prices, the holding period may similarly be predictive of list prices. A longer holding period also indicates that a particular seller has been out of the market longer and therefore have less recent market experience.

With these additional variables to model expected losses and gains, we begin estimating list prices. The first model is a restricted specification that uses only variables that are available in most transactional datasets. Since we have the full information set to compare, we are motivated to find a model that is limited to variables common in housing studies and has similar explanatory power. We find such a model with the requirement being inclusion of the variables that measure anticipated gains and losses. Thus, the only additional variable required is the initial purchase price. While purchase price is generally not provided in most transactional datasets, researchers can extract it by restricting the sample to repeat sales.

Model 1 in Table 3 reports the restricted model. Meeting with our priors, the partial elasticities on the expected value at listing, size, and quality are significant and positive. Structural atypicality measures are not significant. Sellers who expect a nominal loss set their list prices higher by an amount of 46 % of the difference between their purchase prices and the expected lower selling prices.

Model 2 in Table 3 includes all available information in an unrestricted specification. In comparing models 1 and 2 we note that the fit is just slightly better in model 2. Further, models 1 and 2 demonstrate that researchers can produce a specification that proxies for some of the hard-to-observe characteristics. The change in the slope coefficient suggests that seller characteristics and other transactional attributes are summarized largely by the estimated value at the time of listing.

The specific results in model 2 demonstrate that the determinants of list price include seller, structural, and transactional characteristics. Size and home quality continue to positively impact list prices. Two variables that are not significant in the restricted model 1 but are predictive in model 2 are *Many bathrooms* and *Resort*. Both of these are seemingly measuring additional quality, condition, or amenity considerations. *Many bathrooms* is likely measuring an increase in values at the upper end of the price distribution not found in the other variables as the mean list price of the 37 homes with 5 or more bathrooms is $1,048,554 versus $300,181 for the entire sample. Resort properties also offer additional features not measured in the other covariates, such as locations and views.

Two transactional characteristics that result in lower list prices are short sales and sales due to job relocation. These are consistent with an immediate preference for liquidity. Using Kennedy (1981) for proper interpretation of a binary variable in a lognormal equation, the approximate reduction in list prices is 9.1 % for short sales and 3.7 % for job relocations.

Other significant determinants concentrate with sellers' attributes. The partial elasticity on *Loss* is similar to the magnitude in model 1. The values in Table 3

Table 3 Log list price models using fixed effects

	Parameter estimate	Standard error	Parameter estimate	Standard error
Expected loss	0.460**	(0.051)	0.463**	(0.099)
Expected gain			−0.020	(0.082)
Estimated value	0.821**	(0.042)	0.480**	(0.138)
Quality proxy	0.528**	(0.034)	0.535**	(0.089)
Holding period	0.001	(0.001)	0.001	(0.004)
Log square feet	0.175**	(0.041)	0.405**	(0.104)
Log home age	0.008	(0.008)	0.008	(0.009)
New home	0.038	(0.055)	0.089	(0.061)
Old home	−0.021	(0.052)	−0.057	(0.054)
Small home	0.050	(0.055)	0.062	(0.058)
Large home	0.007	(0.060)	−0.008	(0.061)
Many bedrooms	−0.042	(0.105)	−0.090	(0.107)
Many bathrooms	0.116	(0.069)	0.228**	(0.072)
Detached SFR	0.015	(0.019)	0.013	(0.019)
Suburban	0.019	(0.022)	0.044*	(0.023)
City	0.014	(0.022)	0.026	(0.022)
Small town	0.010	(0.013)	0.023	(0.014)
Resort	0.111	(0.064)	0.210**	(0.073)
Inverse Mills ratio	−0.013	(0.396)	0.217	(0.390)
High urgency			−0.024	(0.018)
Some urgency			−0.019	(0.014)
Short sale			−0.108**	(0.039)
Sold to a friend			−0.036	(0.028)
Avoid foreclosure			−0.016	(0.032)
Relocation			−0.047*	(0.019)
Family change			0.010	(0.022)
Too expensive to keep			0.050	(0.046)
Income 35–44 k			0.051	(0.052)
Income 45–54 k			0.006	(0.051)
Income 55–64 k			0.042	(0.049)
Income 65–74 k			0.110*	(0.052)
Income 75–84 k			0.080	(0.053)
Income 85–99 k			0.125*	(0.057)
Income 100–124 k			0.144*	(0.059)
Income 125–149 k			0.161*	(0.065)
Income 150–174 k			0.170*	(0.070)
Income 175–199 k			0.190**	(0.073)
Income 200–249 k			0.195*	(0.080)
Income 250–499 k			0.271**	(0.088)
Income 500–999 k			0.264*	(0.115)
Income 1,000 k +			0.301*	(0.140)

Table 3 (continued)

	Parameter estimate	Standard error	Parameter estimate	Standard error
First time seller			0.005	(0.016)
Ages 40–44			0.069**	(0.017)
Ages 45–50			0.051*	(0.022)
Ages 50–54			0.053*	(0.025)
Ages 55–59			0.027	(0.029)
Ages 60–64			0.078*	(0.032)
Ages 65–69			0.116**	(0.035)
Ages 70–74			0.085	(0.044)
Ages 75–79			0.110*	(0.056)
Ages 80+			0.061	(0.075)
African American			−0.109	(0.066)
Asian			0.064	(0.044)
Hispanic			−0.044	(0.054)
Log number of earners			0.016	(0.042)
Log number of children			−0.018	(0.014)
Log separation distance			0.008*	(0.004)
Speaks English			−0.027	(0.053)
Born in US			0.029	(0.031)
No agent			0.001	(0.041)
MLS			−0.006	(0.018)
Open house			0.023	(0.014)
Internet			−0.007	(0.029)
Magazine			0.002	(0.014)
Video			0.007	(0.018)
Television			−0.017	(0.033)
Print			0.020	(0.013)
Sign			0.017	(0.017)
Web			0.001	(0.013)
Flyer			0.017	(0.017)
Social media			0.014	(0.019)
Constant	1.041**	(0.299)	3.381**	(0.961)
Observations	3,302		3,302	
Adjusted R^2	0.808		0.812	

The model control for annual and locational fixed effects. The annual fixed effects use the year of listing. The locational fixed effects control for the exogenous bargaining factors of local market thinness, uncertainty, and liquidity, and cover the US using 455 areas at the 3-digit ZIP code level. Standard errors robust to heteroscedasticity. ** and * denote p-value <0.01 and <0.05, respectively

are greater than in Genesove and Mayer (2001) but comparable to results in Bokhari and Geltner (2011). Examining the commercial real estate market, Bokhari and Geltner (2011) find increases in list prices of approximately 38 % with institutional investors and as high as 50 % for equity funds.

The results in Table 3 further demonstrate that sellers who experience nominal gains do not set asking prices that are different than expected. This result is a departure from Bokhari and Geltner (2011). Owners who will recognize gains upon sale will not forego compensation by setting asking prices lower than the expected selling price.

Three other sellers' characteristics that impact list prices are income, age, and separation distance, all of which exhibit positive relationships. There are a couple of interpretations for the increase in list prices due to income. One is that owners with higher incomes should have fewer liquidity constraints and an increased ability to stay on the market longer to obtain a higher price. Another is that there are unobservable factors that correlate with income. For instance, we use fixed effects at the three-digit ZIP code level and the income levels may be measuring additional price considerations at the neighborhood level.

While there is not a monotonic trend across sellers' age ranges, all of the slope coefficients are positive and a number are significant. Compared to the control group of younger sellers, this is consistent with fewer liquidity constraints. The largest parameter estimates concentrate with the ages from 60 to 79, which also suggests a lower preference for a quick sale around the retirement years. Higher list prices for ages 60–69 in particular is consistent with sellers entering retirement and preferring higher values for an asset that is presumably a significant portion of their net worth.

Other attributes in Table 3 are notable because they are insignificant. The reduction in sellers' search costs by selling to a friend or acquaintance is not capitalized into list prices. The age of the home is not a determinant.

Despite self-reporting as urgent to sell their property, both high urgency and some urgency sellers do not set significantly lower list prices relative to the omitted group of non-urgent sellers. Clearly the expectation is that urgent seller would forego typical overpricing to increase buyers' arrival rate but the Table 3 results do not support this hypothesis.

Employing a real estate agent also does not indicate a change in list prices. Owners who do not use agents set mean list prices consistent with market expectations. Another measure for agency is MLS. This factor is also insignificant. The other marketing mechanisms similarly do not impact list prices, although some methods (e.g., open house) may not be expected during the setting of list prices.

List Prices with Predicted TOM

Given the tradeoff between prices and TOM, we also consider two additional variables that may provide further insight into sellers' liquidity preferences. In the first model in Table 4, we include the predicted TOM. In model 2, we replace predicted TOM with predicted LPR. When setting prices, sellers will not know the TOM and LPR outcomes with certainty, but they will set their list prices with an understanding of their liquidity preferences and willingness to reduce their list prices. Hence, either may be a determinant and provide additional insight.

Although both TOM and LPR are expected values at the time of listing, we must consider whether either measure is endogenous with list prices. Test statistics do indeed indicate that both are endogenous. We therefore use a system of equations and two-stage least squares (2SLS) specifications to create instrumental variables. In the first

Table 4 Log list price models adding predicted TOM and LPR

	(1) Adds TOM	Standard error	(2) Replaces TOM with LPR	Standard error
Log TOM IV	0.049**	(0.009)		
Log LPR IV			0.127**	(0.023)
Expected loss	0.450**	(0.082)	0.422**	(0.087)
Expected gain	0.015	(0.068)	−0.006	(0.073)
Estimated value	0.667**	(0.083)	0.597**	(0.088)
Quality measure	0.536**	(0.074)	0.554**	(0.079)
Holding period	0.001	(0.003)	−0.000	(0.003)
Log square feet	0.255**	(0.065)	0.295**	(0.069)
High urgency	−0.014	(0.016)	−0.038*	(0.017)
Some urgency	−0.012	(0.013)	−0.030*	(0.014)
First time seller	0.018	(0.014)	0.008	(0.015)
Income 35–44 k	0.037	(0.046)	0.026	(0.047)
Income 45–54 k	−0.022	(0.043)	−0.022	(0.043)
Income 55–64 k	0.011	(0.040)	0.002	(0.041)
Income 65–74 k	0.073	(0.041)	0.075	(0.042)
Income 75–84 k	0.045	(0.041)	0.044	(0.042)
Income 85–99 k	0.080	(0.043)	0.079	(0.045)
Income 100–124 k	0.096*	(0.043)	0.103*	(0.045)
Income 125–149 k	0.109*	(0.048)	0.119*	(0.049)
Income 150–174 k	0.113*	(0.052)	0.119*	(0.054)
Income 175–199 k	0.130*	(0.054)	0.144**	(0.055)
Income 200–249 k	0.131*	(0.060)	0.149*	(0.061)
Income 250–499 k	0.188**	(0.061)	0.203**	(0.064)
Income 500–999 k	0.144	(0.080)	0.180*	(0.083)
Income 1,000 k +	0.184	(0.098)	0.258*	(0.112)
African American	−0.090	(0.057)	−0.098	(0.059)
Asian	0.048	(0.040)	0.042	(0.039)
Hispanic	−0.038	(0.051)	−0.054	(0.051)
Ages 40–44	0.062**	(0.016)	0.061**	(0.017)
Ages 45–50	0.051*	(0.021)	0.051*	(0.022)
Ages 50–54	0.042	(0.023)	0.037	(0.023)
Ages 55–59	0.014	(0.027)	0.021	(0.028)
Ages 60–64	0.060*	(0.029)	0.061*	(0.029)
Ages 65–69	0.104**	(0.032)	0.101**	(0.033)
Ages 70–74	0.066	(0.040)	0.072	(0.041)
Ages 75–79	0.082	(0.050)	0.079	(0.052)
Ages 80+	0.025	(0.066)	0.032	(0.069)
Speaks English	−0.006	(0.050)	0.002	(0.050)
Born in US	0.023	(0.028)	0.016	(0.025)
Log number of earners	0.055	(0.033)	0.043	(0.033)
Log number of children	−0.027*	(0.013)	−0.025	(0.013)

Table 4 (continued)

	(1) Adds TOM	Standard error	(2) Replaces TOM with LPR	Standard error
Short sale	−0.102**	(0.035)	−0.087*	(0.035)
Avoid foreclosure	−0.012	(0.029)	−0.021	(0.030)
Relocation	−0.031	(0.017)	−0.032	(0.018)
Family change	−0.005	(0.020)	0.007	(0.018)
Too expensive to keep	−0.009	(0.037)	−0.009	(0.040)
Log separation distance	0.005	(0.003)	0.006	(0.003)
No agent	0.038	(0.026)	0.034	(0.025)
Resort	0.140*	(0.063)	0.153*	(0.064)
Log home age	0.006	(0.008)	0.004	(0.008)
Many bathrooms	0.146*	(0.070)	0.179*	(0.076)
Suburban			0.042*	(0.020)
City			0.027	(0.021)
Small town			0.027*	(0.012)
Constant	2.020**	(0.585)	2.602**	(0.619)
Observations	3,302		3,243	
Adjusted R^2	0.807		0.808	
Robust score chi^2 (p-value)	0.000		0.000	
Robust regression (p-value)	0.000		0.000	
Partial R^2	0.333		0.191	
Robust F	67.22		32.61	
Overidentification (p-value)	0.729		0.983	

Models include annual and locational fixed effects. The annual fixed effects use the year of listing. The locational fixed effects are 453 areas at the 3-digit ZIP code level. Heteroscedasticity-consistent and IV-robust errors in parentheses. ** and * denote p-value <0.01 and <0.05, respectively

stage, we model TOM and LPR separately using instruments that do not correlate with list prices. Table 8 in the Appendix 2 details the instruments.

Search theory shows that expected TOM and expected prices are determined by the same variables at time of listing. The housing literature consequently has been challenged to find suitable instruments that correlate with one and not the other outcome. The NAR dataset provides an attractive resolution to this dilemma. We find a number of unique variables correlate with the predicted variable in the first stage that do not impact list prices. As examples, selling to an acquaintance and the marketing methods are highly predictive of TOM and LPR but not prices.

Model 1 in Table 4 details the second stage structural specification including predicted TOM, with results of endogeneity tests at the bottom of the table. Since our models use standard errors robust to heteroscedasticity, we calculate the Woolridge (1995) score and regression-based tests of exogeneity. The p-values are less than 0.00, which rejects the hypothesis that TOM and list prices are exogenous.

We also compute Shea's partial R^2 statistic, which tests for a weak IV. The test measures the strength of IVs after partialling out the effect of the exogenous variables. The coefficient on the TOM IV is a significant 0.332. We follow the recommendation of Stock et al. (2002) that the F statistic on the partial R^2 test be not only statistically significant but greater than 10. Table 4 reports the statistic is 66.63. In addition to testing that the instruments be correlated with the endogenous regressor, we also confirm that they lack significant correlation with the error terms in the second-stage structural equation. Using the Woolridge (1995) test for overidentification, the test statistic demonstrates an insignificant p-value of 0.770, which indicates neither an invalid instrument nor an incorrectly specified structural equation.

The results in model 1 of Table 4 are generally consistent with the OLS findings. Urgency, first-time sellers, and race remain insignificant in explaining list prices. The estimated value of the property at listing, structural quality, and size continue to exhibit positive elasticities with log prices. Short sales demonstrate the same reduction of approximately 10 % in list prices. Sellers who expect nominal losses set higher list prices of a similar magnitude as in the previous OLS regression.

With the inclusion of predicted TOM, we note a couple of additional determinants. TOM itself exhibits a positive and significant partial elasticity. This result indicates that sellers with lower (higher) liquidity preferences set higher (lower) list prices by approximately 5 %. This finding clearly supports search theory.

The other new predictor is the number of children in the household, which exhibits an inverse relation with list prices. After holding constant liquidity preferences through predicted TOM, the slope coefficient indicates that households with more children set lower list prices. This finding is consistent with lower bargaining power as argued by Harding et al. (2003a).

We observe that the slope coefficients decrease across the income levels in Table 4 relative to the OLS parameter estimates. This is consistent with predicted TOM subsuming the lack of liquidity constraints represented by higher incomes. The residual relation between the higher incomes and list prices can be expected to be additional quality and amenities in more expensive homes.

Lastly, we note that the coefficient on *No agent* increases from 0.01 in the previous base model to 0.038 in Table 4, but it is still insignificant. The unbalanced design of the data unfortunately hinders our making any further inference. Transactions that do not use an agent are approximately 6 % of the sample and those that start as FSBO and end up with an agent are another 2 %. The 8 % is not informative enough to reject the null hypothesis that brokerage does not have an impact on list prices.

List Prices with Predicted LPR

The next specification replaces predicted TOM with the predicted number of reductions in list prices. As with the predicted TOM, we find LPR is endogenous with list prices. We again use 2SLS and report the first-stage reduced model in Table 7. Test statistics at the bottom of the column in Table 4 report that the IV is not overidentified and not a weak instrument.

The results in Table 4 confirm that the number of LPR significantly and positively affects asking prices. One seller attribute that is different in the LPR model is urgency. After holding constant urgent sellers that expect to reduce their list prices, we observe that the remaining urgent owners set lower prices. The combined findings suggest that some urgent sellers set their list prices close to the expected value but due to their motivation for quicker sales will reduce their list prices and more often. For the remaining urgent sellers who do not expect to reduce their list prices during the marketing period, they set lower asking prices at the time of listing of approximately 3 %.

Looking at both the TOM and LPR models in Table 4, we note that most of the covariates in the LPR model are the same sign and significance as in the TOM model. The fact that the results are consistent across the models suggests that TOM and LPR are measuring similar effects, a finding first noted in the univariate analysis. The Pearson correlation coefficient between TOM and LPR is 0.69.

Since the model already holds constant a direct measure of urgency, the coefficients on TOM and LPR suggest additional secondary effects. Certainly the positive relation between TOM and price is expected but with LPR similarly positive, we can think of a couple of additional economic rationales. Since predicted LPR is an expectation of future events, a positive relation between list prices and LPR can indicate learning or price fishing. Sellers who are unclear about an appropriate starting price may set a higher list price, glean information from the market, and adjust as needed. Since the LPR measure is the number of reductions and not the overall percentage, a positive relation also indicates price fishing. Sellers who expect to reduce their list prices a greater number of times set higher list prices in hopes of finding a matching buyer but, if not, are willing to incrementally reduce their list prices more than once.

Robustness Tests

To confirm the robustness of the findings, we next consider two scenarios related primarily to the expected nominal losses, although the tests may also impact expected gains. The first test is to include the holding period return (HPR) for the 3 and 5 years prior to owners listing their properties. This additional variable considers whether sellers' recognition of expected losses differs based on the changes in house prices in the local market. For instance, the continuously-compounded return for homes in Las Vegas, Nevada from 2006 to 2009 is negative 73 %. In contrast, homes in Boulder, Colorado during the same period experienced a slight price increase of 1 %. The empirical question is whether, for example, Las Vegas owners that experience such a dramatic decrease temper their overpricing of list prices due to anticipated losses when compared to other locations such as Boulder that has not experiencing such price decreases.

To test the hypothesis, we include the HPR in both the unrestricted specification from Table 3 and the models in Table 4 that include the expected TOM and LPR. Table 5 details the results including the 5-year HPR. The 3-year HPR findings are the same so are untabled for brevity. The results demonstrate that the prior findings are robust to the inclusion of HPR. The added variable is not significant in any of the three models and there are no major change in the other covariates.

The HPR in Table 5 is computed using the Housing Price Index (HPI) from the Federal Housing Finance Agency. We first use the all-transactions index because it has the greatest coverage of Core Based Statistical Areas, which include micropolitan areas as small as 10,000 people. The index is not seasonally adjusted. To confirm the index is not driving the results, we include the purchase-only HPI, which is seasonally adjusted and covers the 100 largest metropolitan statistical areas. The sample consequently decreases to 2,351 observations. The results and conclusions are the same as in Table 5. HPR is not significant and the parameter estimates on expected losses are slightly greater than 0.50 and significant.

Table 5 Robust test including prior 5-year holding period returns

	(1) Base model	Standard error	(2) Adds TOM	Standard error	(3) Adds LPR	Standard error
HPR	−0.148	(0.098)	0.093	(0.066)	0.054	(0.065)
Log TOM IV			0.046**	(0.008)		
Log LPR IV					0.119**	(0.023)
Expected loss	0.512**	(0.108)	0.513**	(0.090)	0.485**	(0.094)
Expected gain	0.031	(0.092)	0.034	(0.076)	0.015	(0.080)
Estimated value	0.538**	(0.146)	0.697**	(0.093)	0.628**	(0.098)
Quality proxy	0.506**	(0.098)	0.502**	(0.081)	0.519**	(0.086)
Holding period	0.001	(0.004)	0.002	(0.003)	0.001	(0.004)
Log square feet	0.371**	(0.113)	0.245**	(0.074)	0.284**	(0.078)
High urgency	−0.016	(0.020)	−0.002	(0.018)	−0.025	(0.019)
Some urgency	−0.013	(0.016)	−0.006	(0.014)	−0.024	(0.015)
First time seller	0.008	(0.018)	0.018	(0.015)	0.009	(0.016)
Income 35–44 k	0.046	(0.057)	0.039	(0.050)	0.024	(0.051)
Income 45–54 k	0.003	(0.056)	−0.020	(0.048)	−0.026	(0.048)
Income 55–64 k	0.038	(0.051)	0.014	(0.044)	−0.001	(0.045)
Income 65–74 k	0.104	(0.055)	0.075	(0.046)	0.075	(0.047)
Income 75–84 k	0.075	(0.057)	0.052	(0.045)	0.047	(0.046)
Income 85–99 k	0.109	(0.060)	0.073	(0.047)	0.072	(0.049)
Income 100–124 k	0.136*	(0.062)	0.097*	(0.048)	0.104*	(0.049)
Income 125–149 k	0.155*	(0.069)	0.113*	(0.053)	0.122*	(0.055)
Income 150–174 k	0.155*	(0.073)	0.110	(0.057)	0.116*	(0.058)
Income 175–199 k	0.180*	(0.077)	0.131*	(0.059)	0.145*	(0.060)
Income 200–249 k	0.187*	(0.085)	0.134*	(0.067)	0.153*	(0.068)
Income 250–499 k	0.252**	(0.092)	0.184**	(0.067)	0.202**	(0.070)
Income 500–999 k	0.245*	(0.121)	0.145	(0.086)	0.177*	(0.090)
Income 1,000 k +	0.294*	(0.148)	0.192	(0.105)	0.269*	(0.118)
African American	−0.081	(0.066)	−0.068	(0.058)	−0.074	(0.060)
Asian	0.026	(0.043)	0.008	(0.038)	−0.007	(0.038)
Hispanic	−0.044	(0.057)	−0.040	(0.053)	−0.052	(0.053)
Ages 40–44	0.062**	(0.018)	0.057**	(0.017)	0.057**	(0.017)
Ages 45–50	0.035	(0.023)	0.034	(0.022)	0.034	(0.023)
Ages 50–54	0.032	(0.026)	0.020	(0.024)	0.014	(0.024)
Ages 55–59	0.000	(0.031)	−0.013	(0.029)	−0.007	(0.029)
Ages 60–64	0.057	(0.033)	0.041	(0.030)	0.040	(0.030)
Ages 65–69	0.091*	(0.037)	0.081*	(0.034)	0.080*	(0.035)
Ages 70–74	0.056	(0.047)	0.042	(0.042)	0.043	(0.043)
Ages 75–79	0.093	(0.059)	0.070	(0.053)	0.058	(0.054)
Ages 80+	0.047	(0.083)	0.016	(0.074)	0.006	(0.076)
Log home age	0.013	(0.009)	0.011	(0.008)	0.011	(0.008)
Many bathrooms	0.203*	(0.083)	0.139	(0.084)	0.178	(0.091)
Resort	0.184*	(0.084)	0.135	(0.072)	0.142*	(0.071)
Log number of earners	0.006	(0.044)	0.033	(0.034)	0.022	(0.034)

Table 5 (continued)

	(1) Base model	Standard error	(2) Adds TOM	Standard error	(3) Adds LPR	Standard error
Log number of children	−0.023	(0.015)	−0.032*	(0.014)	−0.032*	(0.015)
Log separation distance	0.008*	(0.004)	0.006	(0.003)	0.007*	(0.004)
Short sale	−0.113**	(0.041)	−0.110**	(0.037)	−0.098**	(0.038)
Avoid foreclosure	−0.011	(0.036)	−0.010	(0.032)	−0.018	(0.032)
Relocation	−0.051*	(0.020)	−0.039*	(0.018)	−0.041*	(0.018)
Family change	0.002	(0.025)	−0.010	(0.021)	−0.002	(0.020)
Too expensive to keep	0.043	(0.054)	−0.005	(0.041)	0.008	(0.044)
No agent	0.008	(0.034)	0.035	(0.027)	0.034	(0.026)
Constant	2.970**	(0.981)	1.753**	(0.632)	2.347**	(0.667)
Observations	2,938		2,938		2,889	
Adjusted R^2	0.811		0.807		0.808	

Specifications examine if price changes prior to the listing of the property effect nominal losses and gains. All models include annual and locational fixed effects. The annual fixed effects use the year of listing. The locational fixed effects are 453 areas at the 3-digit ZIP code level. Additional insignificant independent variables in the base model used as instruments of TOM and LPR in Models (2) and (3) are suburban, city, small town, detached SFR, sold to an acquaintance, marketing methods, atypicality measures, and the IMR. Heteroscedasticity-consistent and IV-robust errors in parentheses. ** and * denote p-value <0.01 and <0.05, respectively

Another robust test we consider is the uncertainty of the predicted selling price. Losses and gains are a function of the expected selling price at time of listing. In a market with greater uncertainty, sellers may not be as able to determine whether they will experience a gain or loss. The magnitude of the nominal return may also be more difficult to determine with greater market uncertainty. To measure market variability, we normalize the loss and gain levels by the standard errors of the expected selling price. We use both the standard errors of the prediction or fitted values as well as the standard errors of the forecast, which is more conservative (larger) because it is the standard error of the point prediction and includes the uncertainty in the regression line and the individual observation. The results are invariant to the uncertainty measure.

Table 6 details the base, TOM, and LPR models including the scaled expected gains and losses. The results indicate that sellers' behavior is unchanged by including market variability. Due to the standardization, the slope coefficients on anticipated losses and gains cannot be interpreted as previously, yet the expected losses continue to exhibit an increase in list price while expected gains does not significantly impact list prices. The other covariates behave as in prior specifications.

Conclusion

Homeowners face a tradeoff between obtaining a higher transaction price and reducing marketing durations. Property varies by liquidity such as proxied by atypicality in markets

Table 6 Robust test using standardized nominal losses and gains

	(1) Base model	Standard error	(2) Adds TOM	Standard error	(3) Adds LPR	Standard error
Log TOM IV			0.049**	(0.009)		
Log LPR IV					0.125**	(0.023)
Expected loss standardized	0.176**	(0.038)	0.174**	(0.032)	0.162**	(0.033)
Expected gain standardized	−0.003	(0.032)	−0.002	(0.026)	−0.012	(0.028)
Estimated value	0.485**	(0.131)	0.654**	(0.079)	0.581**	(0.083)
Quality proxy	0.564**	(0.082)	0.559**	(0.068)	0.578**	(0.073)
Holding period	−0.001	(0.003)	0.000	(0.003)	−0.001	(0.003)
Log square feet	0.400**	(0.099)	0.264**	(0.062)	0.307**	(0.065)
High urgency	−0.022	(0.018)	−0.013	(0.016)	−0.037*	(0.017)
Some urgency	−0.017	(0.015)	−0.012	(0.013)	−0.030*	(0.013)
First time seller	0.006	(0.016)	0.018	(0.014)	0.008	(0.015)
Income 35–44 k	0.049	(0.052)	0.038	(0.046)	0.028	(0.047)
Income 45–54 k	0.004	(0.050)	−0.021	(0.043)	−0.020	(0.043)
Income 55–64 k	0.038	(0.047)	0.012	(0.040)	0.004	(0.041)
Income 65–74 k	0.107*	(0.050)	0.074	(0.041)	0.078	(0.042)
Income 75–84 k	0.078	(0.051)	0.048	(0.040)	0.047	(0.041)
Income 85–99 k	0.123*	(0.055)	0.082	(0.042)	0.083	(0.044)
Income 100–124 k	0.140*	(0.056)	0.098*	(0.043)	0.108*	(0.044)
Income 125–149 k	0.158*	(0.063)	0.112*	(0.047)	0.124*	(0.048)
Income 150–174 k	0.167*	(0.067)	0.117*	(0.051)	0.125*	(0.052)
Income 175–199 k	0.186**	(0.070)	0.134*	(0.053)	0.150**	(0.054)
Income 200–249 k	0.192*	(0.078)	0.136*	(0.059)	0.156**	(0.059)
Income 250–499 k	0.266**	(0.084)	0.194**	(0.059)	0.211**	(0.062)
Income 500–999 k	0.260*	(0.110)	0.152	(0.078)	0.192*	(0.081)
Income 1,000 k +	0.297*	(0.137)	0.191*	(0.096)	0.268*	(0.110)
African American	−0.109	(0.066)	−0.094	(0.057)	−0.102	(0.059)
Asian	0.054	(0.039)	0.039	(0.035)	0.036	(0.035)
Hispanic	−0.044	(0.053)	−0.041	(0.050)	−0.056	(0.049)
Ages 40–44	0.069**	(0.017)	0.062**	(0.016)	0.061**	(0.017)
Ages 45–50	0.053*	(0.022)	0.052*	(0.021)	0.053*	(0.022)
Ages 50–54	0.056*	(0.025)	0.045*	(0.023)	0.040	(0.023)
Ages 55–59	0.030	(0.029)	0.017	(0.027)	0.024	(0.027)
Ages 60–64	0.082**	(0.031)	0.064*	(0.028)	0.065*	(0.029)
Ages 65–69	0.118**	(0.035)	0.106**	(0.032)	0.104**	(0.033)
Ages 70–74	0.088*	(0.043)	0.069	(0.039)	0.076	(0.040)
Ages 75–79	0.112*	(0.054)	0.084	(0.049)	0.083	(0.051)
Ages 80+	0.066	(0.074)	0.029	(0.066)	0.037	(0.069)
Log home age	0.006	(0.009)	0.004	(0.008)	0.003	(0.008)
Many bathrooms	0.224**	(0.072)	0.148*	(0.070)	0.181*	(0.076)
Resort	0.202**	(0.073)	0.137*	(0.063)	0.152*	(0.063)

Table 6 (continued)

	(1) Base model	Standard error	(2) Adds TOM	Standard error	(3) Adds LPR	Standard error
Log number of earners	0.025	(0.043)	0.059	(0.033)	0.046	(0.033)
Log number of children	−0.019	(0.014)	−0.027*	(0.013)	−0.025	(0.013)
Log separation distance	0.007	(0.004)	0.005	(0.003)	0.006	(0.003)
No agent	0.008	(0.033)	0.038	(0.026)	0.034	(0.025)
Short sale	−0.102**	(0.039)	−0.099**	(0.035)	−0.085*	(0.035)
Avoid foreclosure	−0.018	(0.032)	−0.014	(0.029)	−0.023	(0.030)
Relocation	−0.046*	(0.019)	−0.031	(0.017)	−0.032	(0.018)
Family change	0.008	(0.023)	−0.005	(0.020)	0.007	(0.018)
Too expensive to keep	0.042	(0.048)	−0.011	(0.038)	−0.010	(0.040)
Suburban	0.043	(0.023)			0.042*	(0.020)
City	0.024	(0.022)			0.026	(0.021)
Small town	0.023	(0.014)			0.028*	(0.012)
Sold to a friend	−0.038	(0.028)				
Constant	3.361**	(0.918)	2.131**	(0.559)	2.741**	(0.588)
Observations	3,302		3,302		3,243	
Adjusted R^2	0.811		0.807		0.808	

Nominal losses and gains are scaled by the standard error of the forecast of predicted sale prices. All models include annual and locational fixed effects. The annual fixed effects use the year of listing. The locational fixed effects are 453 areas at the 3-digit ZIP code level. Additional insignificant independent variables in the base model used as instruments of TOM and LPR in Models (2) and (3) are sold to an acquaintance, marketing methods, atypicality measures, and the IMR. Heteroscedasticity-consistent and IV-robust errors in parentheses. ** and * denote p-value <0.01 and <0.05, respectively

of varying activity while owners vary in their resources, urgency, and other characteristics that may lead them to prefer a quicker sale. Unfortunately, many of the variables that can affect the list price decision do not appear in typical transactional datasets.

This article consequently examines list prices using a rich dataset that includes seller, structural, transactional, and locational attributes. As expected, the results first demonstrate that physical characteristics of homes are highly influential determinants of pricing. These structural attributes include quality, size, and other variables that suggest changes in prices due to additional features (e.g., resort properties). We observe that neither home age nor atypicalities are predictive of list prices.

Aversion to nominal losses is another determinant that is consistently predictive of prices. No matter the specification and other pricing considerations, we find sellers who expect losses will set higher list prices. Alternatively, sellers who should experience nominal gains upon sale do not set list prices different than expected.

The seller characteristics that impact prices include income, certain age levels, and urgency. Other measures are notable because they do not impact the setting of list prices. Various measures of market experience are not predictive. Owners of different races do not significantly set differing asking prices. Using an agent also does not significantly change prices.

Lastly, this article has an implication for applied practice. We examine a parsimonious fixed-effects model that includes structural and transactional attributes that are available in most MLS datasets. This restricted model behaves similarly to the full model in most regards but can be estimated using transactional data. A key variable is the purchase price of the home, which can be uncovered using repeat sales. The fit of the parsimonious model suggests variables that can proxy for sellers' characteristics and motivations.

Appendix 1: Sample Selection Bias

The NAR survey is sent to both buyers and sellers of homes. A small percentage of the buyers have purchased a new home but have not sold their previous residence. The unsold properties occur in each survey year. We thus examine for potential selection bias using the traditional Heckman two-step procedure and compute the IMR. The first step estimates a probit model of whether the house has sold or not, which Table 7 details. From this specification, we obtain the IMR, which is included in the second stage specifications of list prices.

IMR allow us to potentially control for those responders who have their home listed but may be less motivated to sell and thus have unique price-liquidity preferences. The results in Table 8 in Appendix 2 are consistent with this difference in price-liquidity preferences. The IMR computed from the specification in Table 7 is highly significant and positive in the TOM model in Table 8. This finding indicates a longer expected TOM for those sellers who have a lower propensity to sell.

Table 7 Probability of sale

	Parameter estimate	Standard error
High urgency	−0.118	(0.254)
Some urgency	−0.040	(0.191)
African American	−0.499	(0.405)
Hispanic	−0.320	(0.335)
Log seller's age	0.510	(0.515)
First time seller	−0.225	(0.220)
Log number of children	0.137	(0.174)
Log number of earners	0.580	(0.394)
Short sale	−0.458	(0.289)
Avoid foreclosure	0.200	(0.366)
Relocation	0.285	(0.220)
No agent	0.680	(0.476)
Vacant	−2.421**	(0.408)
Log seller's income	0.141	(0.082)
Log separation distance	−0.002	(0.044)
Log square feet	0.077	(0.222)
Log home age	0.194*	(0.081)

Table 7 (continued)

	Parameter estimate	Standard error
Sold to a friend	−0.127	(0.281)
Family change	1.184**	(0.449)
Too expensive to keep	0.246	(0.336)
Suburban	−0.214	(0.247)
Detached SFR	−0.853*	(0.364)
MLS	0.227	(0.213)
Open house	−0.123	(0.172)
Internet	0.338	(0.244)
Magazine	0.425	(0.305)
Video	0.176	(0.218)
Television	0.010	(0.318)
Flyer	−0.359	(0.189)
Print	−0.108	(0.213)
Sign	0.235	(0.175)
Web	−0.287	(0.170)
Social media	0.324	(0.312)
Year 2010	0.151	(0.247)
Year 2011	0.531*	(0.217)
Year 2012	0.515*	(0.259)
Constant	−2.661	(2.612)
Observations	4,144	
Pseudo-R	0.304	

The table reports a probit model, which is the first stage of the traditional Heckman two-step procedure. Errors are robust to heteroscedasticity. ** and * denote p-value <0.01 and <0.05, respectively

Appendix 2: Simultaneity

Search theory shows that prices and marketing durations are determined simultaneously. LPR should also be endogenous with the other two. We control for endogeneity using a system of simultaneous equations and 2SLS. Table 8 reports the instruments with the instrumented variable denoted in the heading. For brevity, the exogenous variables are omitted from Table 8 but available in a separate appendix.

Finding quality instruments is always a challenge in housing studies examining prices and TOM because the two outcomes are determined by the same set of attributes. In our case, the NAR dataset provides high-quality instruments that do not exhibit a correlation with the dependent variable in the second stage but economic theory, prior studies, or our analysis indicates have a potential relation with the instrumented variable.

We provide test statistics of each instrumented variable in the table detailing the second-stage structural equation. Because the model estimates a heteroscedasticity-robust variance-covariance matrix, we report Woolridge's (1995) score test and regression-based test of exogeneity. A second test detects weak instruments. We report both Shea's partial R^2 and the F statistic. The partial R^2 measures the correlation between the IV and the instruments after partialling out the effect of the exogenous variables. We note that the F statistic is generally statistically significant even with weak instruments. Thus, we take the recommendation of Stock et al. (2002) that the F statistic be greater than 10. To check the correlation between the instruments and structural error term, a third test statistic we examine and report is the Woolridge robust score of overidentifying restrictions. Again, the Woolridge (1995) score considers the robust variance-covariance matrix. With the understanding of the caution in interpreting the overidentification test argued by Parente and Santos Silva (2012), an insignificant test statistic implies the IV does not exhibit a statistically significant correlation with the error term in the structural equation.

Note, we use the linear probability model for the number of LPR to avoid the forbidden regression and incidental parameters problems. The forbidden regression makes the error of replacing a nonlinear function of an endogenous explanatory variable with the same nonlinear function of fitted values from a first-stage estimation (Woolridge (2010) and Angrist and Pischke (2008)). The incidental parameters problem arises with binary response variables like LPR. When fitting linear models, fixed effects correctly measure the mean value of the dependent variable for a particular attribute, location in our models. However, as the number of areas increases in our model, the slope coefficients on the fixed effect variables become biased (Neyman and Scott (1948)). We have 455 locational fixed effects so we use the linear probability model to avoid the incidental parameters problem.

Table 8 First stage instruments

	TOM	LPR
Sold to a friend	−0.354**	−0.114**
	(0.089)	(0.043)
Detached SFR	0.259**	0.099**
	(0.070)	(0.037)
MLS	0.327**	0.123**
	(0.059)	(0.033)
Open house	0.579**	0.329**
	(0.052)	(0.028)
Internet	0.299**	0.028
	(0.085)	(0.044)
Magazine	0.387**	0.083**
	(0.048)	(0.027)
Video	0.067	0.064
	(0.065)	(0.036)
Television	−0.094	−0.126
	(0.118)	(0.070)
Print	0.209**	0.100**
	(0.046)	(0.026)
Sign	0.049	−0.026
	(0.057)	(0.030)
Web	0.034	0.021

Table 8 (continued)

	TOM	LPR
	(0.044)	(0.025)
Flyer	0.296**	0.189**
	(0.061)	(0.034)
Social media	−0.028	−0.012
	(0.079)	(0.043)
New home	−0.080	0.117
	(0.259)	(0.150)
Old home	−0.153	−0.157
	(0.176)	(0.113)
Small home	−0.045	−0.000
	(0.188)	(0.090)
Large home	0.067	0.064
	(0.160)	(0.085)
Many bedrooms	−0.570**	−0.214
	(0.200)	(0.123)
Inverse Mills ratio	3.147**	0.803
	(0.930)	(0.496)
Suburban	0.179*	
	(0.076)	
City	0.101	
	(0.069)	
Small town	−0.029	
	(0.049)	
Constant	22.205**	10.174**
	(3.185)	(1.752)
Observations	3,302	3,243
Adjusted R^2	0.387	0.234

The table reports the instruments used in the first stage of a 2SLS model. Additional exogenous variables not reported in this table. The models include locational and annual fixed effects. The annual variables use the year of listing. Heteroscedasticity-consistent standard errors in parentheses. ** and * denote p-value <0.01 and <0.05, respectively

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