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List price and sales prices of residential properties during booms and busts

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ABSTRACT

This paper investigates the relationship between the list and sale price of residential properties over the housing cycle. In down or normal markets the list price generally exceeds the sales price; however, when the housing market is strong, homes sell for more than their list price. This observation is not consistent with the assumptions made in the standard model of home sellers' search behavior. We consider alternative models. In one, sellers set list prices based on their expectations of future changes in sales prices and the arrival rate of buyers; however, demand shocks occur. This model partially explains our data from the Belfast, U.K. housing market, but it fails to predict the list to sales price ratio during a sustained housing boom. We next describe a model where sellers' endogenously select their search mechanism depending on the strength of the housing market. We find support for the conjecture that sellers switch to an auction-like model during housing booms. There also is evidence that during a downturn in the market, sellers' list prices are sticky.

1. Introduction

In many locations, the sales process for residential properties follows the pattern of a seller setting a list price, waiting for offers, and eventually selling the property or withdrawing the listing. In general, this model is followed in both U.S. and U.K. markets.[2] Consistent with the model's prediction, it is commonly observed that list price exceeds the eventual sales price. However, this model breaks down during housing booms when observations of houses selling for a price above the list price become more common.

Formal models of seller behavior tend to assume that list price will exceed sales price and thus are not applicable during boom periods. A simple extension of the standard model is to include unexpected increases in the distribution of buyers' offer prices. Unexpected demand shocks could explain observations of offers (and sales prices) exceeding list prices during a boom. We propose a test of this model based on separating expected from unexpected house price changes. Our results suggest that this model is not sufficient to fully explain the extent and duration of periods when sales prices exceed list prices. We then propose an alternative model where home sellers change search mechanisms during a housing boom. Specifically, during normal housing markets a seller's strategy follows the standard search model, but during a boom it changes to an auction-like process. This shift in strategic behavior is consistent with an emerging literature on seller search mechanisms (Gan, 2013).

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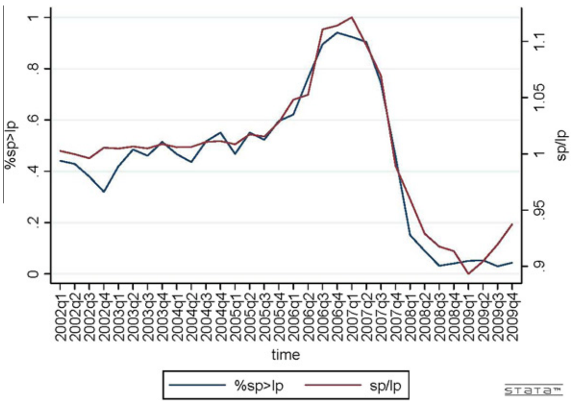

Fig. 1. Percentage of transactions where sales price exceeded list price.

The empirical analysis is based on a sample of over 4700 sales from the Belfast, U.K. metropolitan area from the first quarter of 2002 to the fourth quarter of 2009. For each transaction, information on sale price, list price, marketing period, and various property characteristics are known. During boom periods (e.g., 2006:4) the percentage of transactions where sales price exceeded list price reached 94%, but it was as low as 3% during the bust in home prices late in the decade (2009:3). The time series of percentage of cases where the sales price exceeded the list price is displayed in Fig. 1 (left vertical axis). On the right vertical axis the average ratio of sales price to list price is reported. This ratio was near 1.0 from 2002 to 2005 and then is rose to a peak in 2007:1 of 1.12. During the downturn it fell to a low of 0.89 in 2009:1. Our goal is to explain these inter temporal variations.

2. Theoretical perspectives

2.1. Literature

The setting of list prices is a problem that is often modeled from the perspective of optimal search behavior. Theoretical studies of sellers' behavior began with DeGroot (1970) who determined that the optimal seller strategy involved setting a reservation price and accepting the first offer that exceeds it. Haurin (1988) applied this theory to the housing market, noting that sellers set reservation prices that reflect their strategies, but these reservation prices are almost always unobservable (an exception is Glower et al., 1998). However, neither DeGroot nor Haurin included list prices in their models; rather, they focused on reservation prices, transaction prices, and expected marketing time.

The literature about how sellers set list prices has been developed since the 1990s. Theoretical contributions include papers by Horowitz (1992), Knight et al. (1994), Yavas and Yang (1995), Arnold (1999), Anglin (2006), Haurin et al. (2010). These papers argue that list prices have two roles in the U.S. institutional setting. One is that list price signals a property's quality. The other is that list price signals a price that is acceptable to the seller.

Regarding the first role, it is a simple relationship that states that, independent of search strategies, a property with a greater expected "market value" will be listed with a higher price. The expected market value of a property can be derived from a dwelling's set of characteristics (including those of the neighborhood), the set of implicit prices of these characteristics, and current housing market conditions. The implicit prices of dwellings' characteristics can be estimated from past sales of properties in the locality. Thus, one implication of a high list price for a property is that it has a high market value (and quality).

The "market value" of a property is often interpreted to be a single number that results from the transaction between a buyer and a seller. As noted by formal housing search models such as that by Wheaton (1990) or Albrecht et al. (2007), and in a search model for commercial property (Fisher et al., 2003), there is a set of potential buyers for a property and within this set, buyers' valuations of a particular property are heterogeneous. When setting the list price, a seller will rationally account for both the mean and variance of the distribution of potential buyers' offers.

Search theory suggests that the greater the list price compared with the expected value of the buyers' distribution of offers for the property, the fewer the number of buyers who will find the property to be a "good value". That is, if a buyer's valuation of the property is substantially less than the list price, the behavioral assumption about buyers is that their probability of tendering an offer is relatively low compared with the situation where a buyer's valuation is near or exceeds the list price. For example, a seller's own valuation of the property could be out of line with the market valuation because of poor information about the property's characteristics' implicit prices or the strength of the housing market. If the result is a list price nontrivially greater than the dwellings' market value (or the mean of the buyers' distribution of offers), then a potential buyer will likely use the list price as a signal that an offer near the expected market value will be rejected by the seller. Making an offer is costly to a potential buyer as it likely prohibits simultaneously making an offer on another property. The implication is that a potential buyer's likelihood of making an offer falls when a dwelling's list price improperly signals a set of characteristics associated with a higher valued property. From the seller's viewpoint, the result of a too high list price is that the probability of a sale is lower throughout the marketing period, raising the expected time cost of holding the property. Horowitz (1992) summarized this argument by assuming that the arrival rate of potential buyers' offers is a decreasing function of a (time invariant) list price.

Given the above, why aren't list prices set relatively low compared with the mean of the distribution of buyers' offers? Existing search models nearly always assume that a property's list price is an implicit agreement by the seller to sell at the listed price. That is, the list price effectively forms an upper bound on buyers' offers. In practice, it is assumed that exceptions to this assumption are relatively rare and tend to happen only when a localized market becomes unusually hot. Thus, the models in the papers cited above conclude that there is an optimal list price that is determined by balancing the marginal gains and losses from a marginal change in the list price. In this framework the list price should exceed the sales price *throughout* the housing cycle. However, this assumption that list prices are an upper bound is clearly violated, often to a great degree in particular markets.

Alternative models of list prices have been proposed. The Yavas and Yang (1995) model included the above two roles of list prices and added the assumption that real estate agents' efforts to sell a house are related to the list price. The two offsetting effects are that an ''overpriced'' house elicits relative little effort by the agent; however, the potential return of selling at a relatively high price yields greater effort. Thus, their model predicts that high list prices have an ambiguous effect on broker search effort and the expected marketing time of a property. Arnold's (1999) study allows for bargaining between seller and buyer, and this model is then embedded within a search framework. His results regarding the relationship of list price and a seller's time rate of discount are similar to those of Yavas and Yang. Genesove and Mayer (1997) argued that some homeowners are constrained by the amount of debt they have on a property and this debt affects their reservation and list prices when selling. They used a sample of Boston condominiums and found that sellers with relatively high loan-to-value ratios set relatively high list prices, ceteris paribus.[3] None of these models predict the circumstances when sales prices would systematically exceed list prices. Levin and Pryce (2007) argue that the more bidders that can be encouraged to participate, the more likely that extreme bids in excess of the list price will occur.

Knight (2002) uses Lazear's, (1986) theory of multiperiod pricing with uncertain demand to argue that the level of the initial list price affects the rate at which a seller learns about the buyers' distribution of offers. That is, setting a relatively low list price compared to the mean of the buyer offer distribution increases the flow of potential buyers, resulting in more bids and learning about the unknown properties of the bid distribution. This theory could be consistent with the observations of sales prices exceeding list prices, but it does not explain why this case would be observed only in hot markets.

2.2. An alternative model: exogenous demand shifts in the housing market

We first extend existing search models to include unexpected changes in the strength of the housing market. Assume that sellers set their list prices at time t_0 conditional on expectations of the path of house prices during the expected marketing time for the property. If the distribution of buyers' potential offers unexpectedly shifts toward higher prices, then the likely outcome is a shorter marketing period and higher offers. Thus, allowing for an exogenous demand shift yields the prediction that observation of list prices less than sales prices is more likely during periods when buyers' offers and sales prices increase more than expected. In particular, this hypothesis could be characterized by observations of multiple potential buyers engaging in a competitive bidding process.[4] The model predicts a negative coefficient of a measure of the unexpected rate of house price appreciation in a regression explaining list to sales price ratios.

A change in the housing market also could be characterized by an unexpectedly high arrival rate of offers for a property. In a static setting, sellers would account for high expected rates of offers when setting list price. But if the arrival rate unexpectedly increases, one could observe a shorter time on market and a higher sales price. Thus, this version of the demand shock model predicts that it is more likely that sales prices will exceed list prices during periods when the arrival rate of offers increases more than expected. The arrival rate of offers is difficult to observe, but the number of transactions is observable.

During the beginning of a market downturn prices may unexpectedly fall. Sellers would have previously set list prices based on higher expected prices and thus their list price would be high compared to the expected selling price. The greater the unexpected fall in house prices, the higher should be the ratio of list to sales prices (again, a negative coefficient is expected).

2.3. Alternative model: endogenous sales mechanism choice

The search model described above represents one among many possible strategies that could be adopted by home sellers. There are alternative strategies for selling homes, such as auctions (Lusht, 1996). The model described in this section considers the possibility that a seller switches strategies when the strength of the housing market changes. The basic conjecture is that during normal housing markets or downturns, sellers adopt the standard strategy, resulting in list prices exceeding sales prices. However, during a strong market, sellers switch to an auction-like model where list price is set relatively low and a high arrival rate of buyers is expected. In this case, it is more likely that the sales price will exceed list price.

Gan (2013) develops a model that allows home sellers to select between two search processes. In one, sellers search until an optimal number of bidders is achieved, while in the other sellers search during a specified amount of time. Gan characterizes the second mechanism as being an auction-like format, but it takes a discrete amount of time.[5] He shows that: (1) sufficiently risk averse sellers prefer the auction mechanism, (2) different sellers could select different mechanisms in the same housing market if they have different levels of risk aversion, even if they have the same holding cost, and (3) the hotter the market (a greater number of potential buyers per unit time), the more likely

[3] Our sample does not contain data about loan-to-value ratios and thus we cannot test this competing hypothesis.

[4] Examples can be instructive. During the beginning of a boom period in our sample (May, 2005), a dwelling was listed for £525,000. The eventual sales price was £560,000 after 11 bids were received from two bidders.

[5] Gan characterizes the model as a combination of standard search and auction mechanisms. Specifically he notes that it ''can be treated as a private valuation, no reservation price, first-price sealed-bid auction in which all remaining buyers send in their offers in sealed envelopes and the seller chooses the highest offered price.'' The seller selects the optimal time to accumulate bids. This is the essence of the alternative model that we are attempting to capture, where the list price conveys information about the minimum bid.

is a seller to choose the auction-like framework to sell their home.[6]

Two of these conclusions are relevant for our empirical observations. First, at any point in time we observe heterogeneity of whether sales prices are greater or less than list price. Perhaps this is a result of sellers selecting different sales mechanisms due to their heterogeneous levels of risk aversion. Second, Gan concludes that the hotter a housing market, the more houses will be sold through the auction-like mechanism. Assuming that an auction-like mechanism involves setting a low list price to encourage bidding, we argue that an extension of Gan's model would predict that sales price would be more likely to exceed list prices in hot markets. During strong markets where potential buyers are plentiful, some sellers change their strategy to one similar to a "best-offer-over" model.[7] In this case the list price is a floor rather than a ceiling.

The exogenous demand shock and the endogenous mechanism choice models can be distinguished by the frequency of occurrence of sales prices exceeding list prices during a sustained housing boom. While a boom in the market could be unexpected during its initial stage, household expectations of changes in house prices and volume of sales eventually will adjust, resulting in expectations that match the higher observed rate of price change and arrival rate of offers. The exogenous demand shock model predicts that sales prices are more likely to exceed list prices only during the beginning of a boom and the unexpected component of increases in house price and transaction volume is large. In contrast, the endogenous mechanism choice model predicts that sales prices will tend to exceed list prices throughout the housing boom as households switch to an auction-like mechanism.[8]

The two models' predictions about the time path of the ratio of list price to sales price (LP/SP) over a housing cycle are shown in Fig. 2.[9] The exogenous demand shock model argues that substantial departures from the standard search model's predictions only occur during periods of unexpected change in price or transactions volume. The model also predicts that LP/SP will vary to a relatively minor extent over the housing cycle due to changes in the expected arrival rate of potential buyers. Specifically, the model predicts that the list price to sales price ratio will be modestly higher during a stable boom market (characterized by a high arrival rate of offers) compared with a stable normal market and LP/SP will be modestly lower during a bust (Haurin et al., 2010).[10]

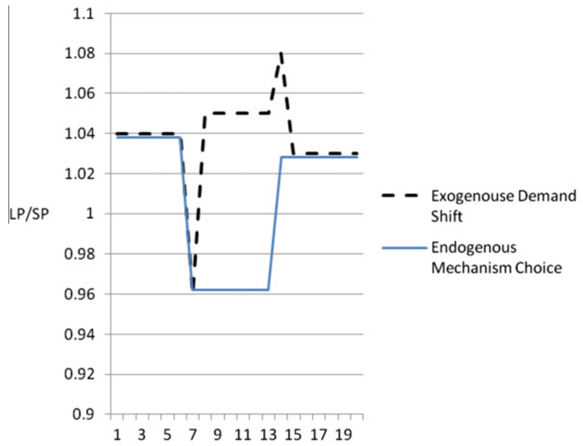

Fig. 2. Predicted ratio of list price to sales price—hypothetical example.

In contrast, the endogenous mechanism choice model argues that during a boom the ratio of list to sales prices will be relatively low. In other periods, the model is the same as the standard search model. It is sensible to combine the predictions of this model with those of the exogenous demand shock model. In this case, the two models differ in their predictions only during sustained boom periods.

Neither model predicts that LP/SP will rise substantially during a sustained housing bust. Should that occur the likely explanation is that sellers are engaging in a form of loss aversion.[11]

Next, we focus on the two models' predictions regarding the marketing time of properties (TOM). In the exogenous demand shift model TOM would fall during a positive shock and rise during a negative shock. When the new equilibrium is attained, TOM would be only modestly different than the initial stable period, consistent with the now stable arrival rate of buyers. In contrast, in the endogenous mechanism choice model, not only would TOM fall at the beginning of a housing boom but it would remain low throughout the boom, consistent with an auction-like process. During a bust, sellers would return to their normal search strategy. Thus, the key difference in predictions is what happens to TOM after the initial shock during a boom. If sellers exhibit a form of loss aversion, TOM would increase substantially during a bust.

3. Empirical models

In the empirical work, we use two alternative measures of the relationship between list and sales prices. One is the ratio of sales price to list price and the other is a dummy variable that indicates the list price is greater than or equal to the sales price. The control variables should include those factors that affect sales and list price, such as the characteristics of a dwelling (X), and factors that affect sell-

[6] Gan states that more (less) sellers will prefer the alternative strategy (fixed time/auction) when the market is hot (cold) or when holding cost is higher (lower).

[7] The best-offer-over model is used in parts of the U.K. and Australia. A list price is posted (representing a floor bid) and then potential buyers submit bids, generally above the list price.

[8] Another example from our sample is for a dwelling listed two years into the boom. Its list price was £575,000. After the first bid was received, 19 additional bids followed (5 bidders) over 24 days. The final sales price was £655,000.

[9] The data in the figure are illustrative, not from our sample.

[10] Intuitively, assuming sellers' holding cost is the same as in a normal period; a higher arrival rate of offers suggests that sellers should search the buyers' distribution of offers "more thoroughly" by receiving more offers. Their strategic response would be to modestly increase the list price compared to the expected sales price, as displayed in Fig. 2.

[11] Nominal loss aversion in the context of home sellers is discussed by Genesove and Mayer (2001) and Engelhardt (2003).

ers' pricing strategy such as the atypicality of a property (A).[12] Our focal tests are measuring the responses to changes in the expected rate of house price change (P_t^e) and rate of transactions (T_t^e) over the housing cycle as well as the responses to the corresponding unexpected components (P_t^u and T_t^u).

Let j represent the j-th property in the data set and define Y_{jk} as one of the $k = 2$ measures of whether sales price (SP) is greater than list price (LP).

$$Y_{j1} = LP_j/SP_j \tag{1}$$

$$Y_{j2} = 1 \; if \; LP_j \geqslant SP_j \text{ and } Y_{j2} = 0 \; if \; LP_j < SP_j \tag{2}$$

The regressions have the forms:

$$Y_j = f(A_j, X_j, P_j^e, P_j^u)$$

$$Y_j = f(A_j, X_j, T_j^e, T_j^u) \tag{3}$$

and are estimated using OLS and probit models. The time on market equations are estimated with a Cox proportional hazards model.

4. Data

The data for this study are based upon sales of existing dwellings in the Belfast (U.K.) metropolitan area.[13] The analysis is based upon sales over 32 consecutive quarters from the first quarter of 2002 through the final quarter of 2009. After the elimination of observations with missing data and the removal of outliers (list prices more than four standard deviations from the mean) the sample contains 4781 observations. The time path of the observed rate of increase in the transaction price of houses is shown in Fig. 3. The highest quarter to quarter rate of (average) house price increase occurred in 2006:3 (21.8%) and largest reduction in prices occurred during 2008:4 (−14.8%).

Dwelling characteristics include a set of indicators about the type of dwelling, age of dwelling, square footage, number of bedrooms, and whether the property has a garage, central heating, reception room, or is in need of modernization (see Appendix 2 for variable definitions). The means of the variables are presented in Table 1, separated into the set of dwellings that sold for more than list price, and the set that sold for list price or less.

The mean list price of both sets of observations are similar (£122,200 and £118,600), but the sales price of those dwellings that sold for more than list price is greater (£127,100 versus £116,900). In the full sample, the average square footage is 1042, the number of bedrooms is 2.94,

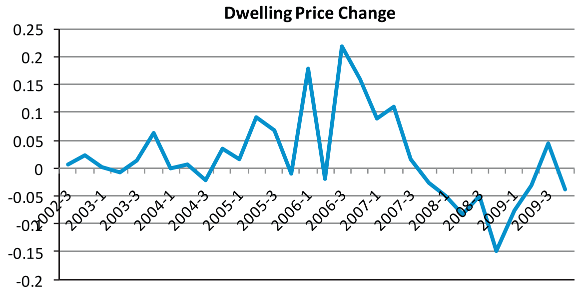

Fig. 3. Rate of house price change.

and most houses were semi-detached followed by terraced properties. The measure of atypicality has a mean that is about 46 percent of sales price.

The unexpected component of the rate of house price increase (UNXPRATE) must be estimated. We use four methods to estimate the expected rate of house price increase, and in all cases the unexpected rate equals the difference between the observed and expected rate. The methods alternatively assume the expected rate in period t_0 is:

- XPRATE_{t-1}
- $(\text{XPRATE}_{t-1} + \text{XPRATE}_{t-2})/2$
- $(\text{XPRATE}_{t-1} + \text{XPRATE}_{t-2} + \text{XPRATE}_{t-3})/3$
- $(\text{XPRATE}_{t-1} + \text{XPRATE}_{t-2} + \text{XPRATE}_{t-3} + \text{XPRATE}_{t-4})/4$

These alternatives allow for households' price expectations to be based on a short period (one quarter lag) or longer periods up to a four quarter moving average.[14] The regression results differed relatively little among these specifications; we present those that used the three quarter moving average to determine the expected rate of price change.[15] The expected and unexpected rate of transactions is calculated similarly.

The endogenous mechanism choice model predicts that LP/SP will be lower in a very strong housing market compared to a normal market. We test this hypothesis by separating the sample into three periods: normal (2002:1–2005:1), boom (2005:2–2007:2), and bust (2007:3–2009:4).[16] We create three variables, each equaling the expected rate of house price increase during a particular stage of the housing cycle, but otherwise its value equals zero. These variables are named NORM-XPRATE, BOOM-XPRATE, AND BUST-XPRATE. Note that these

[12] See Haurin et al. (2010) for a model and empirical verification that the atypicality of a dwelling affects the ratio of list price to sales price. Their model predicts that the ratio of list price to expected sales price will be larger the greater is the variance of the distribution of potential buyers' offers. The proxy for the variance is the atypicality of properties compared to the local market. Atypicality is measured by computing the aggregate value of the deviations of a property's characteristics from the mean values in the market, using characteristics' implicit prices (derived from a hedonic price estimation) as the value weights.

[13] Additional detail regarding the data set provider is in McGreal et al. (2009). Institutional detail regarding list prices in the U.K. context is provided in Appendix 1.

[14] We implicitly assume that all households in the Belfast area have the same expected rates of house price increase. All formulations required our using the first and second quarter's data as the base years in order to compute the rate of house price increase in 2002:2. Thus, transactions in these quarters are excluded from the regressions. The value of XPRATE1 in 2002:3 can be calculated directly. To conserve observations, we assume that the transactions in 2002:3 have a value of XPRATE2 through XPRATE4 equal to XPRATE1. In 2002:4, we assume that XPRATE 3 and XPRATE4 equal XPRATE2.

[15] Given that the measure of atypicality, XPRATE, and UNXPRATE are calculated variables, we report bootstrapped standard errors.

[16] Identification of the periods is based on our review of the rate of change in house prices.

Table 1
Descriptive statistics.

	Mean All	Std. Dev. All	Mean LP>=SP	Std. Dev. LP>=SP	Mean LP < SP	Std. Dev. LP < SP
List price	12.03	6.45	12.22	7.02	11.86	5.84
Sales price	12.21	6.58	11.69	6.65	12.71	6.48
LP/SP	0.99	0.09	1.04		0.94	
TOM	98.07	142.40	132.30	159.30	64.59	114.20
Terrace	0.37	0.48	0.36	0.48	0.38	0.48
SD house	0.39	0.49	0.37	0.48	0.42	0.49
D house	0.09	0.29	0.11	0.32	0.07	0.26
SD bung	0.03	0.18	0.04	0.19	0.03	0.18
D bung	0.04	0.20	0.05	0.22	0.04	0.19
APARTMENT	0.07	0.25	0.07	0.26	0.06	0.24
BUILT PRE 19	0.04	0.20	0.04	0.20	0.04	0.19
BUILT 20–39	0.12	0.32	0.12	0.32	0.11	0.32
BUILT 40–59	0.16	0.36	0.16	0.37	0.15	0.36
BUILT 60–80	0.36	0.48	0.34	0.47	0.38	0.48
BUILT POST 80	0.33	0.47	0.34	0.47	0.32	0.47
SQFT	1.04	0.33	1.05	0.35	1.03	0.31
BED	2.94	0.69	2.94	0.75	2.93	0.62
REC	1.20	0.44	1.22	0.47	1.18	0.41
GARAGE	0.31	0.46	0.31	0.46	0.30	0.46
Heat	0.98	0.12	0.98	0.14	0.99	0.10
Modernization	0.04	0.19	0.04	0.20	0.04	0.18
Atypicality	5.57	2.58	5.80	2.81	5.34	2.32
Rate	0.03	0.07	0.01	0.06	0.05	0.07
Trans	205.40	87.52	196.60	98.73	214.00	75.26

Notes: $N = 4781$. List price, Sales price, and Atypicality are measured in tens of thousands of pounds. Square feet are measured in thousands.

variables interact the time period with the expected rate of house price change, thus allowing unexpected price changes to have an independent effect on LP/SP. The variables NORM-XTRANS, BOOM-XTRANS, AND BUST-XTRANS are calculated similarly, replacing the expected house price change with the expected number of transactions (XTRANS).

5. Results

5.1. When does list price exceed sales price?

The exogenous demand shock model predicts that increases (decreases) in unexpected house price changes (UNXPRATE) will lower (raise) the probability that list price exceeds sales price, and thus a negative regression coefficient is expected.

The endogenous mechanism model predicts that during a boom XPRATE will have a larger negative effect on the ratio of list to sales price compared with a period with a stable housing market. Thus, the coefficient of BOOM-XPRATE should be more negative than that of NORM-XPRATE. During a bust, seller behavior involving some form of nominal loss aversion will result in list price being relatively high compared with sales price. Thus, with a low XPRATE, LP/SP will be relatively high and a negative coefficient is predicted for BUST-XPRATE. According to the standard search model, during a period with relatively stable house prices, changes in the expected rate of house price increase should have only modest effects on LP/SP. However, if our measure of XPRATE is incorrect and from the seller's perspective some part of the price change is unexpected, then a negative coefficient could result for NORM-XPRATE.

The results for the unexpected and expected price variables are displayed in Table 2. The first data column is an OLS regression where LP/SP is the dependent variable. Also reported is a probit model where the dependent variable is defined in Eq. (2). As predicted by the exogenous demand shock model, the coefficient of UNXPRATE is negative and significant. Thus, it is more likely that sales prices will exceed list prices when there is a positive shock to house prices. This is a sensible result because list prices are set based on price expectations at the time of listing the property. Similar results are found for the other methods of calculating price expectations.

The competing theoretical models can be distinguished by the response to expected house price changes. The endogenous mechanism choice model predicts the coefficient of BOOM-XPRATE will be negative and larger in absolute value than NORM-XPRATE, this prediction is confirmed by the results. The difference in coefficients of these two variables is significant given each is estimated with a small standard error.

Assume that at the mean expected house price appreciation (0.03) the ratio of list price to sales price is 1.03. If BOOM-XPRATE rises by one standard deviation to 0.09 then the ratio of list price to sales price changes by −0.05 and thus would equal 0.98 (sale prices is a two percentage point premium above list price). If UNXPRATE rises by the same amount, then the ratio of list to sales price changes by only −0.02. The results suggest that the response to unexpected changes in price is smaller than to expected price changes during boom periods.

The coefficient of BUST-XPRATE is the most negative of the three expected price change variables. The likely explanation for this result is that during a market downturn, households continue to set list prices at levels comparable to the recent past even though prices are falling. For example, if expected prices fall by 0.06 during a down market,

Table 2
Regression result for list price relative to sales price.

	OLS: LP/SP		Probit: LP>=SP		OLS: LP/SP		Probit: LP>=SP	
	Coeff.	Std. error	Marginal effects	Std. error	Coeff.	Std. error	Marginal effects	Std. error
UNXPRATE	−0.301**	0.020	−1.549**	0.150				
NORM-XPRATE	−0.595**	0.063	−2.021**	0.441				
BOOM-XPRATE	−0.904**	0.029	−5.753**	0.250				
BUST-XPRATE	−1.174**	0.042	−6.056**	0.359				
UNXTRANS					−0.016**	0.002	−0.092**	0.012
NORM-XTRANS					−0.045**	0.009	−0.155**	0.056
BOOM-XTRANS					−0.137**	0.007	−0.748**	0.046
BUST-XTRANS					0.143**	0.015	−0.506**	0.088
SDHOUSE	0.004	0.003	−0.012	0.022	0.005	0.003	−0.002	0.021
DHOUSE	−0.001	0.005	0.026	0.040	0.003	0.006	0.052	0.038
SDBUNG	−0.005	0.007	−0.004	0.046	0.000	0.007	0.031	0.043
DBUNG	0.007	0.005	0.025	0.044	0.007	0.007	0.034	0.042
APARTMENT	0.002	0.006	−0.017	0.040	0.005	0.006	0.001	0.038
BUILT 20–39	0.005	0.008	−0.047	0.045	0.003	0.007	−0.049	0.044
BUILT 40–59	−0.005	0.007	−0.027	0.045	−0.007	0.007	−0.039	0.044
BUILT 60–80	−0.002	0.007	−0.068	0.043	−0.007	0.007	−0.064	0.042
BUILT POST 80	0.003	0.007	0.013	0.044	−0.002	0.007	−0.027	0.042
SQFT	−0.014*	0.006	−0.153**	0.050	−0.011	0.007	−0.105**	0.050
BED	0.004	0.002	0.009	0.016	0.004	0.003	0.001	0.016
REC	−0.008*	0.003	−0.048*	0.021	−0.003	0.003	−0.008	0.020
Garage	−0.002	0.003	0.009	0.020	−0.005	0.003	−0.004	0.019
Heat	−0.001	0.014	−0.047	0.071	−0.004	0.012	−0.079	0.070
Modernization	−0.003	0.008	−0.099*	0.044	0.004	0.008	−0.037	0.045
Atypicality	0.003*	0.001	0.032**	0.006	0.002	0.001	0.023**	0.006
CONSTANT	1.015**	0.014	0.534*	0.238	1.005**	0.015	0.437	0.232
Sample size	4781		4781		4781		4781	
R^2 and Pseudo R^2	0.29		0.17					

Notes: For the probit a pseudo R^2 is reported.
* Significant at 5%.
** Significant at 1%.

the results indicate LP/SP will rise by 0.07, or (using the above example), from 1.03 to 1.10. Perhaps sellers' price expectations have not adjusted downwards or they set a relatively high list price and are waiting for demand to return to normal levels. In either case, their behavior is consistent with loss aversion.[17]

House characteristics are relatively unimportant in this regression. The exceptions are that dwellings with more square footage or a reception room tend to have a relatively low list to sales price ratio. Another significant factor is that the greater is the atypicality of a dwelling, the greater is the ratio of list to sales price, as predicted by search theory.

An additional specification test was to include quadratic terms of the four price appreciation variables.[18] The quadratic term for UNXPRATE was not significant. Those for BOOM-XPRATE, NORM-XPRATE, and BUST-XPRATE were significant and positive, revealing a diminishing marginal effect of expected house price expectations on LP/SP. For example, the predicted changes in LP/SP for XPRATE values of 0.01, 0.05 and 0.10 are shown in Table 3.

The results for the transaction rate variable are displayed in the right half of Table 2. The unexpected rate of transactions has a negative coefficient, as expected. Thus, if the rate of transactions jumps, LP/SP falls. Changes in the expected rate of transactions have the expected signs and relative magnitudes. The coefficient of NORM-XTRANS is small and negative, while that of BOOM-XTRANS is larger in absolute value (similar to the results for the BOOM-XPRATE variable). During a bust, the transaction rate falls but remains positive and thus the large positive coefficient indicates that LP/SP is quite large. This result is consistent with sellers exhibiting loss aversion.

An additional specification was to include both the expected and unexpected rate variables for price and transactions in the regression.[19] We find that both measures of the demand shock (unexpected price and transaction rates) remain significant and negative, as expected. The XPRATE results remain the same in relative magnitude, but the NORM-XPRATE coefficient becomes insignificant. The XTRANS variables retain their signs and remain significant, with the one anomaly being that the coefficient of NORM-XTRANS is larger in absolute value that that of BOOM-XTRANS.

Overall, we draw the following conclusions. We find support for an extended standard search model that allows unexpected demand shocks to affect the ratio of list to sales price. Further, the results support the predictions of

[17] We expected the coefficient of NORM-XPRATE to be zero, however it is negative and significant. Although we have used multiple methods to separate house price changes into expected and unexpected, it is still possible that some of the unexpected shocks are included in our measure of expected price appreciation. In a specification described below that includes quadratic terms, we find very little response of LP/SP to changes in NORM-XPRATE.

[18] Results are available from the authors.

[19] Results are available from the authors.

Table 3
Responses of LP/SP to changes in expected house price appreciation.

	Change = 0.01	Change = 0.05	Change = 0.10
NORM-XPRATE	−0.01	−0.04	0.00
BOOM-XPRATE	−0.01	−0.05	−0.09
	Change = −0.01	Change = −0.05	Change = −0.10
BUST-XPRATE	0.01	0.05	0.08

the model where households switch from a standard search model during normal or depressed housing markets to an auction-like model during booms. We also find that the LP/SP ratio is relatively high during a strong market downturn; this is consistent with sellers exhibiting a form of loss aversion.

5.2. Time on market

Next, we turn to attempting to distinguish the competing models using data on the marketing time of properties (TOM).[20] In the exogenous demand shock model TOM should fall, perhaps substantially, when the housing market unexpectedly becomes stronger. Then, when the new equilibrium is attained, TOM would be only modestly lower than the initial stable period, consistent with the higher (now stable) arrival rate of buyers. When the market unexpectedly weakens, TOM should rise, but again return to a level modestly above the initial stable period's value. In contrast, in the endogenous mechanism choice model, not only would TOM fall at the beginning of a housing boom but it would remain low throughout the boom, consistent with sellers adopting an auction-like process. During a bust, sellers would return to their normal search strategy, unless loss aversion keeps TOM relatively high. Thus, the key difference in the two models' predictions is what happens to TOM after the initial shock in a booming housing market.

During the sample period, the correlation of TOM with the series of unexpected price changes is only 0.10, but that of TOM with the expected changes in house prices is −0.88. During the stable housing market (2002:1–2005:2), the average TOM was 102 days, during the boom (2005:3–2007:3) it fell to 50 days, and post boom it rose to 179 days. Further, during the boom there was little trend in TOM, suggesting a change in sellers' strategies. To explain this period of stable but short marketing time during a boom, the exogenous demand shock model would have to argue that sellers were continuously surprised by the strength of the housing market and they failed to adjust their sales strategy. Again, neither model predicts a persistently high TOM during the bust, but this observation is consistent with a loss aversion model.

We use a proportional hazards model to relate TOM (measured in days from listing to sale) to the set of household characteristics and the price appreciation variables. Table 4 reports the hazard ratios; that is, the responses of TOM to a one unit change in the explanatory variable.

The hazard ratio of UNXPRATE is greater than 1.0 and is significant. Thus, as the demand shock model predicts,

Table 4
Proportional hazards model of time on market.

	Marginal effects	*z* Score	Marginal effects	*z* Score
UNXPRATE	4.62**	5.73		
NORM-XPRATE	3.65	1.59		
BOOM-XPRATE	670.62**	17,56		
BUST-XPRATE	2154.49**	14.82		
UNXTRANS			1.13**	4.65
NORM-XTRANS			1.35**	2.58
BOOM-XTRANS			2.62**	12.02
BUST-XTRANS			0.45**	5.40
SDHOUSE	1.01	0.36	0.99	0.27
DHOUSE	0.77**	3.36	0.77**	3.34
SDBUNG	1.09	1.02	1.05	0.56
DBUNG	0.86	1.80	0.87	1.71
Apartment	0.86	1.94	0.87	1.84
Built 20–39	1.10	1.08	1.10	1.15
Built 40–59	1.19*	2.03	1.18*	1.98
Built 60–80	1.43**	4.41	1.40**	4.17
Built POST 80	1.33**	3.46	1.38**	3.91
SQFT	1.00	1.70	1.00	1.89
Bed	1.06	1.87	1.06	1.72
Rec	1.12	2.62	1.10**	2.23
Garage	1.01	0.16	1.03	0.74
Heat	1.28	1.75	1.28	1.78
Modernization	1.05	0.52	1.02	0.18
Atypicality	0.99	1.19	1.00	1.06
Sample size	4781		4781	

* Significant at 5%.
** Significant at 1%.

unexpected (short duration) price shocks change marketing time. A positive demand shock that results in rising prices raises the hazard ratio of a sale and thus reduces the market time of dwellings.

We find that the hazard rates for the three expected price appreciation variables are all above 1.0, but that for NORM-RATE is not significant. If the expected rate of appreciation rises during a boom or falls during a bust, then there is a significant and substantial response of marketing time. For example, an increase in BOOM-XPRATE by 0.01 increases the probability of a sale by a factor of 6.7. During a downturn, a decrease in BUST-XPRATE by 0.01 decreases the probability of a sale by a factor of 21.5.

Among the dwellings characteristics, a detached house tends to have a shorter marketing time, as do newer dwellings (built after 1940). Homes with more reception rooms tend to take less time to sell.

The effects of changes in the unexpected and expected rate of transactions also are displayed in Table 4. An increase in the unexpected rate raises the probability of a sale, as predicted by the demand shock model. Increases in XTRANS during a boom also raise the hazard rate and thus decrease the time on market, as predicted by the endogenous mechanism choice model. Decreases in XTRANS during a bust also increase the hazard rate, this result consistent with sellers having an aversion to realizing a loss when selling their home.

6. Conclusions

At times the sales price of a dwelling exceeds the list price. This observation contradicts one of the assumptions

[20] The relationship between list price and time on market is studied by McGreal et al. (2009)

of the standard search model, which assumes the list price form an upper bound to offers. We first extend the standard model to allow for unexpected shocks to demand, predicting that the shocks will affect both the ratio of list to sales price and the marketing time of dwellings. Our empirical model provides support for these hypotheses, but it does not explain why sales prices continue to exceed list prices after the initial demand shock. Our data indicate that sales prices are high relative to list prices throughout housing booms.

We next offered a conjecture that during a boom period in the housing market, sellers change their selling strategy, this consistent with the model developed by Gan (2013). Rather than follow the typical mechanism whereby a seller sets a list price that is a ceiling on the sales price, we suggest that the seller changes the strategy to be similar to a "best offer over" process where the list price becomes a floor on sales price. Implicitly, the mechanism changes to become a form of auction, played out over multiple days with multiple bidders. We find strong empirical support for this hypothesis. Specifically, there is clear empirical evidence that the ratio of list to sales prices remains low long into a boom period; sufficiently long such that expectations of house price appreciation and the arrival rate of potential buyers should match actual appreciation and arrivals. In other words, sellers continue to set list prices relatively low even when there are no price shocks. This behavior, in the context of our endogenous mechanism choice model, suggests that sellers switch their strategy during a boom to an auction-like mechanism. We also find that the list to sales price ratio is unusually high during a sustained housing bust. The most likely explanation is some form of loss aversion by sellers.

These results lead to a number of other questions about the real estate market and the mechanisms adopted to sell properties. Are there other cases in the U.S., U.K., or other countries that have a similar residential sales process where sales prices systematically exceed list prices? If yes, when and why is this observed? Why are auctions used in some markets and not others? How do differences in sellers' level of risk aversion affect selling strategies?

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Appendix 1. Institutional details

In the U.K. (noting there is a different system in Scotland) list prices are typically set within a market valuation framework as determined by the selling agent. The concept of market value follows the global standard of the International Valuation Standards Committee and codified in the U.K. by the RICS Appraisal and Valuation Standard or Red Book Practice Statement 3.2 (RICS, 2008). U.K. professional valuation and estate agency bodies consider the market value concept as the objective measure of the most probable amount that a purchaser and seller, under defined conditions, will transact the property.

More specifically, the market value concept contains a number of elements each of which has its own definition relating to the estimated amount for which a property would sell on the date of valuation, given a willing purchaser and seller, an arm's length transaction, proper marketing, and each party acting knowledgeably, prudently, and without duress (IVSC, 2007). The conceptual framework recognizes the volatility of the market cycle by specifying that value is time specific as of a given date. The list price reflects the actual condition of the market allowing for proper marketing of the property. The length of exposure will vary with market conditions and is normally considered to be sufficient to allow the property to be brought to the attention of an adequate number of potential purchasers. Consequently it is assumed that both buyers and sellers will act in accordance with best market information as in any other market with changing prices.

However, there may be circumstances where the seller asks the agent to list higher than market value; for example, where the seller believes that special features of the property merit a higher price than the market value. Alternatively, a lower list price than the valuation may be set as a tactic to start bidding on the property.

There is evidence from other studies of the U.K. property market that show there can be substantial variation of sale price from the valuation. According to Crosby (2000), in the U.K., 75% of sale prices fall within a bracket of 10–15% of the valuation. Thus sales prices can oscillate above or below the list price (valuation) depending on market conditions. In this case, the list price does not act as an upper bound on offers. Indeed, Crosby (2000) concluded that valuers undervalue in bull and overvalue in bear markets. Also, the anchoring of valuation on past transaction information (Gallimore, 1996) is likely to result in lower list prices in the U.K.

Appendix 2. Definition of variables

LP/SP	ratio of list to sales prices
TOM	time on market
XPRATE	expected rate of house price change
NORM-XPRATE	XPRATE when the housing market is stable
BOOM-XPRATE	XPRATE when the housing market is booming
BUST-XPRATE	XPRATE when the housing market is declining
UNXPRATE	unexpected shock to house prices
XTRANS	expected number of transactions in the housing market
UNXTRANS	unexpected shock to the number of transactions in the housing market

(*continued on next page*)

TERR	terraced house (omitted variable)
SDHOUSE	semi-detached house
DHOUSE	detached house
SDBUNG	semi-detached bungalow
DBUNG	detached bungalow
APT	apartment
BUILT PRE 19	property constructed pre1919 (omitted variable)
BUILT 20-39	property constructed between 1919 and 1939
BUILT 40-59	property constructed between 1940 and 1959
BUILT 60-80	property constructed between 1960 and 1980
BUILT POST 80	property constructed post 1980
SQFT	floor area of property
BED	number of bedrooms
REC	number of reception rooms
GARAGE	whether property has a garage
HEAT	whether property has central heating
MODERNIZATION	whether property is in need of modernization
ATYPICALITY	a monetary measure of how different a dwelling is from other properties in the locality

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