

When Price Stops Clearing: Valuation Disagreement and Housing Illiquidity

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Abstract

How does difficulty valuing a home affect its sale price and time on market? Using Beijing resale records, I measure valuation difficulty by asking-price deviations from a benchmark for nearby homes with similar observed characteristics. Among recorded sales, moving from the smallest to the largest deviation within a community and month is associated with about five percent longer selling time. More users save these listings online, yet the homes receive fewer in-person viewings. A search model provides an interpretation: less reliable information reduces risk-averse buyers' willingness to pay, while greater disagreement encourages sellers to wait for a high offer. The model also shows when disagreement weakens the effect of a small price cut on agreement. The paper connects valuation risk to the selling process: disagreement can lengthen the search for a buyer rather than simply raise the sale price, and more online attention need not lead to an easier sale.

Keywords: housing illiquidity; valuation uncertainty; disagreement; search and matching; asking prices; buyer attention.

JEL codes: G12, G14, R21, R31.

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1 Introduction

When a housing market turns, transaction volume can fall sharply even as prices change relatively little. Seller equity constraints and reference prices help explain why owners wait rather than accept a lower price (Stein, 1995; Genesove and Mayer, 2001; Andersen et al., 2022). Reaching a sale also requires buyers and sellers to assess what a particular home is worth. I ask how difficulty valuing a home affects its sale price and the time it takes to sell.

The question highlights a tension in the standard disagreement argument. When an asset cannot be sold short, pessimists can remain outside the market and an optimistic buyer can set its price (Miller, 1977). Housing is a natural setting for this logic. Homes differ in their characteristics, are difficult to hedge, and are effectively impossible to sell short. But a seller cannot choose from all potential buyers at once. The buyer who values a particular apartment most must first find it, inspect it, and agree to buy. A potential buyer's high valuation does not provide the seller with an offer today.

A home's asking price may reflect features that buyers cannot assess from an online listing, such as the quality of renovation, interior condition, or noise. Such features can justify either a premium or a discount relative to otherwise similar homes. An unusual asking price can therefore signal a valuation question: what accounts for the difference, and can a buyer assess it before visiting? This is the sense in which I study valuation difficulty. A price difference need not be a mistake; understanding what justifies it may require more information than the listing provides.

I study this question using 586,312 Beijing resale records, mostly associated with the 2015–2021 period. Apartments are organized into residential communities, or *xiaoqu*, whose units share location, neighborhood amenities, and property management. I use housing attributes and community and calendar effects to construct a benchmark for asking prices. The records also report time on market, the number of users who save a listing online, and in-person viewings for a matched subset. These activities distinguish inexpensive online monitoring from the more costly decision to visit a home.

The uncertainty measure ranks homes by their squared asking-price deviations within each community and month. Higher ranks identify homes whose recorded asking prices are further from the benchmark. Using ranks reduces the influence of extreme deviations and puts the measure on a common scale across local markets. A second measure captures how unusual a home's physical characteristics are among nearby recorded transactions, without using prices. Both measures can reflect features that are difficult to assess online, but features missing from the data need not be unknown to buyers. Asking-price deviations also reflect seller choices, and physical rarity may narrow the set of suitable buyers. I therefore interpret the estimates as associations with valuation difficulty, rather than as identified effects of disagreement.

Two findings describe how these homes sell. First, moving from the bottom to the top of the uncertainty rank within a community and month is associated with approximately five percent longer time on market. The estimate is similar after removing the largest one percent of residual squares and when restricting the sample to listings from periods less affected by retrospectively assigned posting dates. Homes with unusual physical characteristics also take longer to sell, including when the regression controls for the asking-price measure.

Second, homes with larger asking-price deviations attract more online saves but fewer in-person viewings. Both activities are measured for the same 158,089 completed transactions. The pattern remains after accounting for time on market: moving from the bottom to the top of the rank is associated with 1.5 percent more online saves and 4.4 percent fewer viewings. Online attention and the willingness to spend time inspecting a home can move in opposite directions. These are differences in total activity across homes; the records do not link an individual user's decision to save a listing to a later visit.

The pricing evidence is less uniform. In the sample less affected by retrospectively assigned posting dates, sale prices are about 0.74 percent lower at the top of the rank than at the bottom. This discount is sensitive to extreme deviations and to whether unusual asking prices lie above or below the benchmark. Asking-to-sale gaps also deviate further from their benchmark, but this comparison shares the asking price with the uncertainty measure and does not by itself establish greater price risk. The association with the number of price revisions is no longer statistically significant after controlling for time on market. The strongest findings concern the time needed to sell and the contrast between online attention and visits, neither of which is imposed by the construction of the asking-price measure.

I interpret these facts using a search model in which buyers arrive one at a time. When comparable prices provide less reliable information, buyers face more uncertainty about value and rely more on their own assessments. Risk aversion lowers their average willingness to pay, while differences in assessments widen the range of valuations. The seller chooses the minimum offer to accept, trading off an immediate sale against the value of waiting. Even if the average buyer valuation stays unchanged, greater dispersion can make waiting attractive enough to delay the sale. This result holds under the model's stated conditions even when the seller adjusts the minimum acceptable offer optimally. Allowing buyers to decide whether to visit also distinguishes online interest from in-person activity. If fewer potential buyers visit but those who do are more likely to buy, fewer total viewings can coexist with a longer wait for a sale.

The model also explains when disagreement weakens the response to a small price cut. A reduction in the seller's minimum acceptable price makes agreement possible with buyers whose valuations lie just below that price. Near the center of the valuation distribution, greater dispersion places fewer buyers in this range. The same reduction can then produce a smaller increase in the

chance of agreement, holding other search conditions fixed. This is a local result about the seller's acceptance decision, rather than a claim that price reductions generally fail.

Section 5 examines the corresponding relationship between relative asking prices and recorded sale timing in markets with more and less dispersed comparable prices. The archive covers completed transactions, not a verified inventory of sold and unsold listings, and the timing indicator depends on the precision of recorded dates. This comparison is descriptive; it does not identify the response to an actual price cut. The model supplies an economic interpretation of the empirical patterns, while the data leave room for unobserved quality and seller learning.

Related literature. The paper connects valuation risk to the process of selling an asset. In the literature on idiosyncratic housing risk, [Peng and Thibodeau \(2017\)](#) and [Giacoletti \(2021\)](#) document risk in house prices, while [Sagi \(2021\)](#) explains the role of transaction-level risk and selection in observed real estate returns. [Amaral \(2024\)](#) links housing-price uncertainty to discounts and returns and is the closest measurement comparison. I examine how unusual asking prices relate to waiting and buyer activity before a recorded sale. The contrast between online saves and in-person viewings adds a distinction that a sale price or asking-to-sale discount alone cannot reveal.

The housing-search literature studies the matching of heterogeneous homes and buyers. [Haurin \(1988\)](#) connects atypicality to marketing duration, and [Wheaton \(1990\)](#), [Krainer \(2001\)](#), and [Head et al. \(2014\)](#) model the joint determination of prices and housing liquidity. [Genesove and Han \(2012\)](#) and [Han and Strange \(2015\)](#) emphasize search, bargaining, and brokerage; [Piazzesi et al. \(2020\)](#) studies segmented search, and [Badarinza et al. \(2024\)](#) measures stages of matching. My contribution is to relate valuation difficulty to both the time needed to sell and buyers' participation at different stages of search, and to interpret these patterns through buyer valuation risk and seller waiting.

Within this literature, [Guren \(2018\)](#) supplies the closest price-setting comparison. His analysis connects the shape of the relationship between relative asking prices and sale probabilities to strategic complementarity and house-price momentum. I ask how valuation dispersion changes how strongly the chance of agreement responds to a small price change. The distinction is between where a seller sets the asking price and how differently buyers assess the home's value. The empirical comparison here is descriptive and does not reproduce his causal demand estimate or establish a momentum mechanism.

Finally, the paper draws on models of disagreement when trading is restricted ([Miller, 1977](#); [Hong and Stein, 2007](#); [Scheinkman and Xiong, 2003](#)). Counterparty search makes the timing of trade central in decentralized markets ([Duffie et al., 2005](#)). I combine buyer valuation risk and disagreement with the seller's choice of which offers to accept. This links the optimistic-buyer argument to the time needed to find that buyer and complements explanations based on seller equity

constraints, reference dependence, and learning (Stein, 1995; Genesove and Mayer, 2001; Andersen et al., 2022; Anenberg, 2016).

The paper proceeds as follows. Section 2 describes the setting and measurement. Section 3 presents the joint empirical patterns. Section 4 develops the model, and Section 5 examines its price-sensitivity implication. Section 6 discusses alternative explanations and the interpretation of the evidence. Section 7 concludes. The integrated appendix contains model derivations and measurement details.

2 Setting, data, and measurement

2.1 The housing market and the selling process

Beijing’s resale market consists largely of apartments in residential communities, or *xiaoqu*. A community shares a location, local amenities, property management, and a common identity as a residential development. These features make communities useful local markets for comparing homes. Within a community, however, apartments differ in layout, floor, orientation, renovation, and other features that can make an otherwise similar home difficult to value.

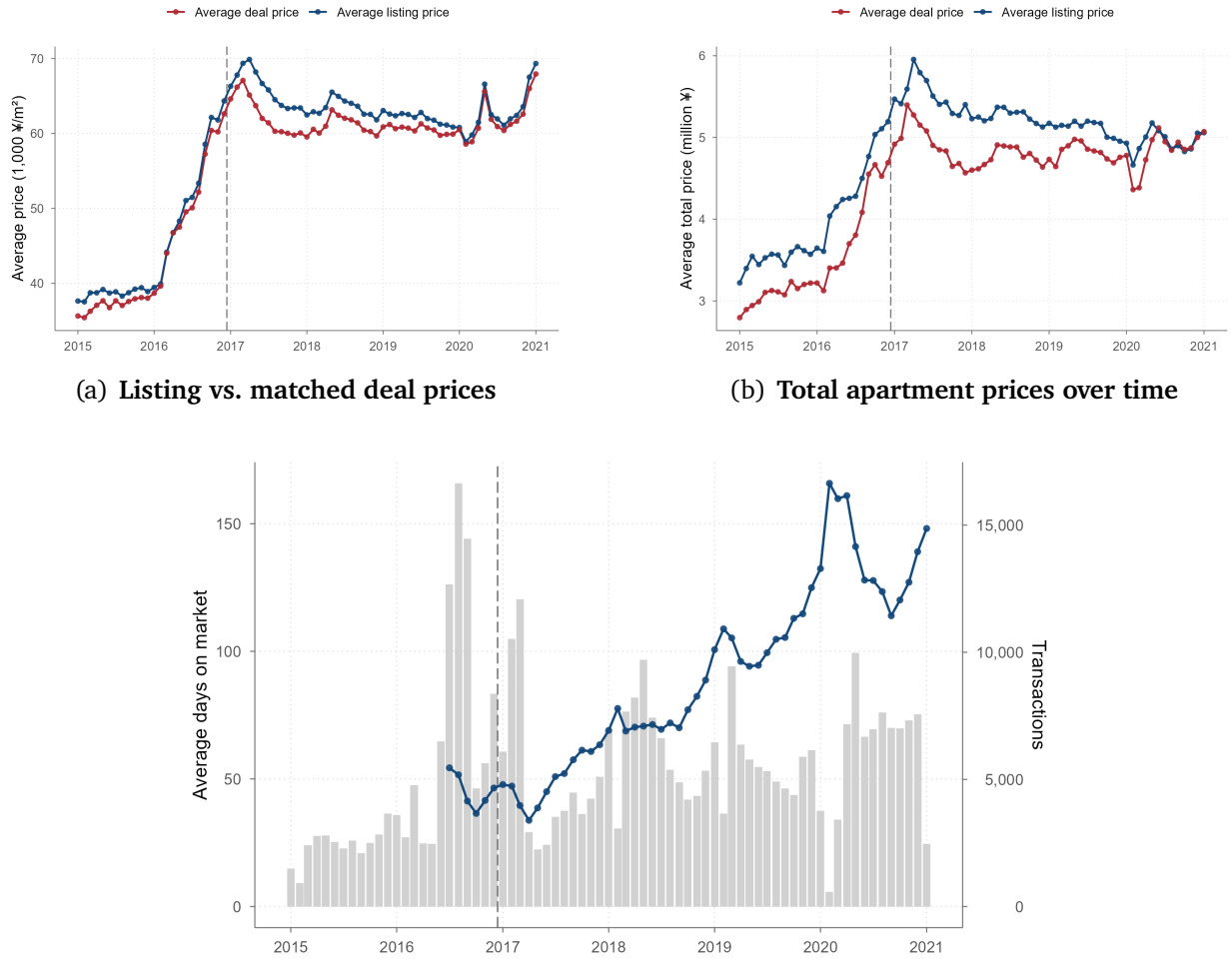
Homes sell through a sequence of search and negotiation. Sellers post asking prices; buyers browse advertisements, save listings, and arrange in-person viewings; and the parties negotiate a sale price. Each stage reveals a different aspect of demand. Browsing indicates initial interest, saving a listing allows a buyer to monitor it, and an in-person viewing requires a more substantial commitment. Comparing these activities with prices and time on market helps describe where the selling process slows down.

Figure 1 places the analysis in its market setting. Recorded resale transactions in the six months after the March 2017 tightening were 62 percent lower than in the preceding six months. Recorded prices rise strongly before the 2017 peak and subsequently adjust more gradually than transaction counts, while recorded time on market rises later in the sample. These movements motivate studying the selling process alongside prices: the price of a completed transaction need not reveal the difficulty of reaching agreement.

2.2 Data and sample

The Beijing archive contains 586,312 housing records across 16 districts, with observations extending to January 2021. Approximately 92 percent of reported posting dates fall from January 2015 onward. The data combine recorded asking and sale prices, housing attributes, posting and transaction dates, and measures of buyer engagement. The median apartment has an asking price

Figure 1: Prices, recorded transactions, and time on market



Notes: The top panels show average nominal recorded asking and sale prices per square meter and per apartment, grouped by reported posting date. The bottom panel shows transaction counts and mean time on market by sale month. The duration series begins in July 2016 because earlier posting dates may be assigned retrospectively. The vertical line marks December 2016, distinct from the March 2017 tightening. These series summarize the recorded sample and dates; they are not constant-quality market indices. Coverage, transaction composition, and date precision can affect their levels and trends.

Table 1: Characteristics of the Beijing housing sample

Variable	Mean	SD	25th pct.	Median	75th pct.
Recorded ask (RMB 10,000)	471	327	280	398	560
Size (square meters)	85.5	41.6	58.4	76.3	99.8
Construction year	2000	9.28	1994	2002	2007
Squared asking-price residual	.0138	.1640	.0006	.0028	.0093
Users saving the listing	35.4	88.2	3	17	44
Page views	1,961	3,219	50	936	2,640

Notes: The first five rows cover 586,312 records across 16 districts; page views are available for 416,435. Asking prices are in RMB 10,000. The squared asking-price residual is defined in equations (1)–(2). Statistics describe the transaction archive rather than an inventory of all homes offered for sale.

of RMB 3.98 million, a size of 76.3 square meters, and a construction year of 2002. Table 1 summarizes the sample.

The cleaning code excludes records without a posting date, reported selling duration, asking price, published sale price, size, or construction year. It retains units smaller than 1,800 square meters and sale prices between 50 and 150 percent of the recorded asking price. These restrictions apply to the cleaned archive before the outcome-specific samples are selected. The price restriction limits the influence of implausible price pairs but also narrows the range of negotiated outcomes represented in those comparisons. Each results table reports its estimation sample.

The archive records transactions rather than the complete population of homes offered for sale. Some transactions report only a month, and a rule requiring complete dates classified these observations as non-sales despite their published sale prices. The resulting indicator measures date availability, not whether a home sells. Accordingly, the evidence below concerns prices, time on market, and engagement among recorded transactions; it does not identify the probability of sale or permanent withdrawal. The relative-price graphic in Section 5 combines date availability with sale timing within thirteen weeks and has the same limitation. Appendix B gives the coding details.

The duration analysis emphasizes postings from July 2016 onward, because some earlier posting dates were assigned the transaction date retrospectively. Postings from July 2016–December 2019 allow time for transactions to be completed and provide usable dates. Within that window, time on market measures elapsed time for completed transactions. Recorded asking prices do not have a consistently verified observation date during the selling process, so they are described as recorded asking prices rather than initial asking prices.

2.3 Measuring valuation difficulty

The empirical measure captures how unusual a home’s asking price is relative to locally comparable housing. The interpretation is that a deviation may reflect features whose value is difficult to assess

online. The deviation can be positive or negative: favorable and unfavorable features can both require information beyond the listing's standard attributes. Let p_{it}^L denote the recorded asking price per square meter of home i in community $c(i)$ and month t . I first estimate a regression relating asking prices to housing attributes:

$$\begin{aligned} \log p_{it}^L = & \mu_{c(i)} + \tau_t + X_i' \theta \\ & + \sum_y 1\{\text{year}(t) = y\} \left(b_{1y} S_i + b_{2y} S_i^2 + d_{1y} B_i + d_{2y} B_i^2 \right) + e_{it}^L, \end{aligned} \quad (1)$$

where S_i is size, B_i is construction year, and X_i contains discrete housing attributes: floor category, orientation, layout, building and construction type, and geographic indicators. The specification includes community and year-month effects. The relationships between price and both size and construction year can vary by calendar year. I estimate a separate regression for sale prices.

The home's squared asking-price residual and its local rank are

$$U_i = (\hat{e}_i^L)^2, \quad R_i = \text{rank}_{c,t}(U_i) \in [0, 1]. \quad (2)$$

A high rank identifies a home whose recorded asking price is particularly far from its quality-adjusted benchmark within the same community and month. Ranking reduces the influence of extreme residuals and makes comparisons across local markets easier to interpret. A coefficient on R_i describes the fitted difference between the bottom and top of the local ranking. The rank measures relative unusualness within a community and month, not the absolute uncertainty of that market.

This price-based measure is a proxy for valuation difficulty. A single squared residual combines unusual pricing, unmeasured attributes, and estimation error; it does not directly observe the dispersion of buyers' valuations or which features buyers can assess before a visit. Omitted quality may be familiar to buyers even when it is absent from the dataset. The squared residual's conditional expectation can reflect residual price variance under an appropriate benchmark, but an individual squared residual is not itself that variance. The measure also treats equally large positive and negative deviations symmetrically. I therefore distinguish the magnitude of the deviation from its sign when interpreting price outcomes. Because the benchmark and the recorded asking price need not be available at the start of marketing, the results describe conditional associations rather than a real-time forecasting exercise.

The relative-price analysis uses local dispersion among other homes:

$$U_{-i,ct} = \frac{1}{n_{ct} - 1} \sum_{\substack{j \in (c,t) \\ j \neq i}} (\hat{e}_j^L)^2. \quad (3)$$

Leaving out home i removes its squared residual from the average, but does not ensure statistical independence from its own price deviation. The residuals share an estimated benchmark and a community-month sample. This mean square describes dispersion around the fitted benchmark. It can rise because quality-adjusted prices differ more from one another or because their average lies further from that benchmark. The comparison requires at least eight records in a community-month. It remains conditional on the mix of homes and the estimated price benchmark in each community and month.

2.4 Price dispersion among comparable homes

Two comparisons describe the measure. First, the measured uncertainty series co-move less across communities than price levels do. Within subdistricts, the median pairwise correlation between community price series is 0.936, compared with 0.136 for the uncertainty series. Second, closely matched homes can have materially different asking prices. Among same-month pairs with closely matched observed attributes, the mean asking-price gap is 4.2 log points and the median is 2.7; the mean for the broader set of pairs listed at the same time is 5.3 log points. These comparisons document price dispersion among homes with similar observed attributes. These patterns motivate looking beyond standard housing attributes. They can also reflect unmeasured quality, seller pricing, and sampling noise; lower comovement alone does not establish that uncertainty is more local.

The asking-price measure complements transaction-based measures of housing risk. A comparison following the transaction-risk approach of [Giacoletti \(2021\)](#) constructs neighborhood-month dispersion from sale-price residuals after adjusting for observed housing attributes. In the 2015–2019 citywide comparison, that measure has higher in-sample fit for six-month price movements: the reported univariate R^2 is 0.63, against 0.32 for aggregated asking-price uncertainty. The role of the asking-price measure here is therefore to study differences in the selling process across homes, rather than to claim superior aggregate return forecasts. [Appendix B](#) describes the time-series comparison.

2.5 Buyer engagement and negotiated prices

The data record page views, users who save listings online (followers), and agent-accompanied in-person viewings (showings). Page views measure browsing. These are recorded counts; a longer selling period can allow more activity to accumulate. The counting window and capture date of page views are not documented consistently. A home may consequently attract many followers because interest is strong, because it remains available for a long time, or both. Counts and count

ratios describe distinct forms of engagement; they are not direct measures of buyer arrival rates or transitions by the same buyers.

Showing histories are matched using community, posting date, transaction date, sale price, and size, with ambiguous matches excluded. The number of showings is available for 250,825 records. The common sample used for Table 3 contains 158,089 observations posted between July 2016 and December 2019, with time on market of at least one day and a follower-to-view ratio no greater than one. Holding that sample fixed makes the engagement outcomes directly comparable within the selected records. The screen uses followers and page views, so it can change their composition; it does not guarantee representative buyer activity. Matching also depends on the availability of dates and prices.

The negotiated price gap is $w_i = \log p_i^D - \log p_i^L$, where p_i^D is the sale price. A more negative value indicates a larger discount relative to the recorded asking price. I also report its absolute deviation from a benchmark based on fixed effects. This deviation can increase when the gap's conditional mean shifts as well as when its dispersion rises. The gap summarizes the relation between recorded asking and sale prices; without a dated initial asking price, it does not measure the full concession during the selling process.

A home's asking price enters both its uncertainty rank and its asking-to-sale gap. Their association can therefore reflect the shared price component as well as differences in the selling process. Section 3 discusses this issue when interpreting the price results.

A complementary measure uses only physical attributes. Homes are grouped by configuration within a community, using room and bathroom counts, size bands, orientation, floor, building type, and elevator congestion. Configuration rarity is $-\log(\text{configuration share})$, ranked locally. It measures how often a configuration appears in the transaction archive, not the stock of comparable homes or the number currently offered for sale. An unusual configuration may be desirable, undesirable, or appealing to a small set of buyers. Its empirical role is to assess whether selling frictions also appear when distinctiveness is measured independently of asking prices.

3 Valuation difficulty and the selling process

3.1 Empirical comparisons

I examine how valuation difficulty relates to the time, attention, and price involved in selling a home. The baseline specification is

$$Y_i = \beta R_i + \mu_{c(i)} + \tau_{t(i)} + F_i' \gamma + \varepsilon_i, \quad (4)$$

where F_i includes floor and construction-type fixed effects, $\mu_{c(i)}$ absorbs stable community characteristics, and $\tau_{t(i)}$ absorbs common monthly movements. Because R_i ranges from zero to one, β describes the fitted difference between the lowest and highest uncertainty ranks. The rank is constructed within community and month; the regression includes separate community and month effects. Section 5 instead allows fixed effects for each community and month combination to examine relative pricing within local markets.

The empirical question is whether unusual asking prices are associated with a distinctive selling process: more time on market, more online monitoring, fewer in-person viewings, and different negotiated outcomes. These are conditional associations. The price-based measure can reflect both valuation difficulty and seller choices, so the analysis also considers a measure based only on physical configuration. Standard errors are clustered by community. They allow dependence within communities, but not unrestricted correlation in regression errors across communities in the same month. Reported significance levels are unadjusted for multiple testing.

3.2 Time on market and accumulated interest

Homes with more unusual asking prices take longer to sell. Table 2 shows a bottom-to-top rank difference of 0.0511 in log time on market, equivalent to approximately 5.2 percent more time on market. The estimate is 0.0524 after dropping the top one percent of squared residuals and rebuilding the rank, and 0.0534 for postings from July 2016–December 2019. Thus, the relationship with time on market remains both after removing extreme pricing deviations and in a sample that avoids early records with retrospectively assigned posting dates.

Homes with more unusual asking prices also accumulate approximately four percent more followers. Selling slowly is therefore compatible with attracting online attention. This combination is economically relevant because a saved listing is an inexpensive way to monitor a home without committing to an in-person viewing or a purchase. Whether that attention reflects greater engagement or simply a longer period on the platform requires a comparison of different forms of activity on the same records.

The duration difference represents additional waiting among completed transactions. For scale, a 5.2 percent difference amounts to about 3.7 days at a hypothetical 70-day reference duration. This illustration translates the rank comparison into days; it is not an estimated average treatment effect or an estimate of the probability that a listing eventually sells.

3.3 Online monitoring and in-person viewings

Online monitoring and in-person viewings move in opposite directions. Table 3 compares both outcomes on the same 158,089 records. The follower coefficient is 0.0427, while the showing

Table 2: Asking-price deviations, time on market, and online followers

	Baseline (1)	Top 1% removed (2)	Later listings (3)
<i>Panel A. Log days on market</i>			
Uncertainty rank	0.0511*** (0.0067)	0.0524*** (0.0067)	0.0534*** (0.0074)
Observations	193,815	191,712	159,888
<i>Panel B. Log followers</i>			
Uncertainty rank	0.0395*** (0.0063)	0.0418*** (0.0063)	0.0428*** (0.0071)
Observations	267,911	265,015	217,967
Community and month FE	Yes	Yes	Yes
Housing-type FE	Yes	Yes	Yes

Notes: Each outcome is regressed on the within-community-month rank of the squared asking-price residual. All specifications include community, year-month, floor, and construction-type fixed effects and cluster standard errors by community. Column (2) drops the top one percent of squared residuals and recomputes ranks. Column (3) uses posting cohorts from July 2016 through December 2019. The sample is restricted throughout to records with no more followers than page views. Panel A uses completed transactions with complete dates and usable time on market; the panels therefore use different samples. Housing-type effects are floor and construction-type fixed effects. Standard errors appear in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

coefficient is -0.0187 . With log duration included, the coefficients are 0.0146 and -0.0437 , respectively. Homes with unusual asking prices are saved by more users online but receive fewer in-person viewings, including when the comparison holds recorded time on market fixed.

The distinction between online monitoring and in-person viewings motivates including buyers' decisions to visit in the model. Saving a listing allows a buyer to learn about future price changes at little cost. An in-person viewing requires time and effort before the buyer knows whether agreement is likely. A property can therefore remain visible to potential buyers while attracting fewer in-person viewings. The log showing-to-follower ratio declines by 0.0614 across the uncertainty rank (standard error 0.0067). With the same sample and controls, this coefficient is the difference between the showing and follower coefficients, $-0.0187 - 0.0427 = -0.0614$. It summarizes their contrast rather than supplying an additional independent result. It is not the probability that an individual follower attends a viewing because followers, visitors, and eventual buyers are not linked.

The opposite signs for followers and showings remain when log time on market is included. The estimated elasticities with respect to time on market are 0.5409 for followers and 0.4794 for showings. Using counts per day as the duration adjustment would impose proportional accumulation with time on market. I therefore report both total counts and estimates that control for time on market. The latter provide a descriptive comparison at a given duration; duration is itself determined by demand, seller behavior, and negotiation, so it is not an exogenous control.

Table 3: Online monitoring and in-person viewings in the same sample

	Log followers		Log showings	
	(1)	(2)	(3)	(4)
Uncertainty rank	0.0427*** (0.0079)	0.0146** (0.0068)	−0.0187*** (0.0070)	−0.0437*** (0.0060)
Log days on market		0.5409*** (<i>n.a.</i>)		0.4794*** (<i>n.a.</i>)
Duration control	No	Yes	No	Yes
Community and month FE	Yes	Yes	Yes	Yes
Housing-type FE	Yes	Yes	Yes	Yes
Observations	158,089	158,089	158,089	158,089

Notes: The sample consists of records matched to reported numbers of showings, posted July 2016–December 2019, with at least one day on market and a follower-to-view ratio no greater than one. Regressions include community, year–month, floor, and construction-type fixed effects; standard errors are clustered by community. Standard errors appear in parentheses. The two marked *n.a.* are unavailable in the retained output; their reported significance levels are shown. Longer selling periods can allow counts to accumulate; conditioning on time on market is descriptive, not a causal adjustment. The significance notation follows Table 2: one, two, and three stars denote $p < 0.10$, $p < 0.05$, and $p < 0.01$.

Price revisions show a different pattern. Their count rises with uncertainty before controlling for time on market; after including that control, the coefficient is 0.0043 (standard error 0.0066) and is not statistically significant. At a given recorded duration, the estimates do not establish more revisions for homes with unusual asking prices. Dated revisions would be needed to measure repricing speed or seller learning.

3.4 Prices and negotiated outcomes

The selling pattern extends to negotiated prices. Table 4 reports a sale-price coefficient of -0.0074 for the sample with more reliable posting dates, approximately a 0.74 percent lower price across the uncertainty rank. Because asking and sale prices co-move, this gradient can also reflect whether unusually priced homes lie above or below their benchmark. Squaring the asking-price residual does not itself imply a negative sale-price association. The absolute deviation of the gap between asking and sale prices from its benchmark rises by 0.0013. This second outcome shares the home’s asking price with the uncertainty measure, so the association can partly reflect their construction. Each outcome uses its available sample; the engagement comparison on identical records is reported separately in Table 3.

The average price association is more sensitive to extreme residuals than the result for time on market. Removing the top one percent of squared residuals makes the linear relationship between uncertainty rank and sale prices statistically insignificant. The top-decile discount remains negative

Table 4: Asking-price deviations, sale prices, and buyer engagement

	Log sale price (1)	Absolute price-gap deviation (2)	Log followers (3)	Price revisions (4)	Log showings (5)
Uncertainty rank	−0.0074*** (0.0015)	0.0013*** (0.0001)	0.0428*** (0.0071)	0.0358*** (0.0070)	−0.0204*** (0.0070)
Community and month FE	Yes	Yes	Yes	Yes	Yes
Housing-type FE	Yes	Yes	Yes	Yes	Yes
Observations	169,967	169,967	217,967	217,967	168,648

Notes: Each column is a separate regression on the within-community–month uncertainty rank, using July 2016–December 2019 listings and restricting the sample to records with no more followers than page views. Community, year–month, floor, and construction-type effects are included; standard errors are clustered by community and shown in parentheses. Sale price is measured per square meter. Price revisions count recorded asking-price changes; showings are in-person viewings. Column (2) is the absolute deviation of the recorded log sale-minus-ask gap from its fixed-effect benchmark. It can reflect a conditional-mean shift as well as dispersion. The gap and uncertainty rank both contain the home’s asking price; column (2) is not an independent measure of buyer disagreement or future price volatility. The price and count outcomes have different units; coefficients should not be compared as percentages across outcomes. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

but falls from 0.73 percent to 0.22 percent, with t -statistics of -6.0 and -2.4 . The evidence supports a price difference concentrated among the most unusual asking prices, rather than a stable linear discount throughout the uncertainty distribution.

The coefficient on the signed price gap is -0.0011 ($t = -6.0$), indicating a slightly larger discount relative to the recorded asking price. This comparison differs from a sale-price comparison, but it does not remove the asking-price component of the uncertainty measure. If a home has an unusually high ask and sells near its benchmark value, both its uncertainty rank and its asking-to-sale discount can be large without greater disagreement among buyers. Centering the gap on fixed effects does not remove that shared component. Larger absolute deviations can also reflect a change in the average gap not captured by those fixed effects. They describe recorded pricing outcomes without independently establishing greater bargaining uncertainty.

Asking and sale prices also move closely together: deviations from their respective price benchmarks are related nearly one for one. This limits a simple explanation in which unusual asking prices are unrelated to sale values, but an average relationship does not establish that the spread of gaps is independent of asking-price deviations. Asking prices contain substantial information about recorded sale prices. Interpreting that information requires the timing qualification in Section 2. An asking price recorded late in the selling process can incorporate negotiation, and unmeasured quality can affect both prices. The price estimates therefore describe negotiated outcomes among recorded sales; they do not separately identify a risk premium or the dispersion of buyers’ valuations.

Table 5: Configuration rarity and the selling process

	Log days on market (1)	Log followers (2)	Revisions (3)	Price gap (4)
<i>Panel A. Physical rarity entered alone</i>				
Physical-rarity rank	0.2192*** (0.0100)	0.0963*** (0.0092)	0.1461*** (0.0092)	-0.0036*** (0.0002)
<i>Panel B. Both measures included</i>				
Physical-rarity rank	0.2054*** (0.0102)	0.0881*** (0.0095)	0.1352*** (0.0097)	-0.0032*** (0.0002)
Price-residual rank	0.0608*** (0.0098)	0.0366*** (0.0094)	0.0453*** (0.0099)	-0.0011*** (0.0002)
Observations	241,043	327,982	327,982	247,994

Notes: Physical rarity uses configuration shares among recorded transactions in communities with at least 20 records and is ranked within community and month. Standard errors are clustered by community. The saved specification description is inconsistent: its fixed-effect row lists community-by-month effects, while its note lists additive community and month effects. The estimates therefore cannot be assigned definitively to either fixed-effect structure. The log-duration sample begins in July 2016. The price gap uses each home's recorded asking and sale prices.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

3.5 A comparison based on physical characteristics

A similar selling pattern appears when distinctiveness is measured without using the home's price. Table 5 relates outcomes to how rarely similar physical configurations appear in community transactions. Entered alone, the rarity rank has a log-duration coefficient of 0.2192. With the price-residual rank also included, the coefficient is 0.2054, while the price-residual rank retains a coefficient of 0.0608. Both measures are associated with more followers, more price revisions, and a more negative gap between recorded sale and asking prices.

The duration association is therefore not confined to a transformation of the seller's chosen asking price. Homes whose configurations appear less often in the archive also take longer to sell and attract more activity during the selling process. This links valuation difficulty to a concrete feature of the housing market: the challenge of evaluating an unusual home and matching it with a buyer.

Rarity and simple indicators of undesirable housing features both predict more time on market, but have opposite relationships with follower counts. An unusual home can attract monitoring even when an undesirable feature discourages it. The distinction complements the follower-showing evidence, although it does not separate disagreement from all quality or matching explanations. A rare layout may be difficult to value, appeal to a narrow buyer population, or both.

Table 6: Price changes and persistence across matched transactions

	Annualized log price change		Change in	Later
	(1)	(2)	position (3)	position (4)
Earlier-sale uncertainty rank	0.0035 (0.0028)	0.0040 (0.0028)	−0.0004 (0.0022)	
Log duration, earlier sale		−0.0008 (0.0010)		
Log duration, later sale		−0.0092*** (0.0014)		
Earlier price position				0.4438*** (0.0270)
Observations	11,697	11,697	11,697	11,697

Notes: Annualized log price change is the log sale-price difference divided by years between records. Position is the sale price's deviation from the mean log price in its community and sale month; column (3) uses its change between records. All columns include separate community and month fixed effects and restrict the sample to records with no more followers than page views. Standard errors are clustered by community. The elapsed-time denominator can include the later home's marketing period. Matching on attributes can link different apartments with the same recorded characteristics. The sample requires complete transaction dates and two recorded transactions. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

3.6 Price persistence across matched transactions

A price discount need not reward the buyer with a higher subsequent return. If the same difficulty reappears at resale, the buyer may buy the home at a discount and later sell it at a discount. Table 6 examines this distinction using pairs of transactions matched on housing attributes. Pairs share a community, rounded size, floor band, orientation, layout, construction year, and building height, with exactly two records sharing these attributes and more than three months between the recorded transactions. These criteria identify repeated transactions in the same property type, which need not be sales of the same apartment. Of 12,445 pairs, 11,697 remain after removing observations that are alone in their fixed-effect group.

Price differences persist across matched records, while the estimated annualized price-change gradient is imprecise. The coefficient on the earlier sale's uncertainty rank is 0.0035 (standard error 0.0028), or 0.35 percentage points of annualized log price change across the rank. The earlier transaction's price relative to its local market predicts the later matched record's relative price with a coefficient of 0.4438, while the change in position has essentially no estimated relationship with the earlier-sale uncertainty rank. The positive price-change coefficient is larger without the restriction on followers relative to page views, but trimming the top and bottom five percent of annualized price changes removes conventional statistical significance with and without that restriction.

The duration coefficient is −0.0092 at the later sale and an imprecise −0.0008 at the earlier sale. These estimates use an annualized price change whose denominator is the time between

transactions. A later sale can extend that interval as well as the marketing period; for a given positive price gain, annualization alone then lowers the measured return. The estimate therefore does not isolate a loss in the sale price from waiting. Moreover, attribute matching need not follow the same apartment. The matched-price comparison describes price persistence and subsequent price changes, without establishing an investor's realized return or compensation for valuation risk.

4 Valuation disagreement and the selling process

Why should difficulty valuing a home affect how it sells? In the disagreement argument of [Miller \(1977\)](#), an asset that cannot be sold short is valued by its optimistic holders. A housing seller must also find a buyer willing to pay an acceptable price. The prospect of meeting an unusually optimistic buyer can make waiting attractive, even as uncertainty lowers other buyers' willingness to pay. This section combines these forces in a model in which buyers arrive one at a time and the seller decides whether to accept each offer.

The model organizes the empirical evidence around three decisions: what buyers are willing to pay, which offers the seller accepts, and whether a prospective buyer finds an in-person viewing worth the cost. Valuation difficulty can affect each decision. It can therefore change the time required to sell and the progression from online interest to in-person viewings, as well as the eventual sale price. The information problem concerns features whose value buyers cannot fully assess from public information. Features that are merely absent from the research data need not create this uncertainty. The model studies the former case; the asking-price measure can capture either.

4.1 Information and buyer valuations

Let $u > 0$ denote uncertainty about a home's value after public information has been observed. Public precision, the inverse of that uncertainty, is $1/u$. Each buyer receives a private assessment of precision $\tau > 0$. With normally distributed information, the uncertainty remaining after combining public and private assessments is measured by the posterior variance

$$v(u) = \frac{1}{u^{-1} + \tau} = \frac{u}{1 + \tau u}. \quad (5)$$

Even for the same home with a fixed underlying value, independent errors in private assessments lead buyers to different expected values. The variance of these expected values across buyers is

$$d(u) = \frac{\tau}{(u^{-1} + \tau)^2} = \tau v(u)^2. \quad (6)$$

Both measures increase in u when private precision is held fixed. Less informative public comparables therefore leave more uncertainty after inspection and give private assessments more weight. Equation (6) measures disagreement among buyers about the same home, rather than differences in expected values across homes.

To separate uncertainty from news about value, I hold the average assessment of the home's value fixed. In the signal model, this corresponds to a home whose value equals the public prior mean; Appendix A.1 states the normalization. For a buyer with constant absolute risk aversion γ , the certainty equivalent is the sure payoff the buyer values as much as the uncertain one. For a normally distributed payoff, it equals the mean minus $\gamma/2$ times the variance. Uncertainty thus has a cost even for a buyer whose expected valuation has not changed. Incorporating housing services and discount factors into the coefficients, write the buyer's willingness to pay as

$$V = \mu(u) + s(u)Z, \quad Z \sim N(0, 1), \quad \mu(u) = a - kv(u), \quad s(u)^2 = b d(u), \quad (7)$$

where $k, b > 0$. The risk discount reduces the mean valuation μ , while differences in private assessments widen the distribution through s . These channels have different implications for selling. A lower mean makes acceptable offers less common at a given minimum acceptable price; greater dispersion increases the possibility of an exceptionally favorable match. The comparisons below hold private precision fixed. Appendix A.1 gives the conditions under which they extend to buyers who acquire more information when public comparables are less useful.

4.2 Agreement, prices, and selection

In this benchmark, the population of buyers who inspect the home is taken as given. These buyers meet the seller at Poisson rate λ : meetings occur randomly at a constant average rate, and valuations are independent across meetings. Let S be the seller's reservation value, the minimum price the seller will accept. A meeting leads to agreement when $V \geq S$. Conditional on agreement, buyer and seller divide the surplus according to

$$P = (1 - \alpha)V + \alpha S, \quad 0 < \alpha < 1. \quad (8)$$

Here α is the buyer's bargaining weight. The gains from trade are the buyer's willingness to pay above the seller's reservation value. The seller receives its reservation value plus the fraction $1 - \alpha$ of the gains from trade.

Define $z = (S - \mu)/s$, $q = 1 - \Phi(z)$, and $m(z) = \phi(z)/[1 - \Phi(z)]$. These are, respectively, the seller's threshold in standard deviations above the mean buyer valuation, the probability of

agreement at a meeting, and the mean standardized valuation among buyers who meet that threshold. The model gives expected time on market, the mean sale price, and the variance of sale prices as

$$\mathbb{E}[T] = \frac{1}{\lambda q}, \quad (9)$$

$$\mathbb{E}[P \mid \text{agreement}] = (1 - \alpha)\{\mu + s m(z)\} + \alpha S, \quad (10)$$

$$\text{Var}(P \mid \text{agreement}) = (1 - \alpha)^2 s^2 \{1 + z m(z) - m(z)^2\}. \quad (11)$$

These expressions distinguish the price an owner eventually obtains from the wait required to obtain it. Sale prices reflect the upper part of the valuation distribution: buyers below the reservation value leave without trading. A fall in the average buyer's valuation can therefore be partly offset in observed prices by stronger selection among the buyers who transact. For the same reason, dispersion in accepted prices depends on both the underlying distribution and the seller's acceptance threshold.

Allowing the reservation value to respond to uncertainty, the change in the probability of agreement per meeting is

$$q_u = -\frac{\phi(z)}{s} \{S_u - \mu_u - z s_u\}. \quad (12)$$

The expression highlights the seller's role. The risk discount reduces agreement when the reservation value does not fall enough to offset it. Dispersion can increase the share of buyers above the threshold, but it also changes the benefit of waiting for another offer. The next subsection makes that response explicit.

4.3 The seller's choice of when to accept

The risk-neutral seller pays a carrying cost per unit of time $c \geq 0$ and discounts future receipts at rate $r > 0$. The seller cannot commit to reject an offer above the value of continuing to search. The reservation value therefore equals that continuation value. Using the bargaining rule above, an optimal stationary reservation value S^* solves

$$rS^* + c = \lambda(1 - \alpha)\mathbb{E}[(V - S^*)_+]. \quad (13)$$

The left side is the cost of waiting, including both carrying costs and the cost of deferring payment. The right side is the arrival rate times the expected gains from trade that the seller retains. The environment is stationary: the arrival rate and valuation distribution stay fixed over time.

Proposition 1 (Dispersion and optimal waiting). *For normal valuations with mean μ and standard deviation s , let S^* satisfy equation (13). Then S^* increases with s . If $c + r\mu > 0$, a mean-preserving*

increase in s raises $(S^* - \mu)/s$, lowers the per-meeting probability of agreement, and lengthens expected time to sale.

A wider distribution makes a particularly favorable match more valuable. Under the stated condition, the seller raises the reservation value enough that a smaller fraction of buyers is acceptable. Disagreement can consequently delay sale even when the seller adjusts optimally. The owner is willing to wait longer for a buyer with an unusually high valuation.

The response to a shift in the mean differs. Writing $L = \lambda(1 - \alpha)$, implicit differentiation gives

$$\frac{\partial S^*}{\partial \mu} = \frac{Lq}{r + Lq} \in (0, 1). \quad (14)$$

An optimal seller responds to a lower mean buyer valuation by lowering the reservation value, but by less than the fall in the mean. With positive carrying costs held fixed, this response approaches one as the discount rate tends to zero. A seller whose reservation adjusts slowly experiences a larger reduction in acceptable offers from the same risk discount. Partial adjustment can be represented by $S = (1 - \nu)\bar{S} + \nu S^*$, where $\bar{S}$ is a reference value and $\nu \in [0, 1]$ measures adjustment toward the optimal threshold. Reference prices and valuation disagreement can thus reinforce one another.

Lower buyer arrival rates offer another reason for delay. They also make the seller less selective, because the next opportunity to trade is further away. This response differs economically from the rise in selectivity induced by greater valuation dispersion. Both can produce longer time on market, but they do so through different changes in the seller's willingness to accept an offer. The distinction motivates examining engagement and sale prices alongside time on market.

4.4 When does dispersion weaken the effect of price?

At a fixed valuation distribution, the agreement probability as a function of the seller's reservation value is $q(S) = 1 - \Phi((S - \mu)/s)$. Its slope is

$$\frac{\partial q}{\partial S} = -\frac{\phi(z)}{s}. \quad (15)$$

The number of buyers with valuations close to the threshold determines how much a small change in the reservation value affects agreement. This is how the model addresses the price-clearing question.

Proposition 2 (Local price sensitivity). *At a fixed standardized threshold z , greater valuation dispersion s reduces $|\partial q / \partial S|$ in inverse proportion to s . At a fixed price gap $S - \mu$, it reduces the slope magnitude if $|S - \mu| < s$ and increases it if $|S - \mu| > s$.*

Around the center of the distribution, dispersion spreads buyers away from the threshold,

making a marginal price change less consequential. Far in the tails, dispersion can instead bring more buyers near the threshold. Price sensitivity therefore depends on where the seller stands relative to buyers' valuations. This local result formalizes the paper's price-clearing question: a price cut has less effect when few buyers are close to accepting the home at the current terms.

For sale within a period of length H , the probability is $1 - \exp(-\lambda qH)$. Its price derivative also depends on λ , H , and the initial level of q . An empirical sale curve therefore combines the sensitivity of agreement with the opportunities to meet buyers. A posted asking price can also affect buyers' decisions to enter the market and may differ from the seller's reservation value. These links connect the question in Figure 2 to the model; the local derivative in equation (15) is the theoretical object of interest.

4.5 Monitoring and inspection

The benchmark takes buyer visits as given. To connect it to the engagement data, consider an extension in which potential buyers first decide whether to visit. Online followers are users who save a listing; showings are in-person viewings. Potential buyers encounter the listing at Poisson rate λ_E . Each buyer can save it with probability $a(u)$ and visit once with probability $\pi(u, S)$. A visit occurs only if its expected benefit covers its cost. Let $q_B(u, S)$ be the probability of purchase conditional on a visit. The probability of a sale per potential-buyer encounter is

$$q_E(u, S) = \pi(u, S)q_B(u, S). \quad (16)$$

The visiting buyers are now a selected group. Their probability of agreement q_B need not equal the normal-tail probability q in the benchmark. The optimal-waiting propositions above hold the visiting-buyer population fixed; they do not by themselves determine the effect of changing who visits.

For a fixed stationary seller policy, independent encounters, $q_E > 0$, and no withdrawal, expected time to sale and total activity through sale satisfy

$$\mathbb{E}[T] = \frac{1}{\lambda_E q_E}, \quad \mathbb{E}[F] = \frac{a}{q_E}, \quad \mathbb{E}[B] = \frac{\pi}{q_E} = \frac{1}{q_B}, \quad (17)$$

where F counts followers and B counts viewings, including the purchaser's visit. Fewer potential buyers choosing to visit can lengthen the wait, but that change alone does not reduce the total number of viewings before sale. Fewer total viewings require a higher chance of agreement among those who do visit. At a fixed encounter rate, longer selling time and fewer viewings can therefore coexist if the visiting buyers are more likely to purchase while the product πq_B falls. More followers can accompany that pattern if a/q_E rises.

Table 7: Economic channels and their observable implications

Channel	Model implication	Relevant empirical comparison
Lower average buyer valuation	Reduces willingness to pay; the change in selling time depends on seller adjustment.	Sale prices and asking-to-sale gaps across the uncertainty rank.
Greater disagreement	At a fixed mean, raises the seller's minimum acceptable price and delays agreement if $c + r\mu > 0$.	Longer time on market.
Viewing costs and buyer selection	Fewer total viewings with longer waits require a higher purchase probability per visit but a lower probability per encounter.	More users saving listings and fewer in-person viewings for the same homes.
Disagreement near the seller's threshold	Weakens the response to a small price change under Proposition 2.	The pattern in Figure 2 motivates this prediction; the recorded sale indicator is defined in Section 5.

Notes: The table links model channels to the empirical comparisons. It reports no additional estimates. The implications are conditional on the assumptions stated in the text; derivations appear in Appendix A. The comparisons are descriptive and do not separately identify the model parameters.

This extension gives a specific interpretation of the engagement evidence. When inspection is costly, fewer buyers may visit and those who do may be better matches. The observed counts are consistent with that selection channel. They do not establish it, because the data do not link individual followers, visitors, and purchasers or directly measure the probabilities in equation (17).

4.6 Mapping the model to the evidence

Table 7 summarizes the empirical content of the model. Its central implication is that valuation difficulty can affect several parts of the selling process. Risk discounts affect willingness to pay, the option to wait affects acceptance, and information costs affect engagement. Studying these decisions together is more informative about the selling process than treating the sale price as its only outcome.

The model offers an explanation for the joint evidence, but its parameters are not estimated. The asking-price residual is a proxy for valuation difficulty, not a direct measure of u or s ; accumulated engagement counts do not reveal individual buyer beliefs or how buyers move from following to viewing and purchase. Arrival rates, hidden quality, and seller learning can also affect these outcomes. Together with the recorded-date limitation in Section 5, these features mean that the plot cannot identify the model's parameters and the selling-time estimates cannot establish that disagreement causes the delay.

The economic lesson is nevertheless distinct from treating uncertainty solely as a price discount.

In a market with sequential matching, an owner must decide how long to wait for a favorable valuation, and a buyer must decide whether gathering more information is worth the cost. Those decisions determine how valuation difficulty affects the sale price, time on market, and effort spent searching. They are the mechanism through which disagreement can become illiquidity.

5 Valuation dispersion and the role of asking prices

5.1 Price sensitivity and local comparables

In the model, the effect of a small price reduction depends on how many buyers value the home near the minimum price the seller will accept. When many buyers are close to that threshold, a small reduction can bring many more buyers into agreement. When valuations are dispersed, fewer buyers may be close enough for the same reduction to matter. Proposition 2 states the conditions for this result. It explains how information from similar nearby homes, or comparables, can affect the role of price in bringing about trade.

The empirical comparison asks whether a home’s asking price has a different relationship with recorded sale timing when local prices are more dispersed. Following the relative-price approach of Guren (2018), I measure the asking price relative to a benchmark that adjusts for observed housing characteristics within the same community and month. Local price dispersion is the mean squared asking-price residual of the other homes in that community and month, as in equation (3). Excluding the home removes its own squared residual from the average, but the measures still share the fitted benchmark and community–month sample. The peer mean square can reflect a local average price deviation as well as variation among homes. The comparison uses community–months with at least eight records and homes posted for sale beginning in July 2016 with at least thirteen weeks of potential follow-up.

The outcome combines sale timing with the precision of recorded dates. Let D_i^R equal one when the parsed transaction date falls within thirteen weeks of the posting date, and zero under the remaining recording outcomes. Month-only transaction dates can enter the zero category even though the property sold. Thus D_i^R measures whether a sale is recorded within the window with sufficient date precision. In this sample of completed transactions, it does not measure the probability that a home offered for sale will sell. The following comparison describes how asking prices relate to this recorded outcome; it does not estimate the causal effect of a price cut or the probability of remaining unsold.

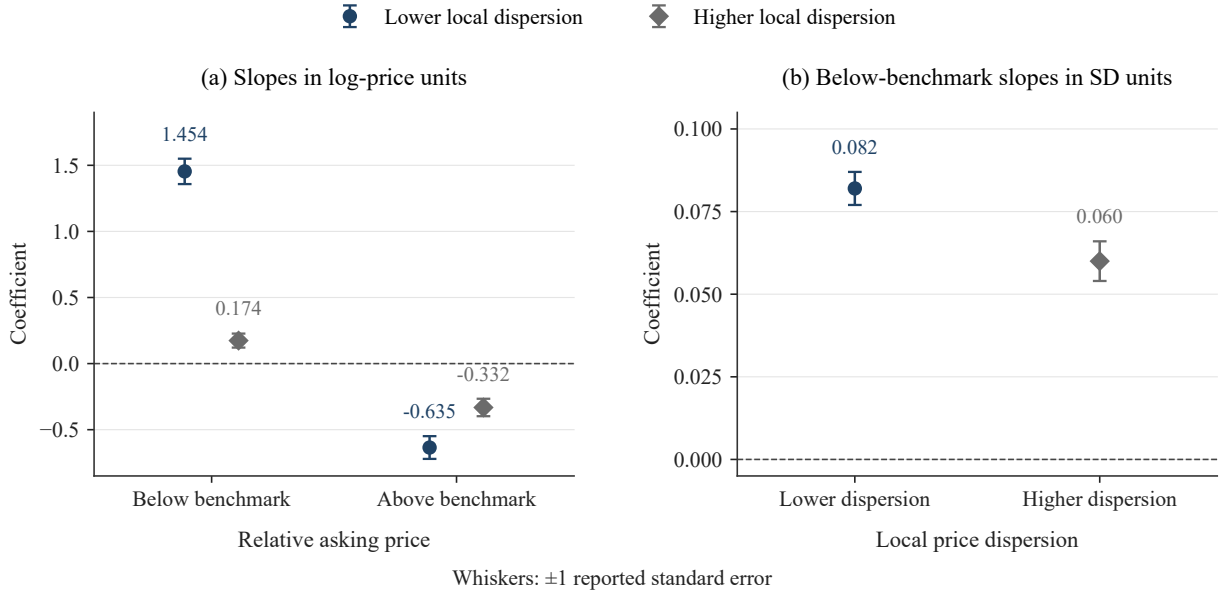


Figure 2: Asking-price slopes by local price dispersion

Notes: Points plot the coefficients in Table 8. Whiskers extend one reported community-clustered standard error in each direction; they are not confidence intervals. The dependent variable is the recorded-date indicator D_i^R defined in the text. Panel (a) uses log-price units and panel (b) uses local standard-deviation units. Homes are grouped at median peer dispersion, measured from the other homes in each community-month. Homes are posted from July 2016 with at least thirteen weeks of potential follow-up; cells contain at least eight records. Regressions include community-by-month, floor, and construction-type effects.

5.2 Asking prices and recorded sale timing

Figure 2 shows a weaker relationship between asking-price deviations and D_i^R where comparable homes' prices are more dispersed. Panel (a) compares the asking-price slopes for homes below and above the median peer dispersion. Panel (b) expresses the below-benchmark slopes in local standard-deviation units, allowing for the wider spread of asking prices in high-dispersion markets. A separate comparison using dispersion quintiles gives the same ordering: among homes priced below the benchmark, the coefficient falls from 1.66 in the lowest quintile to 0.12 in the highest.

Table 8 quantifies the comparison. Below the benchmark asking price, the slopes per log price point are 1.454 and 0.174 in the lower- and higher-dispersion groups. Above the benchmark, the slopes are -0.635 and -0.332 . The positive slope below the benchmark means that homes priced closer to comparable homes more often have a sufficiently precise sale date within the stated window. This compares homes offered at different prices. Moving toward the benchmark from below means a higher asking price, so the positive slope does not show that price cuts speed up sales.

The size of this difference depends on how asking prices are scaled. In raw units, the below-comparables slope is roughly eight times larger in the lower-dispersion group. In within-cell

Table 8: Asking-price slopes by peer price dispersion

	Lower local dispersion (1)	Higher local dispersion (2)
<i>Panel A. Log-price units</i>		
Below comparables	1.454*** (0.096)	0.174*** (0.053)
Above comparables	−0.635*** (0.086)	−0.332*** (0.066)
Observations	40,412	41,182
<i>Panel B. Within-cell standard-deviation units</i>		
Below comparables	0.082*** (0.005)	0.060*** (0.006)

Notes: The dependent variable is D_i^R , the recorded sale-timing indicator defined in the text. Local dispersion is the mean squared asking-price residual among the other homes in a community-month. The groups split at its median. Regressions include community-by-month, floor, and construction-type fixed effects. The sample begins in July 2016, allows thirteen weeks of potential follow-up, and requires at least eight records per community-month. Panel B expresses the asking-price deviation in within-cell standard-deviation units. The standardized pooled interaction is -0.017 with a reported t -statistic of about -4.0 . Standard errors are clustered by community. Stars retain the reported coefficient inference: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

standard-deviation units, the slopes are 0.082 and 0.060, a ratio of approximately 1.37. The difference is substantially smaller in local standard-deviation units, so the raw comparison is sensitive to the scale of price variation. Cell-specific standardization also changes which observations have more influence on the estimated slope. It is a sensitivity check, not a decomposition of how much weaker price sensitivity is caused by dispersion.

The interaction between below-benchmark asking prices and local dispersion changes little after controlling for local record counts or the recorded citywide measure of market conditions: the coefficient is -0.182 in the baseline, -0.174 with the local record-count control, and -0.199 with the market-condition control. Removing the part of dispersion explained by both controls gives -0.153 . The association is therefore similar across these specifications. Each uses the same outcome, which combines sale timing and date precision.

5.3 Economic interpretation

An asking-price deviation may be easier to interpret when close comparables provide a clear guide to value. The price of a close substitute can be a useful guide when comparable homes have similar prices. When those prices are dispersed, the same asking-price deviation may say less about which buyers will be willing to purchase. The model explains how this can happen: fewer buyers may value the home close to the minimum price the seller will accept.

Differences across homes also reflect what asking prices convey about quality and seller behav-

ior. A deep discount can reveal a hidden defect or urgency, while a high asking price can reflect a valuable feature or willingness to wait. These forces help explain why the relationship across homes need not be a downward-sloping demand curve. The nearly one-for-one association between asking-price and sale-price deviations shows that asking prices contain information about eventual sale prices. That association can reflect both housing characteristics and seller decisions, as well as buyers' responses to price.

The price comparisons document how relative asking prices and recorded sale timing vary together. They do not measure the effect of an actual price cut. The model supplies a possible economic explanation: when buyers disagree about features they cannot readily assess, few may value the home close enough to the seller's minimum acceptable price for a small reduction to produce agreement. The shared price benchmark, local sample, and date-recording rules prevent the empirical slopes from isolating that mechanism. The underlying question remains how information about a home's distinctive features shapes both its valuation and the process of finding a buyer.

6 Valuation, participation, and housing liquidity

6.1 From attention to trade

Homes with unusual asking prices remain on the market longer and are saved by more users online, yet receive fewer in-person viewings. The contrast between saved listings and viewings appears when both activities are measured for the same homes. Online interest and willingness to spend time visiting a property can therefore tell different stories about how readily it will sell.

Allowing buyers in the model to choose whether to visit offers an economic explanation for this combination. A prospective buyer can monitor a listing cheaply while waiting for information or a price change. An in-person viewing requires time and effort, and the return to that commitment depends on the prospect of reaching agreement. When valuations are difficult to reconcile, online interest need not lead to a visit. A home can consequently take longer to sell even while many users continue to follow its listing.

This mechanism also explains why prices and buyer activity should be studied together. A lower asking price changes the terms offered to a buyer; better valuation information can change the buyer's willingness to incur the cost of a viewing. Both can matter for reaching agreement. The negotiated-price and buyer-activity results support examining these decisions together. Section 5 relates asking prices to recorded sale timing, which also depends on the precision of transaction dates. The data describe associations in the selling process, and the model offers an explanation. The asking-price measure captures unusual pricing; it does not directly observe differences in buyers' valuations.

6.2 Distinguishing the economic explanations

The comparison based on housing characteristics links valuation difficulty to something observable beyond asking-price deviations. Homes whose configurations appear less often in recorded community transactions also take longer to sell, are saved by more users, undergo more price revisions, and sell at larger discounts to the recorded asking price. Fewer similar transactions can leave buyers with less evidence about value. They can also reflect selective turnover or demand for that configuration, rather than a shortage of competing listings. Unusual layouts may appeal to fewer households, while difficult-to-assess features may complicate valuation. Both can make finding a suitable buyer harder.

Within narrowly defined property types, the time-on-market coefficient is positive but less precise: about 0.032, with a t -statistic of 1.7. Matching on size, layout, floor band, orientation, construction year, and building height compares homes with similar observed characteristics, although interior condition and building features can still vary. This is relevant to the paper's interpretation: some features may justify a price difference while remaining difficult to judge online. Other unrecorded features may be evident to buyers and affect demand directly. Community effects, housing controls, and comparisons within property types therefore improve comparability while leaving some quality differences unobserved.

Seller behavior is a second explanation. A seller may begin with a high asking price, learn from buyer feedback, and revise the price before a sale. Reference dependence can also influence willingness to wait, as emphasized by [Genesove and Mayer \(2001\)](#) and [Andersen et al. \(2022\)](#): sellers may judge an offer relative to a reference price, such as what they paid for the home. When the recorded asking price comes from late in the selling process, its deviation from the benchmark reflects this history as well as the home's characteristics. Once time on market is held constant, the association with the number of price revisions is weak. This does not show how quickly sellers learn. Asking-price histories with dates and linked buyer responses would help separate the seller's initial valuation from later changes.

The contrast between saved listings and in-person viewings is also compatible with buyers and sellers having different information. Buyers can follow a property online while avoiding a visit or seeking information about a possible defect. The mechanisms studied by [Kurlat and Stroebel \(2015\)](#) thus remain relevant. These alternatives share an economic implication with the model: inexpensive online interest can coexist with reluctance to spend time and effort pursuing a purchase. The comparisons do not separate how much of that reluctance comes from differences in valuations, hidden quality, or seller learning.

6.3 Market conditions and the costs of selling slowly

The model makes market conditions relevant because buyers' participation and sellers' willingness to wait depend on their alternatives. A market with few potential trading partners can make an unproductive viewing or a delayed agreement more costly. The interaction between the rank of unusual asking prices and the archive's cold-market classification is 0.0324 for log duration (standard error 0.0132), compared with 0.0275 (0.0133) after trimming and 0.0268 (0.0144) outside 2020–2021. The original classification labels months cold when the Beijing-wide recorded sale rate is below its sample median. Since recorded sale status depends on parsed dates, the grouping can reflect date availability and transaction composition. The estimates show a stronger association with time on market in periods classified this way; they do not establish that an independently measured downturn strengthens that association.

More generally, transaction counts and observed prices reflect both market conditions and the homes that enter the transaction sample. Vendor coverage can also change over time. The 2017 tightening supplies the institutional motivation for examining prices and trading together. The analysis does not use it to identify a policy-induced change in valuation uncertainty.

Owners can face costs from a slow sale even if subsequent price gains are uncertain. Table 6 finds persistence in relative prices across matched transactions and an imprecise association between the earlier uncertainty rank and later price changes. Those pairs can represent different apartments, and annualization can mechanically link selling delays to the measured rate of appreciation. The comparison therefore does not measure an owner's return net of the cost of waiting.

6.4 Measurement and inference

The additional checks clarify which findings are most stable. The association between unusual asking prices and longer time on market remains after trimming extreme observations and restricting the sample to a posting cohort that avoids early records with retrospectively assigned posting dates and allows time for a sale before the sample ends. More saved listings and fewer in-person viewings appear in the same sample, both with and without a control for time on market. The comparison based on uncommon housing characteristics also links distinctiveness to a slower selling process. The results for average sale prices and subsequent matched-price changes vary more across specifications. The strongest evidence therefore concerns time on market and the contrast between online interest and in-person viewings.

Estimated benchmark prices introduce another source of uncertainty. Community-months with few records can produce imprecise price deviations and ranks. Standard errors clustered by community do not automatically account for all uncertainty from estimating the benchmark. For the price specification documented in Appendix B, the analytic standard error of 0.0331 rises to

0.0564 when the price benchmark is re-estimated in bootstrap samples drawn by community. That calculation applies to the specified regression; the adjustment can differ for other estimates.

The central empirical finding concerns how recorded homes are sold: unusual asking prices and uncommon housing characteristics are associated with longer time on market, while more online interest can accompany fewer in-person viewings. Neither selling time nor the two activity counts is calculated from the asking-price residual, so their signs are not imposed by its construction. The model offers an interpretation that combines seller waiting with changes in which buyers visit. The transaction archive does not identify permanent withdrawal, a causal response to a price cut, or welfare gains from improved information; those quantities require observations beyond the completed transactions and recorded activities analyzed here.

7 Conclusion

Homes that are difficult to value may be difficult to sell even when they attract attention. In Beijing's resale records, homes with asking prices further from the benchmark for comparable nearby homes take longer to sell. Moving from the smallest to the largest deviation within a community and month is associated with about five percent longer selling time. These homes also attract more online saves but fewer in-person viewings, even after accounting for time on market. Sale-price differences are smaller and less stable across specifications. The clearest evidence concerns the process of selling: online interest need not translate into visits or a quicker sale.

A search model explains why valuation difficulty can affect both price and waiting. Less reliable information lowers risk-averse buyers' willingness to pay, while disagreement makes waiting for a high offer more attractive to the seller. Under the model's conditions, greater dispersion in valuations delays the sale even when the seller adjusts the minimum acceptable offer optimally. Near the center of the valuation distribution, it can also weaken the effect of a small price cut on agreement. When buyers choose whether to visit, fewer visits by buyers who are more likely to purchase can accompany a longer wait. The optimistic buyer matters, but finding that buyer takes time.

An unusual asking price may reflect features whose value is hard to judge online. It can also reflect seller choices or qualities already apparent to buyers. The evidence does not isolate these explanations, and the model provides an interpretation rather than a confirmed mechanism. The paper's contribution is to connect valuation risk to the steps between interest and trade. The cost of a difficult valuation can appear in the search for a buyer, as well as in the price the buyer eventually pays.

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A Model derivations

This appendix derives the results in Section 4 for the stationary partial-equilibrium model, which holds the buyer arrival rate and valuation distribution fixed over time. It develops the link from information to valuations, the seller's minimum acceptable price, and the effect of a small change in that price on the probability of agreement.

A.1 Public information and private assessments

Let the public posterior for value θ have mean m_0 and precision u^{-1} . Buyer j receives $x_j = \theta + \eta_j$, where $\eta_j \sim N(0, \tau^{-1})$ independently across buyers conditional on θ . The posterior mean and variance are

$$m_j = \frac{u^{-1}m_0 + \tau x_j}{u^{-1} + \tau}, \quad v = \frac{1}{u^{-1} + \tau}. \quad (18)$$

Conditional on θ , the only cross-buyer variation in m_j comes from η_j . Its mean is

$$\mathbb{E}_j[m_j \mid \theta, m_0] = m_0 + \tau v(\theta - m_0).$$

For a general home, changing public precision also changes this mean. The mean-neutral comparison in the main text sets $\theta = m_0$, so that changes in uncertainty affect willingness to pay through risk and disagreement rather than news about average value. The dispersion formula itself does not require this normalization:

$$\text{Var}_j(m_j \mid \theta, m_0) = \left(\frac{\tau}{u^{-1} + \tau} \right)^2 \frac{1}{\tau} = \tau v^2.$$

Integrating over different realized values of θ would add common-value variation. That integrated variance is not the disagreement measure used here. At fixed τ ,

$$v_u = \frac{1}{(1 + \tau u)^2} > 0, \quad d_u = \frac{2\tau u}{(1 + \tau u)^3} > 0.$$

Thus weaker public information increases both the uncertainty remaining for an individual buyer and the disagreement among buyers about the same home.

If buyers choose precision $\tau(u)$, the corresponding derivatives are

$$v_u = \frac{1 - u^2 \tau'(u)}{[1 + \tau(u)u]^2}, \quad \frac{d_u}{d} = \frac{2 + \epsilon[1 - \tau(u)u]}{u[1 + \tau(u)u]}, \quad \epsilon = \frac{u\tau'(u)}{\tau(u)}. \quad (19)$$

Buyers who acquire more precise information can offset the rise in perceived risk. For nonnegative ϵ , the condition $\epsilon < 1/[\tau(u)u]$ is sufficient for both derivatives to remain positive. This condition

limits how strongly buyers increase private precision when public information becomes less useful; convex acquisition costs alone do not establish it. The engagement coefficients in the paper are not estimates of this elasticity.

A.2 Buyer selection and sale prices

For $V = \mu + sZ$ and acceptance at $Z \geq z$, standard integration gives

$$\mathbb{E}[Z \mid Z \geq z] = m(z), \quad \mathbb{E}[Z^2 \mid Z \geq z] = 1 + z m(z).$$

Substitution into the linear bargaining rule yields equations (10) and (11). In particular, the price expression based on the mean valuation of all buyers, $(1 - \alpha)\mu + \alpha S$, omits the selection term $(1 - \alpha)s m(z)$ and is not the mean among accepted trades. This term captures the fact that only buyers with sufficiently high valuations trade. It matters when comparing homes with different dispersion or different seller reservation values.

The normal-tail identity

$$m'(z) = m(z)[m(z) - z]$$

is useful for comparative statics. It shows that the valuations of buyers who trade respond to the seller's threshold relative to the valuation distribution. A change in the mean valuation of all buyers is therefore insufficient to determine whether observed sale prices rise or fall when μ , s , and S all change.

The same point applies to variance. Define $h(z) = 1 + z m(z) - m(z)^2$, the conditional variance of Z . For a change in uncertainty u ,

$$\frac{d}{du} \text{Var}(P \mid \text{agreement}) = (1 - \alpha)^2 \{2ss_u h(z) + s^2 h'(z) z_u\}.$$

The first term captures the change in valuation dispersion; the second captures the change in which buyers trade. The sign of the expression depends on both terms. The empirical absolute deviation of a recorded price gap is a different measure from this model variance.

A.3 Optimal waiting

Write $L = \lambda(1 - \alpha)$ and let

$$H(z) = \mathbb{E}[(Z - z)_+] = \phi(z) - z[1 - \Phi(z)].$$

The reservation equation becomes

$$r\mu + c = s\{LH(z) - rz\}, \quad z = (S^* - \mu)/s. \quad (20)$$

Since $H'(z) = -q(z)$, its right-hand bracket is strictly decreasing in z when $r > 0$. The normal distribution and discounting give a unique stationary threshold in this specification.

At fixed μ , differentiating the original reservation equation with respect to s gives

$$(r + Lq) \frac{\partial S^*}{\partial s} = L\phi(z) > 0. \quad (21)$$

Alternatively, differentiating equation (20) gives

$$\frac{\partial z}{\partial s} = \frac{r\mu + c}{s^2(r + Lq)}. \quad (22)$$

If $r\mu + c > 0$, this derivative is positive. Therefore $q_s = -\phi(z)z_s < 0$ and, holding λ fixed,

$$\frac{\partial \mathbb{E}[T]}{\partial s} = -\frac{q_s}{\lambda q^2} > 0.$$

This proves Proposition 1. The condition is explicit because the normal model allows values on the entire real line; a positive mean value and a nonnegative carrying cost satisfy it.

For a mean shift, differentiating the reservation equation yields

$$(r + Lq) \frac{\partial S^*}{\partial \mu} = Lq,$$

which gives equation (14). A one-unit increase in the valuation mean raises the seller's reservation value by less than one, reducing the standardized threshold and increasing agreement per meeting. The converse holds for a negative mean shift. With $c > 0$ held fixed, q converges to a positive limit as r tends to zero. The reservation value then absorbs the mean shift, and its effect on expected selling time tends to zero. The last conclusion need not hold when $c = 0$, because the agreement probability can also approach zero.

Arrival rates affect seller selection as well. At fixed μ and s ,

$$\frac{\partial S^*}{\partial L} = \frac{sH(z)}{r + Lq} > 0.$$

A seller who meets buyers more frequently can afford to reject more offers. This response partly offsets the direct effect of a higher arrival rate on the rate of agreement λq . It illustrates why

differences in observed time on market cannot be attributed to buyer arrivals without accounting for seller behavior.

A.4 Reservation-price sensitivity

The absolute slope of the agreement probability with respect to the seller's reservation value is $B(s, z) = \phi(z)/s$. Holding z fixed gives $\partial \log B / \partial \log s = -1$. Holding the price gap $x = S - \mu$ fixed instead implies $z = x/s$ and

$$\left. \frac{\partial \log B}{\partial \log s} \right|_x = -1 + z^2.$$

The slope magnitude therefore falls for $|z| < 1$ and rises for $|z| > 1$, proving Proposition 2.

The probability of agreement by time H is $F_H(S) = 1 - \exp[-\lambda q(S)H]$, so

$$\frac{\partial F_H}{\partial S} = -\lambda H \exp[-\lambda q(S)H] \frac{\phi(z)}{s}. \quad (23)$$

Even if dispersion reduces the last factor, its effect on q changes the exponential factor. Dispersion therefore need not make the probability of sale within a fixed period less sensitive to price at every price level. If the posted asking price A affects the reservation and arrival rate, the derivative also contains S_A and λ_A . A cross-sectional coefficient on a recorded asking price need not estimate any one of these responses.

A.5 Time on market, online followers, and withdrawal

In the baseline, Poisson buyer meetings and an independent probability of agreement q give successful arrivals at rate λq , proving equation (9). For the viewing extension, let each potential-buyer encounter have independently and identically distributed saving, viewing, and purchase decisions under a stationary seller policy. Each buyer can save the listing and visit at most once, and purchase requires a visit. These decisions can be correlated within an encounter. The number of encounters through the first purchase has mean $1/q_E$. Summing the saving and viewing indicators through that purchase gives equation (17). It follows that

$$\frac{d \log \mathbb{E}[F]}{du} = \frac{a_u}{a} - \frac{q_{E,u}}{q_E}, \quad \frac{d \log \mathbb{E}[B]}{du} = -\frac{q_{B,u}}{q_B}.$$

A higher follower count alone does not establish greater interest per potential buyer: followers can accumulate because sale is less likely at each encounter. In contrast, fewer total viewings in this stationary extension require greater success per viewing. These identities include activity at the successful encounter and assume neither withdrawal nor censoring. The recorded counts

do not establish these assumptions, and their ratios cannot be interpreted as individual transition probabilities.

An independent withdrawal hazard δ can be added to the baseline model. The probability that agreement occurs before withdrawal is then

$$\mathbb{P}(\text{sale before exit}) = \frac{\lambda q}{\lambda q + \delta}.$$

This is a model implication for homes followed from listing onward. The archive does not observe whether all those homes ultimately sell or leave the market without selling, so δ remains a model parameter rather than an estimated withdrawal hazard. The expression distinguishes a delayed agreement from exit before an agreement occurs.

B Measurement and interpretation details

B.1 Sample boundaries and coefficient units

The samples used to study time on market, sale prices, and in-person viewings differ because of timing and variable availability. Each table reports its estimation sample. Comparisons across outcomes use the common sample where indicated. Coefficients from different samples do not describe how a single population adjusts across outcomes.

For a log outcome, the exact fitted percentage difference associated with a coefficient β on a full unit of rank is $100[\exp(\beta) - 1]$. The text uses the usual small-coefficient approximation when it is immaterial to interpretation. A coefficient on a count or a price-gap level is not a percentage change. Stars and standard errors follow the inference reported for each specification. Where standard errors are unavailable, they are not reconstructed from rounded t -statistics.

The rank compresses extreme residuals and is unchanged by a common positive rescaling of the residual square. It is not invariant to record-level estimation error or changes in sample composition. Removing observations can alter both the hedonic benchmark and the rank order. The trimming specifications re-rank observations after excluding the largest residuals, assessing sensitivity to extreme observations within the estimation sample.

B.2 Shared components in price and activity comparisons

The local peer measure excludes the focal home's squared residual, but this does not ensure statistical independence. Writing $\bar{U}_{ct}$ for the full-cell mean, its definition implies $U_{-i,ct} = (n_{ct}\bar{U}_{ct} - U_i)/(n_{ct} - 1)$. For a given realized cell, the peer measure varies inversely with the home's own squared residual. The residuals also share an estimated hedonic benchmark. Homes in the same

cell can therefore receive different peer measures. Moreover, a mean squared residual equals a centered residual variance plus the squared residual mean; additive community and month effects do not force that mean to zero in every community–month. These facts limit an interpretation of peer dispersion as independently varying valuation information.

The log showing-to-follower ratio is the difference between the two log counts. With identical samples and regressors, its coefficient is therefore the difference between their coefficients. Duration controls provide another description of those same counts, not a separate experiment on waiting. For prices, both the uncertainty rank and the asking-to-sale gap contain the asking price. Absolute gaps around a fixed-effect benchmark can change because of either mean shifts or dispersion. In the matched-transaction comparison, the later sale date enters both selling time and the interval used to annualize price changes. None of these shared components forces the headline duration and activity coefficients to have their reported signs, but they affect what the secondary comparisons can establish.

B.3 Price timing and date precision

The archive contains 586,312 transaction records. A parser recognizing full dates but not all month-only dates assigned 414,979 records to a matched-sale group and 171,333 to a residual group. The latter records also have published sale prices. Thus the resulting 71 percent indicator reflects date parsing and record selection rather than the fraction of offered homes that sell. The relative-price analysis uses a different indicator, D_i^R , which also requires the parsed sale date to fall within thirteen weeks of posting. Its zero category includes both transactions outside that window and transactions without sufficiently precise parsed dates. The archive-wide 71 percent is not the mean of D_i^R in the restricted estimation sample. Figure 2 describes associations with this combined timing and date-availability outcome, not the causal effect of asking prices on sale probability.

The source quintile comparison uses 82,400 observations, while the two-group coefficient table’s sample counts total 81,594. The sample difference cannot be resolved from the reported outputs. Figure 2 plots the two-group estimates in Table 8 and uses that table’s reported samples.

Posting dates before July 2016 can be assigned the transaction date retrospectively. Restricting the sample to later listings avoids that issue. Selection into records with usable day-level timing may nevertheless remain. Separately, the observation date of a recorded asking price is not consistently verified. An asking price recorded during negotiation can already incorporate buyer feedback and therefore is not predetermined with respect to accumulated engagement or concessions. These timing restrictions motivate interpreting the estimates as associations among observed transactions.

B.4 Precision when the uncertainty proxy is estimated

A pairs cluster bootstrap repeatedly draws communities and re-estimates both the hedonic model used to construct uncertainty and the subsequent price regression, using 200 iterations. For the reported coefficient -0.1259 , the analytic standard error is 0.0331 and the bootstrap standard error is 0.0564 . Unlike the additive community and month effects in the main benchmark, this first-stage specification uses community-by-month fixed effects. The specification interacts uncertainty with a post-December-2016 indicator; the coefficient is the pre-period slope. Its sample has 249,378 records with no more followers than page views.

This exercise shows that estimating the uncertainty proxy can affect the precision of the price coefficient. The time-on-market, showing, and relative-price specifications use the community-clustered inference reported in their tables; the bootstrap calculation applies only to the price specification above.

B.5 Aggregate predictive comparison

The comparison with transaction-based uncertainty uses a short 2015–2019 citywide time series and overlapping return horizons. The transaction measure averages neighborhood–month standard deviations of sale-price residuals, weighted by transaction counts and requiring at least five transactions per cell. The asking-price measure is the monthly mean of individual squared asking-price residuals. The six-month comparison uses 54 observations and Newey–West standard errors with eight lags. The reported R^2 values describe in-sample fit, not out-of-sample forecasting performance or an expected-return premium. Community-level comovement and concurrent matched-pair price gaps provide complementary descriptive comparisons. Shared coverage, composition, and estimated benchmarks can affect both series. Neither comparison separates unobserved quality from differences in sellers’ assessments.