

Platform Search and Housing Market Microstructure: Evidence from Odd Pricing*

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ABSTRACT

Price filters on digital platforms can shape search in decentralized asset markets by determining which buyers encounter which assets. Using more than two million North American housing listings, we show that homes priced just below salient round-number thresholds are less likely to sell, transact at lower prices, and remain on the market longer than adjacent round-priced homes. These discontinuities are significantly larger at thresholds embedded in realtor.com search menus. Linked buyer-survey evidence shows weaker bidder competition and lower-budget buyers at odd-priced listings. The results show how platform search design affects market exposure, liquidity, and price formation.

JEL Codes: D47, D83, D91, G41, L85, R21.

In decentralized asset markets, search design shapes not only the terms on which trade occurs, but also which counterparties meet in the first place. Housing provides a particularly useful setting in which to study this margin. Residential real estate is a trillion-dollar asset market, yet homes are heterogeneous and illiquid, trade is decentralized, and buyers must search across properties before bargaining can begin. Increasingly, digital platforms mediate this search by organizing listings around searchable attributes, particularly asking prices. By structuring price-based search through filters and thresholds, platform design can determine which buyers encounter which properties and thereby affect market exposure, liquidity, and transaction outcomes.

We study this interaction between asking prices and platform search design through a ubiquitous pricing practice: listing a property just below a salient round number—for example, \$499,900 rather than \$500,000. The two prices are economically nearly identical, yet they may occupy different positions in buyers’ search sets when platforms organize search around round-number price thresholds. Odd pricing therefore provides a natural setting for studying whether small differences in asking prices can generate discontinuous differences in market exposure and, ultimately, transaction outcomes.

Why should such a small nominal difference matter? In consumer markets, just-below prices such as \$1.99 or \$10.98 are commonly rationalized by “left-digit bias”: buyers process prices from left to right, placing disproportionate weight on leading digits (Schindler and Wiman 1989; Stiving and Winer 1997; Thomas and Morwitz 2005). A just-below price can therefore appear disproportionately cheaper and increase demand (List et al. 2023; Strulov-Shlain 2023). Numerical reference points also matter in financial markets. Bhattacharya, Holden, and Jacobsen (2012) document excess trading around round-number stock prices, while Heraud and Page (2024) find discontinuities in option values around round numbers consistent with left-digit bias. Thus, numerical salience can affect behavior even in sophisticated, high-stakes markets.

Housing, however, introduces a distinct force. Buyers do not evaluate every available property and then respond to its price; they first screen a large set of listings to form a much smaller consideration set. Digital platforms increasingly mediate this screening process through price filters organized around round-number thresholds. A home listed at \$499,900 may appear cheaper than one listed at \$500,000, yet it may also be excluded from searches beginning at \$500,000. Odd pricing can therefore create two opposing effects in housing: a perceptual advantage from appearing cheaper and a loss of market exposure from falling outside some buyers’ search sets. Which force dominates is therefore an empirical question.

This tension makes the prevalence of odd pricing especially striking. Across roughly two million listings from four major U.S. markets — Chicago, Minneapolis, San Diego, and Seattle — as well as Toronto, asking prices bunch systematically just below salient round-number thresholds throughout the price distribution. In the U.S. data, odd prices account for 51.5% of listings versus 7.2% for round prices in 2008–2009, and 46.0% versus 11.3% in 2016–2018, while listings just above round numbers account for less than 0.5%, as shown in Figure 1. Thus, sellers overwhelmingly choose the side of the threshold that may increase perceived affordability but reduce exposure to some buyers—a particularly consequential choice in a market for heterogeneous, six-figure assets traded through search, negotiation, and professional intermediation.

Despite its prevalence—and contrary to the conventional left-digit bias—odd pricing performs worse in the housing market. Comparing observationally similar properties whose list prices differ by as little as \$1,000 around the same round-number threshold - for example, \$499,000 versus \$500,000 - we find that odd-priced homes are approximately 4 percentage points less likely to sell and, conditional on selling, transact for about 0.7% less and remain on the market roughly 7 days longer. The effects are consistent across cities, time periods, and price thresholds, and persist even for properties listed only \$1 below

the adjacent round number. A nearly costless difference in pricing format is therefore associated with economically substantial differences in both asset liquidity and transaction prices.

Our empirical design is deliberately local, comparing odd- and round-priced properties within narrow price neighborhoods around the same threshold. The specifications condition on detailed property characteristics, local market conditions, listing-agent experience and prior performance, and high-dimensional fixed effects, including threshold $\times$ year $\times$ county, postal code $\times$ year, and agent fixed effects. Agent fixed effects absorb persistent differences across agents in pricing styles and performance, while narrow price windows and rich property controls make properties increasingly comparable as their asking prices approach the same threshold.

A series of complementary exercises further narrows the scope for selection on unobservables. Transaction outcomes vary smoothly with list price away from salient round numbers but shift discretely at the thresholds; moreover, the discontinuity is similar whether an odd-priced listing lies \$1,000 or only \$1 below the round number. This pattern points to pricing format, rather than price level itself, as the relevant margin and is difficult to reconcile with smoothly varying unobserved property quality. Adding text-based measures from listing descriptions that capture verifiable quality, subjective quality claims, and seller urgency leaves the estimates essentially unchanged. Finally, sensitivity analyses following Cinelli and Hazlett (2019) and Chernozhukov et al. (2023) imply that an omitted confounder would need substantially greater explanatory power than the observed covariates all combined to eliminate the estimated differences. Taken together, these exercises substantially narrow the scope for property-, seller-, and agent-selection explanations for the joint patterns we document.

The evidence instead supports the search mechanism suggested above. Buyers commonly screen housing listings using price ranges, and digital platforms facilitate this

behavior through menus organized around round numbers. These filters discretize an otherwise continuous price space. An odd-priced property immediately below a round-number threshold can therefore be excluded from searches using that threshold as a lower bound, while an otherwise similar property listed at the threshold remains visible. Two assets differing negligibly in asking price can consequently be exposed to different pools of potential counterparties simply because they fall on opposite sides of an interface-defined search boundary.

Our empirical tests become progressively sharper in distinguishing this platform-search mechanism from generic numerical salience. We first show that the odd-round discontinuity varies systematically with threshold salience: the adverse effects of odd pricing are largest around \$100,000 multiples and generally smaller at less salient thresholds. Salience alone, however, cannot distinguish a psychological response to round numbers from a mechanism operating through platform-mediated search. We therefore exploit variation across cities and over time in the round-number price thresholds explicitly featured in realtor.com’s search menus. The odd-pricing disadvantage becomes significantly larger at these platform-suggested thresholds, including a larger transaction-price discount and roughly twice the days-on-market penalty. This provides direct evidence that digital search architecture contributes to the odd-round discontinuity.

Buyer-level evidence provides a complementary view of the mechanism. Using the Genesove and Han (2016) survey of Toronto home buyers linked to our MLS transactions, we show that reported housing budgets bunch sharply at multiples of \$50,000 and \$100,000—the same round numbers commonly used to organize housing search. Round-priced properties also face greater bidder competition and are purchased by buyers with higher reported initial budgets. Taken together, the progression from threshold salience, to platform-specific boundaries, to bidder competition and composition points to pricing-filter-mediated segmentation of the pool of potential counterparties as an important

channel.

The prevalence of odd pricing despite its underperformance raises a natural question: why does odd pricing persist? One possibility is that sellers and agents extrapolate from the widespread use of just-below pricing in consumer markets, where the strategy can increase demand. Another is that learning is difficult in housing: transactions are infrequent, properties are heterogeneous, and realized outcomes provide noisy feedback about the counterfactual performance of a different list price. Signaling, local pricing conventions, and agency frictions may also contribute. We do not aim to distinguish among these explanations for our main mechanism. Our evidence instead shows that, whatever motivates its use, odd pricing can interact with platform search architecture in ways that reduce listing exposure, bidder competition, and liquidity.

This paper contributes to the finance literature on market microstructure and search in decentralized asset markets. A central insight of this literature is that liquidity and asset prices depend not only on fundamentals and bargaining, but also on the mechanisms through which counterparties meet (O’Hara [1995](#); Duffie, Garleanu, and Pedersen [2005](#)). Housing makes this matching margin especially transparent: assets are heterogeneous and illiquid, trade is decentralized, and buyers must search before bargaining can begin (Han and Strange [2015](#)). Han and Strange ([2016](#)) establish a directing role for the asking price: although it is neither a conventional posted price nor a binding price ceiling, it steers buyer search and affects bidder competition. Relatedly, Piazzesi, Schneider, and Stroebl ([2020](#)) show that housing search is segmented across heterogeneous buyer consideration sets, including price ranges defined by lower and upper bounds. We build on these insights by showing that digital search technology can make this directing role discontinuous. When an interface embeds round-number boundaries into search, nearly identical assets can face different pools of potential counterparties. Pricing design thus becomes an economically consequential component of the matching technology, affecting

market participation, bidder competition, liquidity, and price formation.

Our paper also contributes to the literature on pricing formats in housing and other decentralized markets. Existing work identifies several channels through which pricing format can affect outcomes, including numerical salience and buyer attention (Allen and Dare 2004; Repetto and Solís 2020), focal-point negotiation (Pope, Pope, and Sydnor 2015), and signaling and bargaining (Backus, Blake, and Tadelis 2018). Our contribution is distinct in both the empirical comparison and the economic margin we study. Rather than comparing broad pricing categories, we estimate the local discontinuity between listings immediately below a salient round-number threshold and listings at that threshold.¹ More fundamentally, we study a margin that precedes attention, inference, and bargaining conditional on engagement: whether the asset enters a buyer’s consideration set at all. In the Swedish auction market studied by Repetto and Solís (2020), just-below pricing increases attention and bidder entry; in our setting, a platform-defined lower search bound can instead exclude a just-below listing from some buyers’ searches. Likewise, signaling and bargaining mechanisms emphasized by Mateen et al. (2026) can operate among buyers who encounter a listing, whereas platform design helps determine who encounters it in the first place. The effect of pricing format therefore depends fundamentally on the market architecture through which buyers and sellers meet. Section 6 develops these distinctions in greater detail across pricing definitions, empirical designs, institutional settings, and mechanisms.

Finally, this paper contributes to the broader literature on numerical salience and behavioral pricing, which documents price clustering and left-digit effects in consumer and financial markets (Stiving and Winer 1997; Anderson and Renault 2006; Bhattacharya, Holden, and Jacobsen 2012; Heraud and Page 2024). Numerical salience helps explain why round numbers become natural focal points. Our results identify a distinct amplification

¹As detailed in Section 6, our odd-price interval also cuts across several of the pricing categories studied by Mateen et al. (2026), so the two papers do not estimate the same pricing contrast.

mechanism: digital market design can embed these focal points in the search technology itself. A salient nominal number thereby becomes an institutional boundary, converting an economically trivial difference in asking prices into a discontinuous difference in asset-market exposure, liquidity, and price formation

The rest of this paper is organized as follows. In Section 1, we present a conceptual framework for how odd pricing can interact with online platform design to affect buyer consideration sets and transaction outcomes. Section 2 describes our data, and Section 3 estimates the relationship between odd pricing and sales outcomes in four U.S. cities and Toronto.² Section 4 presents evidence on the platform-search mechanism. Section 5 examines the robustness of these results to property-, seller-, and agent-selection explanations and uses formal sensitivity analysis to bound the potential bias from omitted variables. Section 6 compares our setting and mechanism with closely related work on pricing formats. Section 7 concludes. All prices are in U.S. dollars unless noted otherwise; supplementary tables and figures appear in the Internet Appendix.

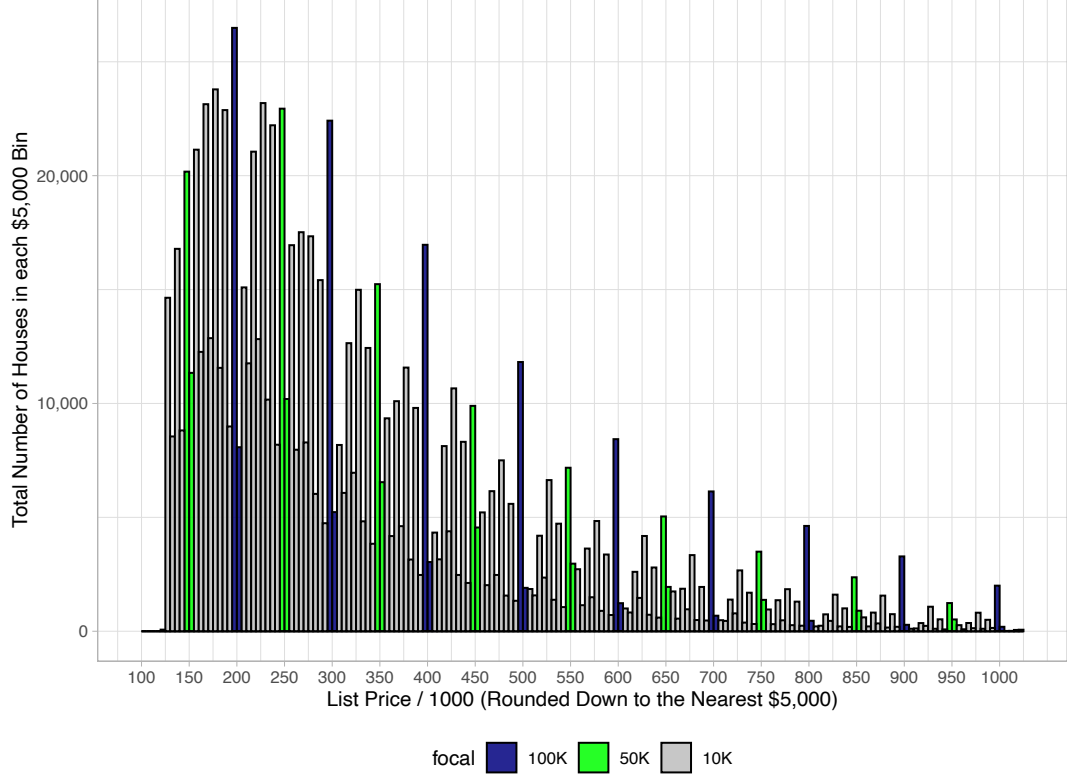
1. Conceptual Framework

We model housing transactions as a multi-stage search process in which buyers first screen listings, then evaluate a subset, and finally visit and bid on selected properties. The key feature of the environment is that the initial screening stage is increasingly mediated by digital platforms. Platform search rules can therefore affect market outcomes by determining which buyers encounter which properties.

Search Environment Houses differ in “search” attributes (e.g., list price, location, number of bedrooms) that can be observed on an online platform, and “experience” attributes (e.g., curb appeal, layout, construction quality) that are revealed only by

²For Toronto, we present the baseline results in Section 3, while relegating supplementary results to the Internet Appendix.

Figure 1: Histogram of list prices in our U.S. data



The figure shows a histogram of U.S. list prices, plotting the total number of houses in each \$5,000 price bin (y-axis) against list prices from roughly \$124,999 to \$1,024,999 (x-axis). Bars are paired around round-number thresholds (multiples of \$10K, \$50K, and \$100K), with the left bar representing prices just below the threshold and the right bar representing prices exactly at or just above it. Across the distribution, the bars just below are consistently taller.

personal inspection. Because visiting is costly, buyers must screen listings before proceeding to in-person evaluation. This leads naturally to a three-stage search process: (i) filtering listings on various search attributes to form a consideration set, (ii) examining the search attributes of houses in the consideration set to make a shortlist, and (iii) visiting shortlisted houses to examine their experience attributes (Badarinza, Balasubramaniam, and Ramadorai 2023).

The first stage is critical. Buyers do not search all listings, but instead construct a consideration set based on searchable characteristics, most importantly list price.

Price-Based Screening Let a buyer's utility from purchasing a property be

$$U = V(q) - p$$

where $V(q)$ denotes reservation value for a house of quality q , and p is transaction price; we expect $V(\cdot)$ to be an increasing function. Buyers do not observe q or p prior to visiting, but form expectations based on the list price p^ℓ . Let

$$\hat{V}(p^\ell) = E[V(q)|p^\ell] \quad \hat{p}(p^\ell) = E[p|p^\ell]$$

denote expected reservation value and expected transaction price, both increasing in p^ℓ . List price thus serves as an informative signal for expected quality and transaction price during the screening stage.

A property enters the buyer's consideration set only if

$$\hat{V}(p^\ell) - \hat{p}(p^\ell) \geq 0.$$

Under standard conditions, this implies the existence of a $\underline{p}^\ell$ and a $\bar{p}^\ell$ such that

$$p^\ell \in [\underline{p}^\ell, \bar{p}^\ell]$$

defines lower and upper bounds on the list price for consideration. The lower bound reflects a minimum quality threshold; the upper bound reflects affordability considerations (Cubbin 1974; Andersen et al. 2022). Since we require $\hat{p}(\bar{p}^\ell) \leq B$, where B is the buyer's budget constraint, the buyer's consideration set is $\mathcal{S} = \{j : \underline{p}^\ell \leq p_j^\ell \leq \min\{\bar{p}^\ell, \hat{p}^{-1}(B)\}\}$.

Platform-Mediated Discretization In principle, buyers’ preferred price ranges could vary continuously. In practice, numerical salience and platform design encourage search around round-number thresholds. Buyers frequently express budgets and price ranges in round numbers, and major real-estate platforms facilitate this behavior by organizing minimum- and maximum-price searches around discrete, round-number options. A large literature documents the human tendency to use round numbers in a variety of contexts (Lynn, Flynn, and Helion 2013; Kuo, Lin, and Zhao 2015; Zinn and Würbach 2016; Argyle, Nadauld, and Palmer 2020). In real estate, Piazzesi, Schneider, and Stroebel 2020 present evidence of buyers screening properties using round-numbered lower and upper price bounds; our own survey of Toronto buyers—discussed later—shows self-reported budgets clustering at multiples of \$50,000 and \$100,000 (see Figure 2). Major real estate platforms, such as [realtor.com](https://www.realtor.com), [Redfin](https://www.redfin.com) and [Zillow](https://www.zillow.com), facilitate this tendency by providing convenient drop-down menus of round-numbered minimum and maximum price filters.

Screening thus partitions the price space into discrete intervals defined by round-number thresholds. A listing is considered if and only if its price falls within one of these intervals. This discretization introduces discontinuities: small differences in list prices around round-number thresholds can determine whether a property is searched or not.

Odd versus Round Pricing Consider two otherwise identical properties, j and j' , with list prices p_j^ℓ and $p_j^\ell - \epsilon$, where p_j^ℓ is a round number and $\epsilon > 0$ is small. Let a buyer’s screening interval be $[\underline{p}^\ell, \bar{p}^\ell]$, where both $\underline{p}^\ell$ and $\bar{p}^\ell$ are round numbers.³ Conditional on $\bar{p}^\ell \geq p_j^\ell$, three cases arise:

- If $\underline{p}^\ell > p_j^\ell$, then neither j nor j' is considered.
- If $\underline{p}^\ell = p_j^\ell$, then j is considered, but j' is not.

³We assume that ϵ is smaller than the minimum spacing between admissible round-number search bounds. Hence, no admissible upper bound can lie in $[p_j^\ell - \epsilon, p_j^\ell)$. If $\bar{p}^\ell < p_j^\ell$, it must therefore also lie below $p_j^\ell - \epsilon$, in which case neither property is considered.

- If $\underline{p}^\ell < p_j^\ell$, then both j and j' are considered.

Thus, whenever an odd-priced property is considered, so is its round-priced counterpart, but not necessarily vice versa. The set of buyers considering the odd-priced property is therefore a subset of those considering the round-priced property, and is strictly smaller whenever a positive mass of buyers uses the round number as a lower search bound:

$$\left\{i : \underline{p}^{\ell i} \leq p_j^\ell - \epsilon \leq \bar{p}^{\ell i}\right\} \subset \left\{i : \underline{p}^{\ell i} \leq p_j^\ell \leq \bar{p}^{\ell i}\right\}.$$

Implications. The framework yields three related empirical implications. First, listings immediately at a salient round-number lower bound should be exposed to a larger pool of potential buyers than otherwise similar listings immediately below it. A larger exposed buyer pool can in turn generate greater bidder competition and improve liquidity and transaction outcomes.

Second, the composition of buyers may differ across the boundary, with round-priced listings reaching buyers searching over higher price ranges. If buyers choosing higher lower bounds also tend to search over higher overall price ranges, the additional buyers exposed to a round-priced property will tend to have higher budgets.

Third, and most directly, the odd-round discontinuity should be especially pronounced where round-number thresholds are particularly salient in the search environment. Generic numerical salience predicts stronger effects at more salient round numbers. The platform-search mechanism makes the sharper prediction that the discontinuity should be especially large at thresholds explicitly embedded in platform search menus.

2. Data

We combine three sources of information on the housing search and transaction process. First, Multiple Listing Service (MLS) data from four U.S. metropolitan areas and Toronto

provide list prices, property and agent characteristics, and transaction outcomes.⁴ Second, a survey of Toronto home buyers provides buyer-level information on budgets and bidder competition that can be linked to the properties they purchased. Third, archived realtor.com interfaces allow us to recover the round-number price thresholds explicitly suggested to buyers by the platform across markets and over time. Together, these data allow us to examine transaction outcomes, buyer composition and competition, and, most directly, whether the odd-round discontinuity is systematically related to the search boundaries embedded in a digital platform.

2.1. U.S. MLS Data

We focus on 2,418,955 listings of single-family homes from 2008-2018 Cotality MLS data, of which 1,688,690 sold (69.81%) and 730,265 did not (30.19%). From these we retain only original listings that: (a) are listed between \$124,999 and \$1,024,999 (2,195,040 observations or 90.74%), (b) are not real estate-owned (REO) sales or short sales (1,930,797 observations or 87.96% of (a)), and (c) contain non-missing agent name, location, house attributes, and lot-size information (1,403,602 observations or 72.70% of (b)).⁵ This leaves us with 1,403,602 listings, 953,759 sold (67.95% of sample) and 449,843 unsold (32.05% of sample).⁶

Table 1 describes these data. Panel A shows that the U.S. housing market improved from 2008 to 2018: average home price increased from \$278,111 to \$342,357 (23%); sale to list price ratio rose from 0.97 to 0.99; days on the market fell from 17 to 11 weeks; and probability of selling within a week of listing went up from 0.02 to 0.11.

⁴MLS data only include publicly-listed properties sold through agents; private and for-sale-by-owner transactions are excluded. Buying and selling processes are broadly the same in the U.S. and Canada.

⁵Of the 1,930,797 observations in (b), 1,896,629 (98.23%) have complete location, house attributes, and lot-size information. Conditioning on non-missing agent information removes an additional 493,027 observations (25.99%), mainly due to the absence of agent information in the Seattle listings.

⁶We classify a listing as sold if its standardized MLS status is “Closed Sale.” All other retained listings are classified as unsold, including expired, terminated, withdrawn, cancelled, and related non-sale statuses. We exclude leased, coming-soon, missing, and unclassified listings from the sample.

Table 1: Summary statistics (U.S. MLS data)

Listing year:	2008-2009 (N=141929)		2010-2012 (N=229152)		2013-2015 (N=445101)		2016-2018 (N=587420)	
Characteristic	Mean	SD	Mean	SD	Mean	SD	Mean	SD
A: Transaction outcomes								
Sales ratio	0.966	0.046	0.964	0.045	0.977	0.037	0.986	0.036
Days on market	118.773	96.525	112.958	104.210	92.339	91.814	75.208	92.029
Quick sale	0.024	0.152	0.031	0.175	0.047	0.211	0.109	0.312
Sales price/1000	278.111	146.743	311.479	171.153	330.490	177.773	342.357	177.749
Probability of Sale	0.527	0.499	0.700	0.458	0.699	0.459	0.693	0.461
B: Listing characteristics								
List Price/1000	298.465	160.997	320.670	175.802	345.090	184.783	367.330	190.511
Round (%)	7.164	25.789	8.293	27.577	9.099	28.759	11.322	31.686
Odd (%)	51.537	49.977	50.953	49.991	48.906	49.988	45.952	49.836
Just above (%)	0.448	6.679	0.463	6.786	0.379	6.147	0.341	5.832
C: House characteristics								
Number of bedrooms	3.277	0.945	3.370	0.936	3.354	0.941	3.330	0.949
Number of washrooms	2.485	0.918	2.595	0.932	2.632	0.947	2.624	0.961
Living area square footage	2110.582	865.265	2147.838	885.572	2113.098	886.091	2079.997	903.202
Lotsize	26408.359	69126.982	27835.523	69704.742	27895.300	68775.559	26696.634	66053.715
Number of fireplaces	0.771	0.801	0.792	0.868	0.727	0.787	0.681	0.728
Number of parking space	0.053	0.435	0.342	1.074	0.502	1.272	0.617	1.400
Gas heat source	0.927	0.260	0.889	0.315	0.880	0.325	0.888	0.316
Forced air	0.021	0.142	0.072	0.258	0.055	0.229	0.066	0.248
D: Agent characteristics								
Average sales ratio	0.980	0.020	0.975	0.021	0.974	0.023	0.975	0.023
Average days on market	74.062	40.876	82.823	44.837	85.309	42.923	82.471	42.325
Number of homes sold	102.679	144.090	83.393	126.168	72.698	118.407	63.072	112.993

Round prices are defined as \$100K, \$50K, and \$10K multiples, and “odd/just above” as prices in \$1K intervals, below/above adjacent round prices. Sales ratio is sale price/list price, and “quick sale” refers to the probability of selling within a week of listing. Some extreme values of sales ratio, days on the market, living area square footage and lot size have been winsorized at the 1 and 99 percentiles; none of our analyses is sensitive to this adjustment.

Panels C and D show that house and agent characteristics were relatively stable, with the exception of agent experience—the average agent selling 40 fewer homes in 2016–2018 than in 2008–2009.

Panel B describes list prices. Consistent with the histogram in Figure 1, odd prices are substantially more common than round prices, ranging from 51.54% versus 7.16% in the 2008–2009 period to 45.95% versus 11.32% in the 2016–2018 period. On the other hand, listing just above a round number is relatively rare.

2.2. Toronto MLS Data

These data cover sales transactions in the Greater Toronto Area (GTA) from January 1, 2000 to November 30, 2018.⁷ Years prior to 2007 do not contain information on housing characteristics, so we focus on the 2007–2018 period, comprising 1,197,837 listings. From these observations, we retain only transactions that: (a) are coded as housing type “semi detached” or “single family house” (733,318 observations), (b) are listed between \$124,999 and \$1,249,999 (677,777 observations), (c) contain non-missing list price, sale price, days on the market, and agent name (677,426 observations), and (d) contain a valid forward sortation area (“district”) (673,231 observations). Our estimation sample further requires non-missing values for all housing and agent controls listed in Appendix A; the 49,606 listings lost here have missing lot dimensions or are an agent’s first observed sale, for which lagged agent characteristics are undefined. This leaves us with 623,625 listings, which is the sample used in Table 2 and in all Toronto regressions, figures, and survey comparisons.

⁷Unlike the U.S. data, these data don’t have unsold listings.

Table 2: Summary statistics (Toronto MLS data)

Listing year:	2007-2009 (N=151,831)		2010-2012 (N=155,830)		2013-2015 (N=169,190)		2016-2018 (N=146,774)	
Characteristic	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
A: Transaction outcomes								
Sales ratio	0.98	0.040	0.99	0.043	1.00	0.052	1.03	0.078
Days on market	30.86	30.391	25.24	27.619	22.84	26.567	18.21	22.285
Quick sale	0.18	0.386	0.26	0.437	0.30	0.456	0.40	0.489
Sales price/1000	417.09	174.559	488.56	199.508	579.00	224.036	730.33	247.107
B: List price characteristics								
List Price/1000	424.54	176.318	493.52	199.159	579.18	219.523	708.43	226.988
Round (%)	2.65	16.047	3.47	18.311	4.75	21.261	7.23	25.901
Odd (%)	64.10	47.971	65.95	47.389	65.96	47.386	66.57	47.176
Just above (%)	0.12	3.460	0.12	3.481	0.11	3.269	0.11	3.331
C: House characteristics								
Number of bedrooms	3.36	0.746	3.36	0.745	3.35	0.736	3.29	0.730
Number of rooms	7.26	1.608	7.39	1.704	7.48	1.789	7.46	1.849
Number of washrooms	2.82	0.986	2.88	0.995	2.91	1.004	2.85	0.993
Lotsize	7399.55	16141.421	8270.33	18656.213	8653.59	19264.649	8481.05	18404.645
Fireplace	0.64	0.479	0.65	0.477	0.65	0.478	0.56	0.497
Semi-detached	0.20	0.402	0.19	0.393	0.18	0.382	0.18	0.383
Finished Basement	0.67	0.470	0.67	0.469	0.68	0.467	0.45	0.497
Family room	0.53	0.499	0.55	0.497	0.57	0.495	0.51	0.500
Driveway	0.30	0.457	0.88	0.330	0.88	0.326	0.59	0.492
Gas heat source	0.93	0.254	0.93	0.258	0.93	0.260	0.84	0.368
Forced air	0.93	0.255	0.93	0.248	0.94	0.237	0.86	0.351
D: Agent characteristics								
Average sales ratio	0.98	0.013	0.98	0.014	0.98	0.015	0.99	0.019
Average days on market	31.98	10.552	30.83	11.108	29.59	11.475	27.52	11.725
Number of homes sold	180.82	283.995	178.14	300.570	199.11	378.846	168.07	344.389

Round prices are defined as \$100K, \$50K, and \$10K multiples, and “odd/just above” as prices in \$1K intervals, below/above adjacent round prices. Sales ratio is sale price/list price, and “quick sale” refers to the probability of selling within a week of listing. Some extreme values of sales ratio, days on the market, and lot size have been winsorized at the 1 and 99 percentiles. All prices are in Canadian dollars (CAD).

The data are summarized in Table 2. Panel A shows that the Toronto real-estate market also improved substantially during our sample period. Average home price rose from \$417,000 to \$730,000 (75%), sales ratio increased from 0.98 to 1.03, and time on the market fell from 31 to 18 days. Panel C shows relatively stable house characteristics, and panel D shows that agents’ average sales ratios and days on market moved with the market while their number of prior homes sold changed little. Finally, Panel B shows listing at odd prices is a common and increasingly popular strategy in Toronto, just as in the U.S. data, rising from 64.10% of listings in 2007–2009 to 66.57% in 2016–2018. By contrast, listing just above a round number occurs rarely.

2.3. Survey of Buyers in Toronto

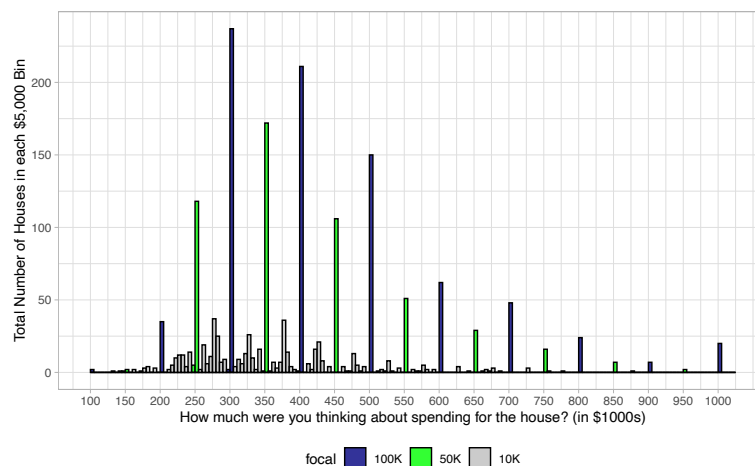
The Toronto MLS records can be linked to a survey of home buyers conducted by Genesove and Han (2016) and used previously by Han and Strange (2016). The survey asked recent buyers about their search and purchase process, including how much they had initially been thinking about spending and whether other buyers were actively bidding on the property when they submitted their first offer.

The underlying survey drew 18,789 single-family transactions from the Toronto MLS during 2006–2009. After excluding institutional and land purchases and accounting for undeliverable surveys, 3,193 buyers completed the survey, for an overall response rate of 19.2%. The purchased properties can be matched back to the MLS records, allowing us to relate buyer-level search and bidding information to the seller’s listing-price format. Table A.3 shows that, compared to the MLS data, the survey sample had slightly higher list and sales prices, and about a 10% lower days on the market; house attributes were remarkably similar.

Three particularly relevant questions in the survey are: “How much were you thinking about spending for the house?” “Were there other people actively bidding on the home

when you submitted your first offer?” and “If yes, about how many other bidders were there?” Figure 2 plots reported initial budgets. The distribution exhibits pronounced bunching at multiples of \$50,000 and \$100,000, consistent with buyers organizing housing search around salient round-number price ranges. The survey also reports the number of competing bidders faced by each respondent. Table A.4 (in the Appendix), shows that just over two-thirds of buyers report only one bidder, while about one-sixth report two bidders, and slightly less than half as many report three bidders. Notably, about nine percent of buyers report more than three bidders.

Figure 2: Histogram of self-reported buyer budget in the Toronto sample



The figure shows a histogram of reported home-buying budgets from the Toronto survey, with the number of respondents on the y-axis and reported budget (in CAD) on the x-axis. Most reported budgets fall on or near these round prices, especially multiples of \$100,000 and \$50,000. The average reported budget is approximately \$412,302 CAD.

2.4. Platform Search Interface Data

To connect the odd-round discontinuity directly to platform search architecture, we collect archived realtor.com search interfaces using snapshots from the Wayback Machine. The platform presents users with discrete round-number price options for screening listings.

Importantly for identification, the particular thresholds offered by the platform vary across metropolitan areas and over time.

For each available city–year, we recover the round-number thresholds appearing in the platform’s price menus and match these thresholds to our MLS listings. This creates variation between round-number thresholds that are explicitly featured by the platform and otherwise comparable round numbers that are not. Because many round numbers are salient even in the absence of a particular platform menu, this distinction allows us to separate generic round-number salience from the incremental relationship associated with a threshold embedded in platform search architecture, as shown in Section 4.1.

3. Odd Pricing and Sales Outcomes

We start by comparing odd-priced and adjacent round-priced properties on sales outcomes, house attributes, and agent characteristics. The first four columns of Table 3 display the means and standard deviations of these quantities in the U.S. data by list-price type, and the last two columns show the differences between those means and the associated t -statistic.

Panel A shows statistically significant differences in sales outcomes, with odd-priced houses showing a lower probability of sale, lower sales ratio, more days on the market, and a lower probability of a quick sale than houses listed at the adjacent round number, previewing our regression results to follow. Since these homes are all priced within \$1K of the same \$100K, \$50K, or \$10K multiple, one might expect them to be fairly similar in house attributes, and Panel B bears this out—for the most part. On some house characteristics there are statistically significant differences; when there are such differences, it is notable that, in general, they favor odd-priced houses. For example, odd-priced houses have more bedrooms, more washrooms, and more square footage than their round-priced counterparts. Finally, Panel C compares selling agent characteristics.

Table 3: Odd- versus round-priced properties near \$100K, \$50K and \$10K listing thresholds (U.S. data)

Characteristic	Odd (N=677519)		Round (N=141565)		Difference	
	Mean	SD	Mean	SD	Mean	<i>t</i> -statistic
A: Transaction outcomes						
Sales ratio	0.975	0.040	0.981	0.043	0.006	37.752
Days on market	92.159	95.431	87.472	99.195	-4.687	-16.273
Quick sale	0.060	0.237	0.094	0.291	0.034	41.246
Sales price/1000	337.908	178.598	352.848	181.106	14.941	23.856
Probability of Sale	0.671	0.470	0.719	0.450	0.048	36.413
B: House characteristics						
Number of bedrooms	3.385	0.937	3.338	0.983	-0.046	-16.278
Number of washrooms	2.645	0.959	2.619	0.973	-0.026	-9.182
Living area square footage	2153.080	906.731	2114.391	931.234	-38.689	-14.281
Lotsize	28259.063	69525.912	31280.964	75903.610	3021.901	9.982
Number of fireplaces	0.755	0.787	0.734	0.802	-0.021	-8.976
Number of parking space	0.485	1.270	0.655	1.421	0.171	41.860
Gas heat source	0.892	0.311	0.853	0.354	-0.039	-38.126
Forced air	0.060	0.237	0.078	0.267	0.018	23.011
C: Agent characteristics						
Average sales ratio	0.975	0.022	0.976	0.023	0.001	6.029
Average days on market	82.000	43.503	82.158	45.478	0.157	0.366
Number of homes sold	75.009	122.180	64.207	112.731	-10.802	-3.628

Sample consists of all properties listed within \$1K of a \$100K, \$50K, or \$10K threshold. “Odd” refers to homes listed in the interval $[z - 1K, z)$ and “Round” refers to homes listed in the interval $[z, z + 1K)$, where z is a \$100K, \$50K, or \$10K multiple. Sales ratio is sale price/list price, and “quick sale” refers to the probability of selling within a week of listing. The *t*-statistic tests the Odd–Round difference using heteroskedasticity-robust standard errors (agent characteristics: clustered by agent).

Agent quality, proxied by sales ratio and average days on the market (of properties sold before current listing) are economically similar across odd- and round-priced listings. Agent experience, proxied by number of homes sold before the current listing, is modestly lower for round-priced listings.

Table 4 repeats the comparison for Toronto. The sales-outcome differences in Panel A mirror the U.S. pattern: odd-priced houses have a lower sales ratio, more days on the market, and a lower probability of a quick sale. The house-characteristic differences in Panel B are again small, but in Toronto they run the other way—round-priced houses have slightly more bedrooms, rooms, and washrooms and larger lots, while odd-priced houses

are more often semi-detached. That the direction of these differences is not consistent across markets, while the outcome differences are, is one reason we control for house characteristics in the regressions that follow. Agent characteristics in Panel C are similar across the two groups.

Table 4: Odd- versus round-priced properties near \$100K, \$50K and \$10K listing thresholds (Toronto data)

Characteristic	Odd (N=409,384)		Round (N=28,787)		Difference	
	Mean	S.D.	Mean	S.D.	Mean	<i>t</i> -statistic
A: Transaction outcomes						
Sales ratio	1.00	0.059	1.01	0.070	0.008	18.11
Days on market	23.71	26.889	23.36	28.219	-0.357	-2.08
Quick sale	0.29	0.455	0.33	0.470	0.036	12.76
B: House characteristics						
Number of bedrooms	3.34	0.745	3.40	0.818	0.065	13.06
Number of rooms	7.39	1.746	7.58	1.938	0.194	16.53
Number of washrooms	2.85	0.997	2.93	1.073	0.081	12.38
Lotsize	8226.87	18250.649	10172.80	22921.091	1945.932	14.09
Fireplace	0.63	0.483	0.64	0.481	0.007	2.32
Semi-detached	0.19	0.391	0.16	0.368	-0.027	-12.14
Finished Basement	0.62	0.485	0.60	0.489	-0.020	-6.73
Family room	0.54	0.499	0.56	0.497	0.021	6.73
Driveway	0.66	0.473	0.70	0.460	0.035	12.34
Gas heat source	0.91	0.284	0.88	0.320	-0.027	-13.35
Forced air	0.92	0.276	0.90	0.304	-0.020	-10.14
C: Agent characteristics						
Average sales ratio	0.98	0.016	0.99	0.017	0.002	4.99
Average days on market	29.71	11.326	29.12	11.314	-0.587	-2.77
Number of homes sold	179.60	320.966	210.70	392.800	31.097	1.26

Sample consists of all properties listed within \$1K of a \$100K, \$50K, or \$10K threshold. “Odd” refers to homes listed in the interval $[z - 1K, z)$ and “Round” refers to homes listed in the interval $[z, z + 1K)$, where z is a \$100K, \$50K, or \$10K multiple. Sales ratio is sale price/list price, and “quick sale” refers to the probability of selling within a week of listing. The *t*-statistic tests the Round–Odd difference using heteroskedasticity-robust standard errors (agent characteristics: clustered by agent).

3.1. Empirical Specification

Our objective is to measure the effect of listing a house at an odd price versus an adjacent round price on sales outcomes. To do so, we estimate a local linear regression in a \$15K neighborhood of each round list price, where round price is defined as a multiple of \$100K

between \$200K and \$1,000K.⁸

Within each neighborhood, we partition list prices into \$1K bins. For a given round price τ , let $\mathcal{O}_\tau := [\tau - 1K, \tau)$ denote the *odd-price bin*—the \$1K interval immediately below τ —and let $\mathcal{R}_\tau := [\tau, \tau + 1K)$ denote the *round-price bin*.⁹ For each property i , let τ_i denote the nearest round price. We define Odd Price_i as an indicator equal to one when property i ’s list price falls in the odd-price bin $\mathcal{O}_{\tau_i}$, and define Bin_i^z as an indicator for each of the 28 remaining \$1K bins in the neighborhood ($z \in \{-15K, \dots, -2K, 1K, \dots, 14K\}$). The round-price bin $\mathcal{R}_{\tau_i}$ serves as the omitted category.

We specify the regression as follows:

$$Y_i = \beta \cdot \text{Odd Price}_i + \text{Bin}_i' \beta_B + \mathbf{X}_i' \alpha_1 + \mathbf{Z}_i' \alpha_2 + \gamma_{\tau_i \times t_i \times c_i} + \mathbf{G}_{pc_i \times t_i} + \mathbf{A}_i + \epsilon_i \quad (1)$$

where Y_i denotes a sales outcome: whether the property sold, sale price ($\mathbf{p}_i^s$), the sale-to-list price ratio ($\mathbf{p}_i^s/\mathbf{p}_i^\ell$)—“sales ratio,” hereafter—days on the market, or whether the house sold within a week of listing. The coefficient of interest is β : the effect on outcomes of listing in the odd-price bin $\mathcal{O}_{\tau_i}$ versus listing in the adjacent round-price bin $\mathcal{R}_{\tau_i}$. The coefficients on the other 28 neighboring bins are collected in the vector β_B .¹⁰

To account for the possibility that odd-priced houses differ systematically from round-priced houses, we include two sets of controls: $\mathbf{X}_i$, a vector of house characteristics (square footage, bedrooms, bathrooms, etc.), and $\mathbf{Z}_i$, a vector of agent characteristics capturing agent experience (number of houses previously sold) and agent quality (previous average sales ratio and days on market); see Internet Appendix A for the full list. To absorb

⁸The \$15K bandwidth balances statistical power against local comparability; because the bin indicators flexibly absorb any residual price-outcome relationship within each neighborhood, results are not sensitive to this choice. In Section 3.3 we examine other definitions of round prices, such as multiples of \$50K and \$10K, where we use the entire sample.

⁹We call $[\tau, \tau + 1K)$ a round-priced bin because it is effectively the singleton set $\{\tau\}$. As noted in Table 1, there are very few houses priced just above a round number. Later, in Section 5.2, we will examine \$1 bins; then the round-number bins will contain nothing but round numbers.

¹⁰In Section 5.2 we compare β and β_B to show that the odd-priced bin is indeed different from the other bins neighboring round prices.

unobserved heterogeneity, we include threshold $\times$ year $\times$ county fixed effects ($\gamma_{\tau \times t \times c}$), postal code $\times$ year fixed effects ($G_{pc \times t}$), and agent fixed effects (A_i). The agent fixed effects are particularly important for our identification strategy: they absorb the persistent tendency of certain agents to favor odd pricing (see Figure 3). Our most comprehensive specification therefore identifies β by comparing odd-priced and round-priced houses centered on the same threshold, listed in the same year, located in the same postal code, and listed by the same agent, while controlling for variations in house and agent characteristics. In Section 3.3, we examine heterogeneity by threshold, threshold type (\$100K versus \$50K versus \$10K multiples), year, and city.

3.2. Baseline Estimates

Table 5 presents our baseline estimates of (1) for the U.S. markets. Panels A–E correspond to our five outcome measures: probability of a sale, and conditional on sale, sale price, sales ratio, days on market, and probability of a quick sale. Columns 1–5 add controls progressively, allowing us to see how the odd-pricing effect evolves as we absorb additional sources of variation.

Column (1) has threshold-year-county fixed effects only. Here we are simply comparing average transaction outcomes for odd- versus round-priced houses within each threshold-year-county, and then averaging those comparisons over all threshold-year-counties. Given our definition of odd price, these comparisons involve houses whose list prices differ at most by \$1,000. What column (1) is telling us is that houses listed at odd prices underperform relative to their round-priced counterparts on all five performance measures.

Of course, homes with very similar list prices within a threshold-year-county may still differ in ways that have a bearing on sales outcomes. To mitigate those concerns, we add additional controls: in column (2), house characteristics, in column (3), in addition, Zip Code-year fixed effects, in column (4), in addition, agent characteristics, and finally, in

Table 5: The effect of odd pricing on sales outcomes at \$100K thresholds (U.S. data)

	Bin size = \$1,000				
	(1)	(2)	(3)	(4)	(5)
<i>A: Dependent variable: log(Sale price)</i>					
Odd Price	-0.0076*** (0.0005)	-0.0077*** (0.0004)	-0.0073*** (0.0005)	-0.0070*** (0.0005)	-0.0066*** (0.0005)
R ²	0.991	0.991	0.992	0.992	0.994
<i>B: Dependent variable: Sales ratio</i>					
Odd Price	-0.0058*** (0.0004)	-0.0059*** (0.0004)	-0.0055*** (0.0004)	-0.0054*** (0.0004)	-0.0046*** (0.0004)
R ²	0.159	0.200	0.249	0.262	0.424
<i>C: Dependent variable: Days on the market</i>					
Odd Price	8.026*** (0.6878)	7.429*** (0.6766)	6.628*** (0.6749)	7.006*** (0.6827)	7.160*** (0.8011)
R ²	0.192	0.226	0.269	0.284	0.437
<i>D: Dependent variable: Quick sale probability</i>					
Odd Price	-0.0382*** (0.0029)	-0.0373*** (0.0029)	-0.0353*** (0.0029)	-0.0355*** (0.0030)	-0.0355*** (0.0034)
R ²	0.079	0.104	0.127	0.132	0.294
Observations	259,668	259,668	259,668	241,704	241,704
<i>E: Dependent variable: Probability of sale</i>					
Odd Price	-0.0549*** (0.0037)	-0.0502*** (0.0038)	-0.0469*** (0.0037)	-0.0501*** (0.0037)	-0.0394*** (0.0043)
R ²	0.134	0.154	0.184	0.189	0.321
Observations	387,152	387,152	387,152	353,758	353,758
House controls		Yes	Yes	Yes	Yes
Agent controls				Yes	Yes
<i>Fixed-effects</i>					
Threshold-Year-County	Yes	Yes	Yes	Yes	Yes
ZIP Code-Year			Yes	Yes	Yes
Agent					Yes

All columns report β estimates from OLS regressions of equation (1). Standard errors, in parentheses, are clustered at the Zipcode level. Stars denote significance at the 1% (***), 5% (**), and 10% (*) levels. Sample consists of properties listed within \$15K of a \$100K threshold. House and agent controls are listed in Internet Appendix A.

column (5), agent fixed effects as well. Across specifications, odd-priced listings perform worse on every transaction outcome. Adding property controls, increasingly local market

fixed effects, agent characteristics, and finally listing-agent fixed effects attenuates some coefficients but leaves the qualitative and quantitative pattern largely intact. Specifically, in our most comprehensive specification (column (5)), odd-priced houses are less likely to sell by about 4 percentage points, and when they sell, they sell at a 0.66% discount and stay on the market about 7 days longer than an adjacent round-priced home. Odd-priced listings also exhibit lower sale-to-list price ratios and lower probabilities of selling within one week.

Table 6 presents estimates of equation (1) in the Toronto market. The same odd-round discontinuity appears: odd-priced homes have lower transaction prices and sale-to-list price ratios, remain on the market longer, and are less likely to sell quickly. The replication suggests that the baseline pattern is not peculiar to the U.S. metropolitan housing market.

3.3. The Salience of Round-Number Thresholds

The conceptual framework predicts that the odd-round discontinuity should be more pronounced at round-number thresholds that are more salient in buyer search. We examine this prediction in several ways, beginning with variation in the type of round-number threshold and then considering heterogeneity across threshold levels, cities, and time.

Threshold Type. Table 7 provides the most direct test of threshold salience by comparing odd-pricing effects around \$100K, \$50K, and \$10K multiples. To keep these categories distinct, the \$50K group excludes \$100K multiples, while the \$10K group excludes both \$50K and \$100K multiples. The adverse odd-pricing effect is largest at \$100K multiples across all five outcomes and is smaller at both \$50K and \$10K thresholds. For example, the days-on-market penalty falls from roughly 6.7 days at \$100K multiples to 2.4 days at \$50K multiples and 1.2 days at \$10K multiples, while the sale-probability difference becomes negligible at \$10K thresholds. These results are consistent with the prediction in Section 1 that the odd-round discontinuity should be stronger at more salient search

Table 6: The effect of odd pricing on sales outcomes at \$100K thresholds (Toronto data)

	Bin size = \$1,000				
	(1)	(2)	(3)	(4)	(5)
<i>A: Dependent variable: log(Sale price)</i>					
Odd Price	-0.0047** (0.0020)	-0.0068*** (0.0018)	-0.0078*** (0.0015)	-0.0073*** (0.0014)	-0.0078*** (0.0015)
R ²	0.98	0.98	0.98	0.98	0.99
<i>B: Dependent variable: Sales ratio</i>					
Odd Price	-0.0048*** (0.0018)	-0.0068*** (0.0015)	-0.0076*** (0.0013)	-0.0071*** (0.0012)	-0.0075*** (0.0013)
R ²	0.17	0.25	0.37	0.37	0.48
<i>C: Dependent variable: Days on the market</i>					
Odd Price	1.582*** (0.4264)	2.646*** (0.3654)	1.719*** (0.3241)	1.278*** (0.3100)	1.265*** (0.3637)
R ²	0.06	0.16	0.23	0.25	0.36
<i>D: Dependent variable: Quick sale probability</i>					
Odd Price	-0.0431*** (0.0089)	-0.0522*** (0.0084)	-0.0448*** (0.0077)	-0.0398*** (0.0074)	-0.0456*** (0.0079)
R ²	0.06	0.10	0.15	0.16	0.29
House controls		✓	✓	✓	✓
Agent controls				✓	✓
<i>Fixed-effects</i>					
Threshold-year fixed effects	✓	✓	✓	✓	✓
FSA-year fixed effects			✓	✓	✓
Agent fixed effects					✓
Observations	214,078	214,078	214,078	214,078	214,078

All columns report OLS regressions of equation (1). Standard errors, in parentheses, are clustered at the FSA level. Stars denote significance at the 1% (***), 5% (**), and 10% (*) levels. Sample consists of properties listed within \$15K of a \$100K threshold. House and agent controls are listed in Internet Appendix A.

boundaries.

Threshold Level. Table 8 next allows the odd-pricing coefficient to vary across individual \$100K thresholds. The estimated signs are remarkably consistent across the price distribution: odd-priced listings generally underperform adjacent round-priced listings at thresholds ranging from \$200K to \$1 million, and for several outcomes the magnitude tends

Table 7: Odd pricing effects by threshold type (U.S. data)

Dependent Variables:	(log) Transaction Price	Sales Ratio	Days on Market	Quick Sale	Probability of Sale
Model:	(1)	(2)	(3)	(4)	(5)
<i>Variables</i>					
Odd Price at \$100K multiple	-0.0060*** (0.0004)	-0.0045*** (0.0004)	6.656*** (0.6974)	-0.0346*** (0.0030)	-0.0365*** (0.0038)
Odd Price at \$50K multiple	-0.0035*** (0.0004)	-0.0025*** (0.0003)	2.407*** (0.6671)	-0.0271*** (0.0024)	-0.0263*** (0.0030)
Odd Price at \$10K multiple	-0.0045*** (0.0002)	-0.0028*** (0.0002)	1.228*** (0.3989)	-0.0300*** (0.0020)	-0.0006 (0.0021)
-Agent Controls	Yes	Yes	Yes	Yes	Yes
-House Controls	Yes	Yes	Yes	Yes	Yes
<i>Fixed-effects</i>					
Threshold-Year-County	Yes	Yes	Yes	Yes	Yes
Zip Code-Year	Yes	Yes	Yes	Yes	Yes
Agent	Yes	Yes	Yes	Yes	Yes
<i>Fit statistics</i>					
Observations	888,332	888,332	888,332	888,332	1,282,462
R ²	0.99402	0.32277	0.34924	0.21047	0.25769
Within R ²	0.06864	0.01132	0.01270	0.00295	0.00402

All columns report β estimates from OLS regressions of equation (1) while allowing those coefficients to vary by threshold type. Standard errors, in parentheses, are clustered at the zipcode level. Stars denote significance at the 1% (***), 5% (**), and 10% (*) levels. The sample consists of all properties (i.e., within \$5K of a \$100K, 50K, or 10K threshold). House and agent controls are listed in Internet Appendix A.

to increase at higher thresholds. Notably, even at the smallest thresholds, odd-priced houses underperform their round-priced counterparts. The key takeaway is that the baseline result is not driven by any single round number; it appears broadly across salient \$100K thresholds.

Cities. Internet Appendix Table A.6 examines the results separately across Chicago, Minneapolis, and San Diego (Seattle is excluded due to missing agent data; see footnote 5). Although the magnitude of the effects varies across cities, odd-priced houses consistently underperform their round-priced counterparts on all five outcomes.

Years. Finally, Internet Appendix Table A.5 reports odd-pricing effects across time

Table 8: Odd pricing effects by threshold (U.S. data)

Dependent Variables:	(log) Transaction Price	Sales Ratio	Days on Market	Quick Sale	Probability of Sale
Model:	(1)	(2)	(3)	(4)	(5)
<i>Variables</i>					
Odd Price at \$200K	-0.0063*** (0.0010)	-0.0050*** (0.0008)	4.331*** (1.349)	-0.0284*** (0.0069)	-0.0279*** (0.0068)
Odd Price at \$300K	-0.0044*** (0.0010)	-0.0036*** (0.0008)	5.661*** (1.277)	-0.0372*** (0.0063)	-0.0293*** (0.0074)
Odd Price at \$400K	-0.0052*** (0.0010)	-0.0035*** (0.0009)	8.324*** (1.742)	-0.0309*** (0.0075)	-0.0462*** (0.0092)
Odd Price at \$500K	-0.0047*** (0.0013)	-0.0032*** (0.0011)	6.933*** (2.347)	-0.0370*** (0.0088)	-0.0522*** (0.0119)
Odd Price at \$600K	-0.0076*** (0.0016)	-0.0062*** (0.0014)	13.60*** (2.638)	-0.0321*** (0.0109)	-0.0617*** (0.0128)
Odd Price at \$700K	-0.0079*** (0.0018)	-0.0076*** (0.0015)	12.34*** (4.095)	-0.0429*** (0.0154)	-0.0321** (0.0159)
Odd Price at \$800K	-0.0120*** (0.0033)	-0.0089*** (0.0025)	14.05*** (4.924)	-0.0645*** (0.0183)	-0.0462** (0.0197)
Odd Price at \$900K	-0.0109*** (0.0034)	-0.0097*** (0.0029)	9.707 (6.748)	-0.0877*** (0.0274)	-0.0485 (0.0312)
Odd Price at \$1,000K	-0.0110 (0.0070)	-0.0067 (0.0042)	6.383 (12.79)	-0.0494* (0.0289)	-0.0809*** (0.0285)
-Agent Controls	Yes	Yes	Yes	Yes	Yes
-House Controls	Yes	Yes	Yes	Yes	Yes
<i>Fixed-effects</i>					
Threshold-Year-County	Yes	Yes	Yes	Yes	Yes
Zip Code-Year	Yes	Yes	Yes	Yes	Yes
Agent	Yes	Yes	Yes	Yes	Yes
<i>Fit statistics</i>					
Observations	241,704	241,704	241,704	241,704	353,758
R ²	0.99419	0.42501	0.43782	0.29520	0.32227
Within R ²	0.36575	0.01298	0.01680	0.00568	0.00525
<i>p</i> -value for equality of coeffs.	0.1792	0.0567	0.0195	0.2673	0.1171

All columns report β estimates from OLS regressions of equation (1) while allowing those coefficients to vary by threshold. Standard errors, in parentheses, are clustered at the Zip Code level. Stars denote significance at the 1% (***), 5% (**), and 10% (*) levels. The sample consists of all properties listed within \$15K of a \$100K threshold. House and agent controls are listed in Internet Appendix A.

periods. The effects persist throughout the sample period, with relatively little systematic variation over time. This persistence is notable given substantial changes in housing-market conditions.

Taken together, these results show that the odd-round discontinuity is larger at most salient thresholds, while remaining broadly present across price range, metropolitan areas, and time periods. Salience alone, however, does not distinguish a generic round-number effect from the platform-search channel proposed in Section 1. We therefore turn next to a sharper test: whether the discontinuity is particularly large at round-number thresholds explicitly embedded in the price menus buyers encounter on a major housing platform.

4. Platform Search Boundaries, Buyer Competition and Composition

The preceding results establish two facts. First, transaction outcomes change discontinuously between listings immediately below and at salient round-number thresholds. Second, this discontinuity tends to be larger at more salient thresholds. We now ask whether it is systematically related to the search architecture of online housing platforms.

4.1. Platform-Suggested Search Boundaries

A generic numerical-salience explanation can generate larger effects at prominent round numbers even if platforms play no role. The platform-search mechanism yields a sharper prediction: the odd-round discontinuity should be particularly pronounced at round-number thresholds that are explicitly embedded in the platform’s search interface.

To test this prediction, we exploit variation across metropolitan areas and over time in the round-number price thresholds featured in realtor.com’s search menus. The platform offers buyers discrete round-number options for setting minimum and maximum prices, and the particular values appearing in these menus vary across cities and years. For example, the suggested lower and upper price bounds at realtor.com San Diego differ from the ones at realtor.com Chicago and Minneapolis. Using archived snapshots from the Wayback Machine, we reconstruct these realtor.com suggested thresholds and denote them by $\mathbf{s}_{ct}$ for city c and year t . Our test is to compare the odd-pricing effect at round-

number thresholds that appear on the platform’s menus with the odd-pricing effect at round-number thresholds that do not appear on the platform’s menus. If search frictions operate through platform-suggested thresholds, the adverse effects of odd pricing should be stronger at those suggested thresholds.

We begin by generating a vector of “all” round prices, $\mathbf{r}$: multiples of \$10K, \$25K, \$50K, and \$100K, starting from a base price of \$100K. By construction, $\mathbf{r}$ is broader than $\mathbf{s}_{ct}$. The next step is to pick out, from the houses in our dataset, those that are listed within \$5K of a round price in $\mathbf{r}$. The dummy variable `Odd Pricei` below identifies the odd-priced houses among them:

$$\text{Odd Price}_i = \mathbf{p}_i^\ell \in [\mathbf{r} - 1000, \mathbf{r}).$$

Now we estimate the following regression:

$$Y_i = \beta_1 \text{Odd Price}_i + \beta_2 \text{Odd Price}_i \cdot 1[\tau_i \in \mathbf{r} \cap \mathbf{s}_{ct}] + \gamma_{\tau_i \times t_i \times c_i} + \mathbf{X}_i' \boldsymbol{\alpha}_1 + \mathbf{Z}_i' \boldsymbol{\alpha}_2 + \mathbf{G}_{pc_i \times t_i} + \mathbf{A}_i + \epsilon_i. \quad (2)$$

This specification includes the full set of fixed effects from (1), including threshold $\times$ year $\times$ county and postal code $\times$ year fixed effects, ensuring that identification comes from within-location, within-year variation. Here, β_1 captures the odd-pricing effect at thresholds not explicitly suggested by the platform, while β_2 captures the incremental effect at suggested thresholds. Under the search-friction mechanism, we expect $\beta_2 < 0$ for all outcomes other than time on the market; for time on the market we expect $\beta_2 > 0$.

Table 9 reports the results. Odd-priced listings underperform even at round-number thresholds not explicitly suggested by realtor.com. More importantly, the underperformance becomes significantly larger at platform-suggested thresholds for all five outcomes. For log transaction price, the baseline odd-price coefficient is approximately -0.0034

Table 9: Odd pricing effect interactions with suggested round-priced bounds on realtor.com (U.S. data)

Dependent Variables:	(log) Transaction Price	Sales Ratio	Days on Market	Quick Sale	Probability of Sale
Model:	(1)	(2)	(3)	(4)	(5)
<i>Variables</i>					
Odd Price	-0.0034*** (0.0002)	-0.0017*** (0.0002)	1.348*** (0.4397)	-0.0237*** (0.0021)	-0.0094*** (0.0021)
Odd Price $\times$ Suggested Round	-0.0008*** (0.0003)	-0.0013*** (0.0003)	1.442*** (0.4879)	-0.0064** (0.0027)	-0.0159*** (0.0029)
-Agent Controls	Yes	Yes	Yes	Yes	Yes
-House Controls	Yes	Yes	Yes	Yes	Yes
<i>Fixed effects</i>					
Threshold-Year-County	Yes	Yes	Yes	Yes	Yes
Zip Code-Year	Yes	Yes	Yes	Yes	Yes
Agent	Yes	Yes	Yes	Yes	Yes
<i>Fit statistics</i>					
Observations	586,410	586,410	586,410	586,410	838,788
R ²	0.99411	0.32618	0.35358	0.22183	0.25642
Within R ²	0.02973	0.01088	0.01493	0.00238	0.00327

All columns report OLS regressions of equation (2). Standard errors, in parentheses, are clustered at the zipcode level. Stars denote significance at the 1% (***), 5% (**), and 10% (*) levels. The sample consists of properties listed within \$5K of a \$100K, 50K, 25K, or 10K multiple. House and agent controls are listed in Internet Appendix A.

and the incremental platform-threshold effect is -0.0008 . For days on the market, the baseline penalty is approximately 1.35 days and increases by another 1.44 days at platform-suggested thresholds. The interaction is also statistically significant for the sale-to-list ratio, quick-sale probability, and sale probability.

This provides our most direct evidence linking the odd-round discontinuity to platform search architecture. Generic numerical salience can explain why discontinuities arise at salient round numbers, but it does not by itself explain why the same odd-round comparison becomes systematically more adverse at thresholds explicitly featured in the platform’s search interface. The evidence therefore indicates that platform-embedded price boundaries amplify the broader round-number effect.

Table 10: The effect of odd pricing on number of bidders and buyers’ budgets (Toronto data)

	Bidders > 1 (1)	Bidders > 2 (2)	(log) Budget (3)
Odd Price at 50k multiples	-0.1731 (0.1560)	-0.3190** (0.1370)	-0.1706** (0.0837)
Agent controls	✓	✓	✓
House controls	✓	✓	✓
R ²	0.26	0.26	0.63
Observations	1,779	1,779	1,808
Threshold fixed effects	✓	✓	✓
FSA-year fixed effects	✓	✓	✓

Based on Genesove and Han’s (2016) survey of Toronto buyers. Standard errors, in parentheses, are clustered at the neighborhood level, defined by FSA (Canada Post’s “forward sortation area”). Stars denote significance at the 1% (***), 5% (**), and 10% (*) levels. House and agent controls are described in Appendix A.

4.2. Buyer Competition and Composition

The exposure mechanism has implications not only for realized transaction outcomes but also for the pool of buyers reaching a property. If a round-number search boundary excludes some buyers from an adjacent odd-priced listing, the round-priced listing should be exposed to a larger potential buyer pool and, as a result, face greater competition *among buyers*. We test this implication using the linked Toronto buyer survey, which reports whether other buyers were actively bidding when the respondent submitted an offer and, if so, how many.

Columns (1) and (2) of Table 10 report the results. Odd pricing is associated with a 17.3 percentage-point lower probability of facing more than one competing bidder, although this estimate is imprecisely estimated. The probability of facing more than two competing bidders is 31.9 percentage points lower and statistically significant. The overall pattern is consistent with a smaller pool of buyers reaching odd-priced listings.

Column (3) provides complementary evidence on buyer composition. Buyers purchasing odd-priced properties around \$50K thresholds report initial home-buying budgets

approximately 17% lower than buyers purchasing adjacent round-priced properties.

Taken together, the platform search boundary, bidder number and budget results are consistent with the mechanism developed in Section 1: Odd-priced listings experience worse liquidity and transaction outcomes; those differences are larger at more salient round numbers and, most directly, at thresholds embedded in the platform’s search architecture; and the properties on the two sides of the boundary are associated with different bidder competition and buyer composition. These joint patterns point to platform-mediated search segmentation as an important channel.

5. Selection and Robustness

The preceding sections document an odd-round discontinuity and show that it varies systematically with threshold salience and platform search architecture. One legitimate concern is that pricing format may proxy for otherwise unobserved differences in properties, sellers, or agents. We examine this possibility using four complementary approaches: within-agent variation in pricing behavior, fine comparisons of outcomes around round-number thresholds, information extracted from listing descriptions, and formal sensitivity analysis for omitted-variable bias.

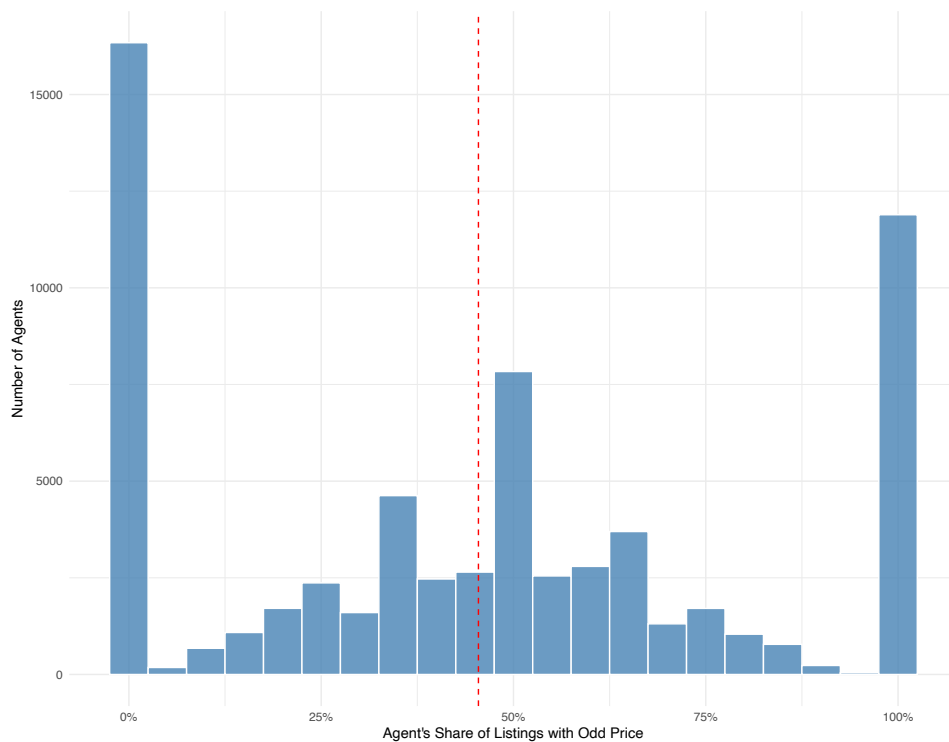
5.1. Agent Heterogeneity and Pricing Behavior

We begin by examining the role of agents in the incidence of odd pricing. It turns out that a substantial portion of the variation in odd pricing is absorbed by agent fixed effects. Conditional on these fixed effects, observed measures of time-varying agent quality and experience explain little additional variation in pricing format, suggesting limited scope for systematic sorting on unobservables at the agent level.

Figure 3 shows a histogram of agents’ propensity to use odd pricing. There is considerable heterogeneity across agents: some agents odd-price all the time and some

never do. However, most agents are in the middle, odd-pricing some of the time and round-pricing at others. Since we have agent fixed effects in the most comprehensive regression of Table 5, our odd-pricing effects can't be driven by the first two groups. Rather, the identifying variation is the one provided by the agents in the middle, those who toggle between odd and round pricing. The question is whether this toggling is systematically related to agent quality and experience, which could potentially affect sales outcomes.

Figure 3: Agent heterogeneity in use of odd pricing



The figure shows a histogram of odd pricing rates across agents, with the number of agents on the y-axis and the share of listings with odd prices (from 0% to 100%) on the x-axis. The distribution spikes at 0% and 100%, along with a substantial mass of agents across intermediate values. A vertical dashed line indicates the median odd-pricing share across agents, approximately 48%.

Table 11 suggests that the answer is no. Here we report regressions based on the U.S. data in which the dependent variable is an indicator of odd pricing, and the covariates

include measures of agent quality—past listing prices, sales ratios, and time on the market—flexible controls for agent experience, property characteristics, and fixed effects. Columns (2) and (3) show that, conditional on agent fixed effects, neither agent quality nor agent experience explain meaningful residual variation in the use of odd pricing. The associated partial R^2 is approximately 10^{-16} —economically zero. In comparison, agent fixed effects by themselves account for 12–15% of the total variation in odd pricing (partial $R^2 \approx 0.15$). Internet Appendix Table A.10 and Figure A.1 show that the Toronto data behave similarly.

In short, although agents differ substantially in their baseline propensity to use odd pricing, residual within-agent pricing variation—the source of identification in our main specification—is not systematically related to observed measures of agent quality or experience. This substantially limits the scope of agent-level selection on unobservables biasing our estimates.

5.2. Unobserved Quality and Discontinuities Around Thresholds

A second concern is that odd prices proxy for unobserved property quality. Such an explanation requires not merely that list price be correlated with quality, but that this relationship generate the sharp outcome differences observed immediately around salient round numbers.

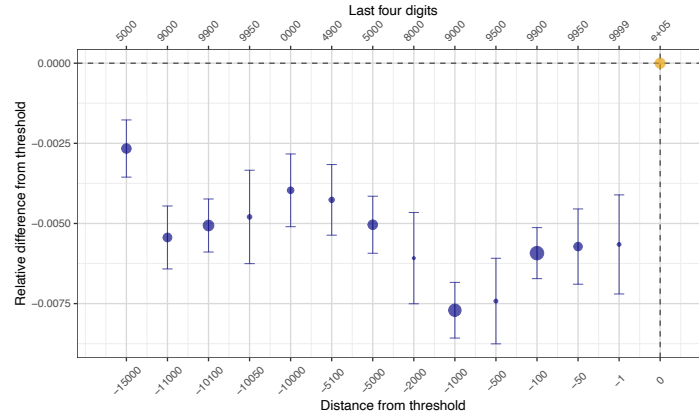
To examine this possibility, we re-estimate the baseline specification using \$1 rather than \$1,000 price bins. Figure 4 presents the results for the U.S. data (with Figure A.3 providing analogous evidence for Toronto). Houses priced exactly at \$100K multiples are marked by a yellow dot at 0 on the bottom x-axis; they form the reference group. The size of each dot represents the number of transactions at that list price. Vertical bars show the 95% confidence intervals for each β coefficient. To avoid clutter, we only show estimates for list prices to the left of round prices with at least 5,000 houses.

Table 11: Predicting the incidence of odd pricing (U.S. data)

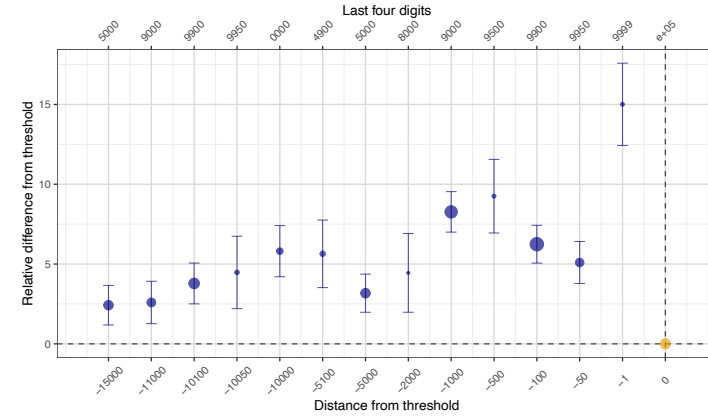
Dependent Variable: Model:	Odd Price Indicator $\times$ 100		
	(1)	(2)	(3)
<i>Variables</i>			
Ave. Agent Asking Price	0.1092 (0.1437)	0.0968 (0.1664)	0.1003 (0.1667)
Ave. Agent Sales/List Ratio	-53.31*** (7.637)	-1.359 (5.930)	-1.186 (5.930)
Ave. Agent Days on Market	-0.0274*** (0.0037)	0.0030 (0.0035)	0.0030 (0.0035)
Agent Experience (Num. of Sales/100)	3.915*** (0.6841)	-0.6268 (0.7899)	-0.6663 (0.7906)
Agent Experience ²	-1.092*** (0.2994)	0.1054 (0.2722)	0.1162 (0.2721)
Agent Experience ³	0.0779*** (0.0292)	-0.0076 (0.0248)	-0.0083 (0.0248)
<i>Fixed-effects</i>			
Threshold-Year-County	Yes	Yes	Yes
ZIP Code-Year	Yes	Yes	Yes
Agent		Yes	Yes
<i>Fit statistics</i>			
Observations	814,386	814,386	814,386
R ²	0.06913	0.20811	0.20835
Within R ²	0.00099	0.00001	0.00031
<i>Partial R²:</i>			
Agent Controls	0.0010	0.0000	0.0000
Agent Fixed Effects		0.1493	0.149
House Controls			0.0003
Joint test: all experience effects = 0 (<i>p</i> -value)	0.0000	0.7777	0.7611

All columns report OLS regressions where the dependent variable is binary, taking the value 100 for an odd-priced house, 0 otherwise. Agent experience is scaled by 100 for presentation purposes. Sample consists of completed transactions only. Standard errors, in parentheses, are clustered at the agent level. Stars denote significance at the 1% (***), 5% (**), and 10% (*) levels. Partial- R^2 s report the explanatory power of specific sets of variables. House and agent controls are listed in Internet Appendix A.

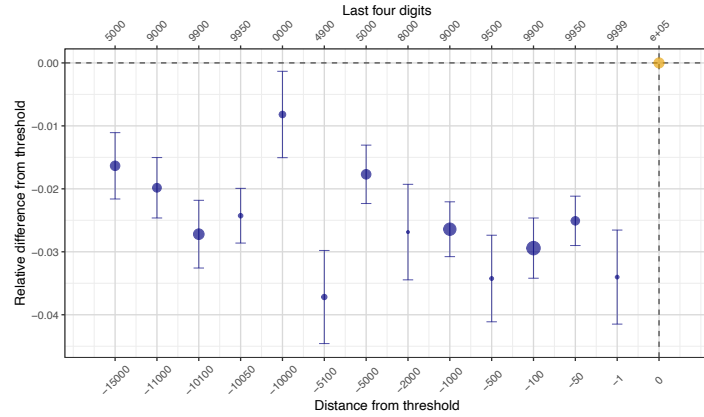
Figure 4: Odd-pricing effects as a function of list price (U.S. data).



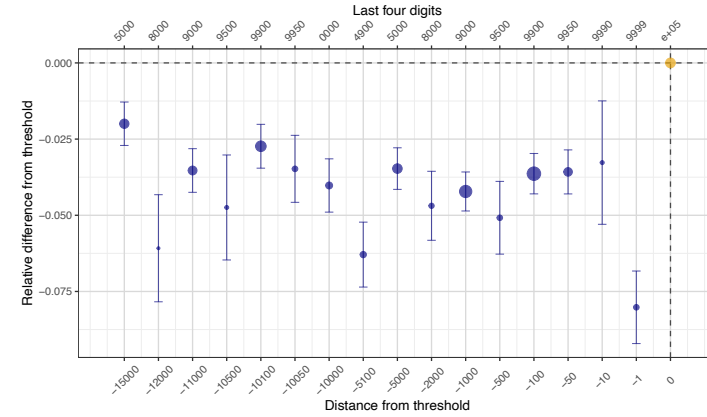
(a) Sales ratio



(b) Days on market



(c) Quick sale probability



(d) Probability of sale

The figure has four panels showing point estimates with confidence intervals for outcomes measured across \$1 price bins relative to a round price. The x-axis in each panel shows distance from the threshold, with a corresponding top axis showing the last four digits of the price. The y-axis report relative differences for each outcome. Panel (a) displays sales ratio, panel (b) days on market, panel (c) quick sale probability, and panel (d) probability of sale. Odd-priced listings underperform relative to comparable round-priced listings priced \$1 apart.

First, note that across all outcome variables—sales ratio, days on the market, probability of a quick sale, and probability of sale—the relationship between outcomes and list price is smooth away from round-number thresholds, but exhibits a discrete discontinuity precisely at those thresholds. For example, in the sales ratio plot, the dot immediately to the left of the yellow dot has a significantly lower sales ratio—by about 0.6 percentage points—than the yellow dot, even though these houses are priced only \$1 apart; however, further left, the \$50, \$100, \$500, \$1,000, \$2,000, and \$5,000 odd-pricing effects are generally similar to the \$1 odd-pricing effect (with the exception of days on the market where the \$1 odd-pricing effect is stronger than other odd-pricing effects). In other words, we don’t see evidence of a continuous list price-unobserved quality correlation. Finally, further analysis (not reported here) shows that the \$1 odd-pricing effects reported here are not present for less salient round numbers, such as \$10K multiples, reprising our earlier observation that the odd-pricing effect is smaller at \$10K multiples (Table 7).

The patterns in Figure 4 are difficult to reconcile with odd-priced houses being systematically worse in unobserved quality than adjacent round-priced houses. The discontinuity at round-number thresholds implies that similar properties priced just \$1 apart are different enough in unobserved quality to generate economically significant differences in sales outcomes. At the same time, the odd-pricing effect for properties priced substantially farther away (e.g., \$1,000–\$5,000 below the threshold) is either the same or lower than the \$1 odd-pricing effect, which suggests that the relationship between unobserved quality and list price moves in one direction for a \$1 difference and then either doesn’t move at all or moves in the opposite direction for larger list price differences. Finally, this relationship would have to be discontinuous precisely at salient round-number thresholds, while remaining approximately continuous elsewhere. For instance, properties priced at \$479,999 and \$480,000 would be deemed similar in unobserved quality, while properties priced at \$499,999 would be deemed systematically inferior to those priced at

\$500,000. Such assumptions are difficult to justify on economic grounds.

These observations suggest that the odd pricing effects are not being driven by unobserved quality differences between odd- and round-priced houses.

5.3. Listing Descriptions, Property Quality, and Seller Urgency

The U.S. MLS data include a “public remarks” field showing how the properties are described verbally (Appendix B.1 provides two examples). The typical description is some combination of verifiable quality claims (“Thermador cooktop,” “Hunter Douglas shades”), unverifiable quality claims/puffery (“rare beauty,” “gorgeous”), and phrases suggestive of seller desperation (“motivated seller,” “seller relocating”). In this section we examine whether controlling for these signals affects our results.

We first parse the text of the public remarks for verifiable quality claims (e.g., “crown molding,” “floor-to-ceiling windows”), high-end amenities (e.g., “Wolf appliances,” “walk-in pantry”), premium materials (e.g., “granite,” “mahogany”), and condition-related signals (e.g., “as is,” “move-in ready”). Table A.1 provides the full list of phrases.

Second, we construct an index of unverifiable quality claims. To do so, we tokenize the public remarks, and remove stop words, sentiment-neutral words, and verifiable quality words. From the remaining, we select a set of 200 commonly used subjective descriptors (listed in Internet Appendix Table A.2). We then estimate a regression of log sale price on indicators for each of these words, controlling for observable property characteristics, agent fixed effects, and flexible controls for description length, capitalization, and punctuation. Importantly, this regression excludes listings within \$15K of round-number thresholds, making the index independent of our main identifying variation. The coefficients of this regression form the basis for our index of unverifiable quality.

Third, we construct a measure of seller urgency based on the frequency of phrases such as “motivated seller” and “ASAP” in the listing descriptions.

Table 12 presents estimates of (1) augmented with these text-based controls. Columns (3)–(6) show that these text-based variables behave as expected. Properties with more high-end features command higher sale prices, exhibit higher sales ratios, and spend less time on the market; the puffery index is positively associated with favorable sales outcomes; and indicators of seller urgency are systematically associated with transaction outcomes. Nevertheless, including these controls has little effect on the estimated odd-pricing coefficients, which remain quantitatively similar to those reported in Table 5.

5.4. Bounding Omitted Variable Bias

Our empirical strategy compares observationally similar houses listed within \$15K of a round price, listed in the same year and postal code, and by the same agent. This design absorbs a wide range of potential confounders. In particular, the inclusion of agent fixed effects removes all time-invariant differences across agents—such as pricing style, bargaining ability, marketing quality, and client composition. And, as discussed in Section 5.1, conditional on these fixed effects, time-varying agent characteristics (e.g., experience and past performance) do not explain the use of odd pricing. Therefore, any remaining confounder capable of biasing our estimates must vary within agent and operate at the level of the specific listing or through time-varying, unobserved agent effort.¹¹

¹¹Formally, in the regression specification, any confounder U_i that is constant for a given agent is absorbed by $\mathbf{A}_i$. Thus, for an omitted variable to bias β , it must satisfy $\text{Cov}(U_i, \text{Odd Price}_i \mid \mathbf{A}_i, \mathbf{G}_{pc_i, t_i}, \gamma_{\tau_i, t_i, c_i}) \neq 0$ and $\text{Cov}(U_i, Y_i \mid \mathbf{A}_i, \mathbf{G}_{pc_i, t_i}, \gamma_{\tau_i, t_i, c_i}) \neq 0$; that is, a remaining confounder must contain variation not absorbed by the agent, postal-code $\times$ year, and threshold $\times$ year $\times$ county fixed effects and must be correlated with both pricing format and outcomes.

Table 12: Odd pricing effects with controls for verbal descriptors (U.S. data)

Dependent Variable: Model:	(1)	(2)	Bin size = \$1000		(5)	(6)
			(3)	(4)		
<i>A: Dependent variable: log(Sale price)</i>						
Odd Price	-0.0066*** (0.0005)	-0.0067*** (0.0005)	-0.0066*** (0.0005)	-0.0066*** (0.0005)	-0.0068*** (0.0005)	-0.0069*** (0.0005)
High-end features			0.0008*** (0.0003)			0.0006** (0.0003)
Urgency				0.00003 (0.00003)		0.00007** (0.00003)
Unverifiable Index					0.0020*** (0.0001)	0.0018*** (0.0001)
R ²	0.994	0.994	0.994	0.994	0.994	0.994
<i>B: Dependent Variable: Sales ratio</i>						
Odd Price	-0.0046*** (0.0004)	-0.0046*** (0.0004)	-0.0046*** (0.0004)	-0.0046*** (0.0004)	-0.0046*** (0.0005)	-0.0047*** (0.0005)
High-end features			0.0008*** (0.0002)			0.0007*** (0.0002)
Urgency				0.00003 (0.00003)		0.00006** (0.00003)
Unverifiable Index					0.0018*** (0.0001)	0.0016*** (0.0001)
R ²	0.42498	0.42629	0.42535	0.42498	0.43113	0.43312
<i>C: Dependent Variable: Days on the market</i>						
Odd Price	6.589*** (0.7981)	6.559*** (0.7987)	6.596*** (0.7986)	6.589*** (0.7980)	6.462*** (0.8093)	6.420*** (0.8086)
High-end features			-1.029** (0.5019)			-0.8450* (0.5077)
Urgency				0.2385*** (0.0537)		0.1777*** (0.0548)
Unverifiable Index					-1.574*** (0.2100)	-1.387*** (0.2102)
R ²	0.439	0.439	0.439	0.439	0.445	0.445
Word Controls	Yes	Yes	Yes	Yes	Yes	Yes
Quality Signal		Yes				Yes
Materials Controls						Yes
Verifiable Controls			Yes			Yes
House Controls	Yes	Yes	Yes	Yes	Yes	Yes
Agent Controls	Yes	Yes	Yes	Yes	Yes	Yes
<i>Fixed-effects</i>						
Threshold-Year-County	Yes	Yes	Yes	Yes	Yes	Yes
ZIP Code-Year	Yes	Yes	Yes	Yes	Yes	Yes
Agent	Yes	Yes	Yes	Yes	Yes	Yes
Observations	238,708	238,708	238,708	238,708	230,795	230,795

(Continued)

Table 12—continued

Dependent Variable: Model:	Bin size = \$1000					
	(1)	(2)	(3)	(4)	(5)	(6)
<i>D: Dependent Variable: Quick sale probability</i>						
Odd Price	-0.0281*** (0.0034)	-0.0279*** (0.0034)	-0.0281*** (0.0034)	-0.0281*** (0.0034)	-0.0259*** (0.0035)	-0.0257*** (0.0035)
High-end features			-0.0015 (0.0014)			0.00009 (0.0014)
Urgency				0.0006*** (0.0002)		0.0006*** (0.0002)
Unverifiable Index					0.0031*** (0.0008)	0.0031*** (0.0008)
R ²	0.301	0.302	0.302	0.301	0.299	0.299
Observations	238,708	238,708	238,708	238,708	230,795	230,795
<i>E: Dependent Variable: Probability of sale</i>						
Odd Price	-0.0390*** (0.0043)	-0.0389*** (0.0043)	-0.0391*** (0.0043)	-0.0390*** (0.0043)	-0.0347*** (0.0044)	-0.0347*** (0.0044)
High-end features			0.0080*** (0.0018)			0.0066*** (0.0018)
Urgency				-0.0004* (0.0002)		-0.00002 (0.0002)
Unverifiable Index					0.0175*** (0.0011)	0.0164*** (0.0011)
R ²	0.328	0.323	0.323	0.323	0.328	0.329
Observations	349,209	349,209	349,209	349,209	336,551	336,551
Word Controls	Yes	Yes	Yes	Yes	Yes	Yes
Quality Signal		Yes				Yes
Materials Controls						Yes
Verifiable Controls			Yes			Yes
House Controls	Yes	Yes	Yes	Yes	Yes	Yes
Agent Controls	Yes	Yes	Yes	Yes	Yes	Yes
<i>Fixed-effects</i>						
Threshold-Year-County	Yes	Yes	Yes	Yes	Yes	Yes
ZIP Code-Year	Yes	Yes	Yes	Yes	Yes	Yes
Agent	Yes	Yes	Yes	Yes	Yes	Yes

All columns report OLS regressions of equation (1). Standard errors, in parentheses, are clustered at the ZIP Code level. Stars denote significance at the 1% (***), 5% (**), and 10% (*) levels. The sample consists of all properties listed within \$15K of a \$100K threshold. House and agent controls are listed in Internet Appendix A. The estimation sample is smaller in columns (5) and (6) due to missing values in the Unverifiable Index; accordingly, R^2 values in these columns are not directly comparable to those in columns (1)–(4).

To assess the potential magnitude of omitted-variable bias arising from such a confounder, we employ the sensitivity analysis framework of Cinelli and Hazlett 2019, Chernozhukov et al. 2023, and Bach et al. 2025. In this framework, bias from an unobserved confounder is represented as a function of two partial- R^2 s: its explanatory power for the outcome (say, sales ratio) and its explanatory power for the treatment (odd versus round pricing), conditional on the full set of observables and fixed effects.¹² Those partial- R^2 s are estimated from the observed partial- R^2 s of the covariates.

We implement this analysis on our most comprehensive specification in Table 12 for the odd-pricing effect on sales ratio (column (6) of Panel B). We compute partial- R^2 s for sets of observables that plausibly capture within-agent heterogeneity: (i) house characteristics, (ii) listing-level public remarks, and (iii) time-varying agent experience and performance measures (after residualizing the outcome, treatment, and covariates with respect to all fixed effects: threshold $\times$ year $\times$ county, postal code $\times$ year, and agent). As Table 13 shows, the full set of observables—house characteristics, agent controls, and public remarks—explains approximately 4.5% of the remaining variation in the sales ratio and less than 1% of the variation in odd pricing; for smaller subsets, the partial- R^2 s are even lower.

The top row of Table 13 shows that a hypothetical confounder as strongly associated with *both* treatment and outcome as *all* observables *combined* would generate a maximal absolute bias of only 0.0029. Therefore, to drive our odd-pricing effect of -0.0047 to zero, a within-agent confounder would need to be more than 1.5 times as predictive of both

¹²The formula is

$$|\text{Bias}| = |\rho| \cdot \sqrt{\frac{R_{Y \sim U|D,X}^2 R_{D \sim U|X}^2 \sigma_{Y \perp D,X}}{1 - R_{D \sim U|X}^2 \sigma_{D \perp X}}},$$

where U is the latent confounder, $R_{Y \sim U|D,X}^2$ is the partial- R^2 of U with the outcome conditional on the treatment and controls, and $R_{D \sim U|X}^2$ is the partial- R^2 of U with the treatment conditional on controls, and $\sigma_{Y \perp D,X}$ and $\sigma_{D \perp X}$ are the residual standard deviations of Y and D . The parameter $\rho \in [-1, 1]$ captures the direction of the confounder’s influence; $|\rho| = 1$ yields the maximal possible bias for a given pair of partial- R^2 values, corresponding to the worst-case scenario in which the confounder’s correlations with treatment and outcome are in the same direction.

Table 13: Bounding the potential bias from confounders on the odd pricing effect on sales ratio (U.S. data)

Benchmark	Estimate -0.0047 (0.0005)				
	$ \text{Bias} $	Bias Bounds	95% CI	R_Y^2	R_D^2
All	0.0029	$[-0.0075 - -0.0018]$	$[-0.0083 - -0.0010]$	0.0445	0.0068
House Characteristics	0.0023	$[-0.0070 - -0.0023]$	$[-0.0078 - -0.0016]$	0.0350	0.0058
Agent Controls	0.0001	$[-0.0047 - -0.0046]$	$[-0.0055 - -0.0038]$	0.0034	0.0001
Public Remarks	0.0004	$[-0.0050 - -0.0043]$	$[-0.0058 - -0.0035]$	0.0058	0.0009

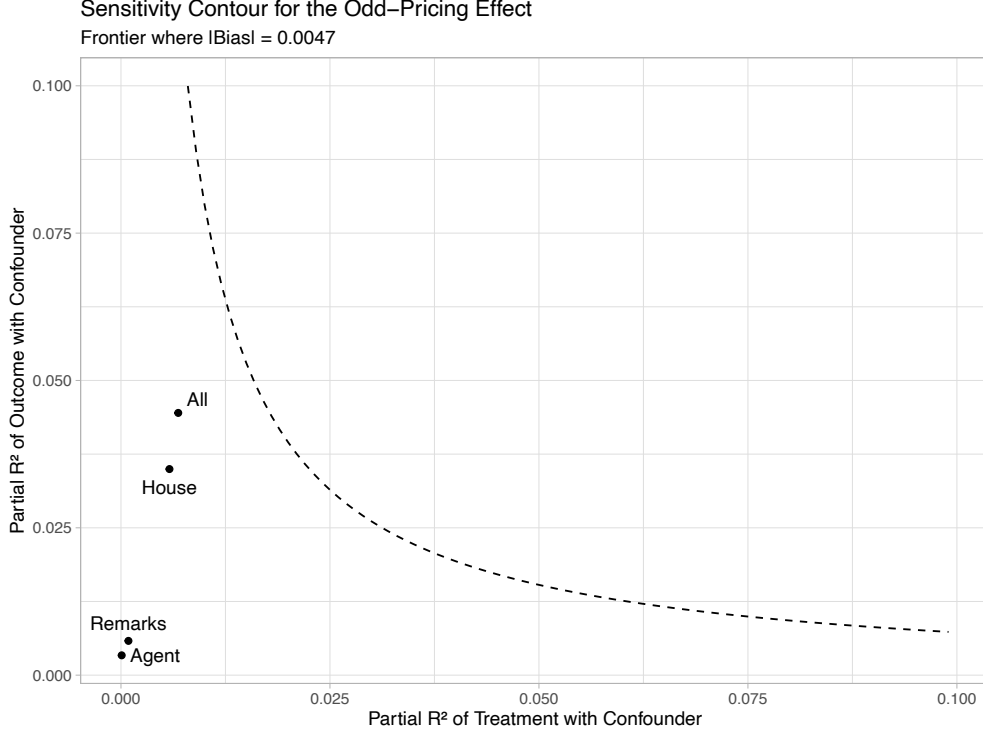
The top-line estimate of -0.0047 (0.0005) is the odd pricing effect on sales ratio from column (6), Panel B, of Table 12. The column labeled $|\text{Bias}|$ reports the maximal absolute bias implied by a hypothetical confounder that explains R_Y^2 of the residual variation in the outcome and R_D^2 of the residual variation in the treatment, assuming a worst-case scenario (i.e. $|\rho| = 1$). “Bias Bounds” gives the resulting range of adjusted point estimates, accounting for such confounding, and “95% CI” provides the corresponding adjusted confidence interval. Each row benchmarks the potential strength of unobserved confounding against a different set of observed covariates: all controls together, house characteristics, agent controls, and public-remarks variables (see Internet Appendix B).

sales ratio and odd-pricing incidence as the entire set of observed house, agent, and listing controls. Even in this worst-case scenario, the bias-corrected 95% confidence interval excludes zero. The remaining rows of Table 13 repeat this exercise using smaller sets of observables. In each case, the implied bias is too small to nullify the odd pricing effect.¹³

Figure 5 provides a visual summary of this analysis. It shows a sensitivity contour that traces combinations of partial- R^2 s for which a confounder would drive the odd-pricing effect to zero. All observed covariates lie well within this frontier, indicating that even confounders with explanatory power comparable to, or exceeding, that of our observed controls would be insufficient to eliminate the odd-pricing effect.

¹³The bounds reported in Table 13 assume a worst-case scenario of confounding paths aligning themselves in such a way ($|\rho| = 1$) as to yield maximal bias consistent with the specified partial- R^2 values. For each set of covariates, we also compute the empirical alignment parameter $\hat{\rho}$ implied by the observed values in that set. These empirical parameter values are modest in magnitude (ranging from 0.04 to 0.35), indicating that the observed covariates tend not to push treatment and outcome in highly aligned directions, once the controls are partialled out. If one were to scale the maximal bias bound by the corresponding $|\hat{\rho}|$ for each benchmark, the implied bias would be even smaller. In short, the bounds we report are deliberately conservative.

Figure 5: Sensitivity analysis of omitted variable bias in the estimated odd pricing effect on sales ratio (U.S. data)



The horizontal axis shows the fraction of residual variation in the “treatment” explained by a potential unobserved confounder, while the vertical axis shows its influence on the outcome. The dashed contour represents the outer boundary of these confounder explanatory powers that would still preserve our estimated odd-pricing effect ($|Bias| < 0.0047$) (assuming a worst-case scenario). Labeled points lying well within the frontier indicate that the explanatory powers of specific sets of observed covariates in column (6) of Table 12 do not approach this frontier.

6. Discussion

The existing literature documents different effects of asking-price format across settings. Compared with our study, these settings differ along three dimensions: the pricing contrast being estimated, the institutional architecture through which buyers and sellers meet, and the stage of the transaction process at which the asking price operates. In particular, asking-price format can affect (i) which properties enter buyers’ *consideration sets*, (ii) how buyers allocate *attention and participation* conditional on exposure, and (iii) what buyers

infer and how they *bargain* once engagement occurs. These channels are complementary to each other, and we discuss the closest comparisons below.

Several studies establish that asking-price format matters in housing, but emphasize margins operating after or conditional on buyer exposure. Allen and Dare (2004) find that houses listed at certain charm prices transact at higher prices than houses listed at round prices, demonstrating that seemingly minor features of an asking price can matter even in a high-stakes asset market. Their empirical object is the average performance of particular charm-price formats; ours is the local comparison immediately around a salient round-number boundary, where platform search generates a specific prediction about exposure. Similarly, Pope, Pope, and Sydnor (2015) show that round numbers can act as focal points in housing negotiations. That mechanism operates once buyers and sellers are engaged, whereas our evidence highlights an earlier margin through which the asking price affects which buyers reach the property in the first place.

Using data from the Swedish housing market, Repetto and Solís (2020) find that apartments listed just below salient round numbers sell for higher prices and attract more bidders and bids. They interpret these patterns as evidence that left-digit inattention makes just-below prices more attractive, drawing additional buyers into ascending-price auctions and intensifying competition. Their empirical strategy, like ours, exploits local variation around salient round-number thresholds, making the difference in signs particularly informative.

The institutional setting, however, differs substantially. Repetto and Solís (2020) study Sweden’s auction-based housing market, whereas we study North American markets with different search institutions, agent representation, platform interfaces, and transaction protocols. The two sets of findings also point to complementary forces. In Sweden, numerical salience appears to increase the attractiveness of a just-below listing and draws additional buyers into the auction. In our North American setting, the evidence points

to an additional, earlier margin: when a round number serves as a lower search bound, a listing immediately below it can be excluded from some buyers’ consideration sets altogether. Left-digit salience therefore operates primarily on *attention conditional on exposure*, while platform search boundaries operate on *exposure itself*. Which margin dominates can depend on the institutions governing search, listing visibility, and the sales process.

Meng (2023) and Wiltermuth, Gubler, and Pierce (2023) document another channel through which round numbers can matter, but at a different reference point and a different point in time. Rather than examining how a property’s current list price affects its current exposure and sale outcome, they study how a *previous transaction price* affects a subsequent transaction. Their evidence emphasizes memory and anchoring: previous round versus just-below transaction prices shape the reference points sellers bring to later pricing decisions. Their mechanism is therefore intertemporal and reference-dependent, whereas ours concerns the contemporaneous matching process.

The comparison with Mateen et al. (2026) is also relevant because they study pricing formats in U.S. housing markets. Their pricing categories, however, do not map directly into ours. They distinguish exact round prices—multiples of \$5K, \$10K, \$50K, or \$100K—from “charm” prices up to \$100 below a round number, “special 9K” prices exactly \$1,000 below a round number, and other nonsalient prices classified as precise. Our baseline comparison instead centers on a round threshold r and compares the entire interval $[r - \$1,000, r)$ with the adjacent interval $[r, r + \$1,000)$; because prices immediately above round numbers are exceedingly rare, the latter is effectively concentrated at r . Our odd-price bin therefore includes charm prices, special 9K prices, and prices they classify as precise, while their precise-price category can occur on either side of our threshold. The two papers consequently estimate different objects: broad pricing-format differences in their case and the local discontinuity from crossing a salient round-number boundary

in ours.

The empirical designs and sample also differ. Mateen et al. (2026) exploit repeat transactions to sharpen controls for property heterogeneity. We focus on narrow comparisons around round-number thresholds and condition on detailed property characteristics, local-market conditions, listing-agent characteristics, and high-dimensional fixed effects. These differences make direct comparisons of estimated coefficients less informative than comparisons of the economic margins isolated by each design.

The deeper complementarity is economic rather than definitional. Mateen et al. (2026) show that pricing formats contain information about sellers and shape bargaining: charm prices are associated with more impatient sellers and faster transactions at modest concessions, while round prices are associated with less precise valuations and different counteroffer behavior. Earlier evidence from Backus, Blake, and Tadelis (2018) also shows that price precision can reveal information about seller bargaining behavior. These mechanisms concern the information conveyed by price format and the bargaining behavior that follows once counterparties engage. Our evidence points to an earlier and novel margin: platform search architecture can change which counterparties encounter the asset and therefore the size and composition of the potential bidder pool. Pricing format can thus shape bargaining among buyers who see a property, while platform search boundaries help determine who sees it in the first place.

Taken together, the evidence from the literature suggests that asking-price format can affect at least three margins of the transaction process: which properties enter buyers' consideration sets, how buyers allocate attention and decide whether to participate conditional on exposure, and what buyers infer and how they bargain once engagement occurs. Different studies provide evidence on different parts of this process, using different pricing comparisons and institutional settings. This paper is among the first to show that platform-embedded search boundaries can make this first margin discontinuous and

economically consequential.

7. Conclusion

This paper shows how digital search architecture can become part of the microstructure of a decentralized asset market. Using more than two million housing listings across four U.S. metropolitan areas and Toronto, we document sharp differences in transaction outcomes between properties listed immediately below salient round-number thresholds and properties listed at the adjacent thresholds. Odd-priced properties are approximately 4 percentage points less likely to sell and, conditional on sale, transact for about 0.7% less and remain on the market roughly seven days longer. These differences are present across markets and price thresholds and remain after conditioning on detailed property characteristics, local market conditions, and listing-agent fixed effects. At the same time, fine price-bin comparisons, listing-text measures of property quality and seller urgency, within-agent pricing variation, and formal sensitivity analysis substantially narrow conventional selection-based explanations for the patterns.

The joint evidence points to platform-mediated search segmentation as an important mechanism. The odd-round discontinuity is largest around more salient round numbers and, most directly, becomes significantly larger at thresholds explicitly featured in realtor.com’s search menus. Buyer-level evidence provides complementary evidence on the intermediate market outcomes implied by this mechanism: round-priced listings face greater bidder competition and are purchased by buyers with higher reported initial budgets.

As the existing literature documents, pricing format can influence attention, participation, signaling, and bargaining, and these forces can operate simultaneously. Our findings identify a novel additional margin that arises before bargaining begins: platform search rules help determine which potential counterparties encounter an asset in the first place.

When search interfaces organize a continuous price space around discrete round-number boundaries, seemingly minor nominal differences in asking prices can generate discontinuous differences in market exposure, which can propagate to bidder competition, liquidity, and transaction prices.

More generally, the results highlight digital platform design as part of the institution through which buyers and sellers meet. In decentralized and illiquid markets, seemingly minor interface choices can shape consideration sets and therefore affect market participation and price formation. The economic consequences of platform design may thus extend beyond housing to other markets in which heterogeneous assets are matched through digitally mediated search.

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INTERNET APPENDIX

A. House and Agent Controls

House characteristics (U.S. data): The vector $\mathbf{X}_{it}$ in equation (1) includes linear controls for the number of bedrooms, washrooms, parking spaces, fireplaces, along with their squares and interactions, and square feet cubed. Additionally, these variables are all interacted with city dummies to allow their effects to vary by city. We also include indicators for the number of stories (19 categories), heating type (94 categories), month, AC (44 categories), year built (125 categories) and appliance features (446 categories).

Agent characteristics (U.S. data): For each agent in our data, we compute the average sales ratio, days on market, and list price of all homes sold by the agent prior to the current transaction. In equation (1) we include these linearly, along with a third-order polynomial in the number of houses sold by the agent in our data prior to the current transaction. There are 102,305 individual agents identified in our data when we include agent fixed effects.

House characteristics (Toronto data): The vector $\mathbf{X}_{it}$ in equation (1) includes linear controls for the number of rooms, bedrooms, washrooms, lot size, front lot, and lot depth, along with their squares and interactions. It also includes a set of indicators for housing style (e.g., number of floors (2-story), sidesplit, backsplit) and a dummy variable for semi-detached (versus detached) homes, along with their interactions with the linear controls for the number of rooms, bedrooms, washrooms, lot size, front lot, and lot depth. In addition, we include indicators for month of sale.

Agent characteristics (Toronto data): For each agent in our data, we compute the average sales ratio, days on market, and list price of all homes sold by the agent prior to the current transaction. In equation (1) we include these linearly, along with a third-order polynomial in the number of houses sold by the agent in our data prior to the current transaction. There are 10,546 individual agents identified in our data when we include agent-fixed effects.

B. Text Analysis of the Listing Descriptions

In the U.S. MLS data, we use the variable “public remarks” that provides a verbal description of each listing. From these descriptions, we construct several control variables for use in the regressions reported in Table 12: “high-end features,” “urgency,” “word controls,” “materials controls,” and “verifiable controls.” See Table A.1. In addition, we develop an Unverifiable Index as a measure of advertising puffery, also used in Table 12, through the following steps:

1. Remove all stopwords,
2. Use the intersection of the remaining words with the Bing lexicon sentiment index (this removes words like "house" that have no sentiment value) and manually remove all the words in Table A.1 from the ones that remain.
3. From the remaining words, choose the 200 most-used and create a dummy variable for each of them,
4. Regress (log) sale prices on these 200 dummies, all controls (from our most fully specified model, including agent fixed effects), and a third-order polynomial in the number of words in the public remarks, number of all caps words, and the number of exclamation marks.
5. The regression only uses data not used in our main regressions (i.e., we do not use data within \$15K of the round-number thresholds),
6. Extract the coefficients on the 200 dummies (most are significant),
7. For all houses, we create an index by $\text{Index} = \beta'_{\text{word dummies}} \cdot X_{\text{word dummies}}$. This summarizes the price of each puffery word and its use in the description. Table A.2 below contains the list of puffery words used in this procedure.

Table A.1: Verifiable features, quality signal, and urgency phrases

High-end features	Verifiable controls	Materials controls
sub-zero	Vaulted ceilings	quartzite
wolf	Hardwood floors	soapstone
miele	Walk-in closets	calacatta
viking	En suite bathroom	carrara
induction cooktop	Recessed lighting	granite
soft-close drawers	Crown molding	corian
undermount sink	Wainscoting	marble
farmhouse sink	Heated floors	limestone
butler's pantry	Floor-to-ceiling windows	quartz
pot filler	Custom built-ins	travertine
double oven	theater	onyx
warming drawer	Wet bar	—
custom cabinetry	Wine cellar	—
integrated appliances	Butler's pantry	—
wine fridge	Dual vanities	—
walk-in pantry	Oversized island	—
vent hood	Outdoor kitchen	—
Bosch	Infinity pool	—
Thermador	Elevator	—
Gaggenau	Sauna	—
La Cornue	steam room	—
Dacor	Rooftop	—
Fisher & Paykel	terrace	—
Liebherr	gym	—
Aga	Library	—
Bertazzoni	study	—
BlueStar	Coffered ceilings	—
Ilve	Safe room	—
SMEG	panic room	—
island	Heated driveway	—
rangetop	—	—
gas range	—	—
Wood Materials	Metals	Quality Signal
maple	wrought	fixer
teak	lead	as_is
bamboo	stainless	tlc
oak	bronze	diamond
cedar	copper	potential
mahogany	aluminum	turnkey
redwood	brass	move-in Ready
walnut	iron	handyman special
—	zinc	needs work
Urgency phrases		
buyer walked	motivated seller	reduced
asap	quick close	below market value
fast	must sell	priced to sell
back on market		

Table A.2: Subjective, unverifiable descriptors (“puffery words”)

1	great	2	beautiful	3	spacious	4	upgraded
5	perfect	6	ready	7	entertaining	8	quiet
9	enjoy	10	gorgeous	11	well	12	nice
13	tops	14	bright	15	beautifully	16	easy
17	charming	18	wonderful	19	bonus	20	lovely
21	desirable	22	fans	23	amazing	24	like
25	top	26	cozy	27	panoramic	28	stunning
29	fresh	30	mature	31	welcome	32	modern
33	entertain	34	miss	35	work	36	love
37	best	38	fantastic	39	good	40	retreat
41	lush	42	pride	43	usable	44	excellent
45	appeal	46	clean	47	sparkling	48	charm
49	available	50	expansive	51	fabulous	52	ideal
53	incredible	54	spectacular	55	peaceful	56	right
57	ample	58	gem	59	hot	60	convenient
61	beauty	62	burning	63	efficient	64	warm
65	nicely	66	cute	67	paradise	68	classic
69	solid	70	leads	71	delight	72	award
73	winning	74	vanity	75	cool	76	conveniently
77	lemon	78	wow	79	friendly	80	dim
81	hard	82	awesome	83	motivated	84	immaculate
85	serene	86	leading	87	elegant	88	fast
89	generous	90	oasis	91	meticulously	92	super
93	dark	94	adorable	95	enough	96	tranquil
97	appreciate	98	split	99	galore	100	comfortable
101	unknown	102	breathtaking	103	quaint	104	rich
105	abundance	106	grand	107	enjoying	108	luxurious
109	fun	110	breeze	111	soft	112	fall
113	terrific	114	finest	115	exquisite	116	useable
117	sweeping	118	improvements	119	exceptional	120	free
121	stylish	122	popular	123	luxury	124	abundant
125	outstanding	126	attractive	127	affordable	128	perfectly
129	restored	130	magnificent	131	roomy	132	delightful
133	prestigious	134	impressive	135	clear	136	plush
137	comfort	138	complex	139	better	140	picturesque
141	smooth	142	sweet	143	peace	144	trust
145	fault	146	alarm	147	convenience	148	wonderfully
149	advantage	150	gentle	151	rough	152	serenity
153	variety	154	warmth	155	satisfy	156	tranquility
157	oversize	158	sleek	159	darling	160	loved
161	accessible	162	steal	163	enjoyment	164	distressed
165	safe	166	smart	167	masterpiece	168	fine
169	upscale	170	enjoys	171	sunken	172	approval
173	ideally	174	reliable	175	desert	176	unbelievable
177	refreshing	178	pretty	179	majestic	180	butcher
181	creative	182	disappointed	183	favorite	184	extraordinary
185	peach	186	cold	187	impeccably	188	golden
189	perfection	190	impeccable	191	scenic	192	elegance
193	remarkable	194	romantic	195	savings	196	exceptionally
197	tumbled	198	immaculately	199	noise	200	superb

Example of text parsing. Suppose the property description is: “This house has walnut cupboards, wrought iron gates, a beautiful kitchen, and a spacious yard.” Our procedure

works as follows:

1. **Remove stopwords:** Exclude common words such as “this,” “has,” “a,” and “and,” leaving: *“house,” “walnut,” “cupboards,” “wrought,” “beautiful,” “kitchen,” “spacious,” “yard.”*
2. **Filter using the Bing sentiment lexicon:** From the remaining words, retain only those that appear in the Bing lexicon, such as: *“wrought,” “beautiful,” “spacious.”* Words like “walnut,” “cupboards,” “house,” “kitchen,” and “yard” are excluded because they are not part of the Bing lexicon.
3. **Manually remove words listed in Table A.1:** If words like “wrought” survive step two, they are manually removed if they are included in Table A.1, leaving: *“beautiful,” “spacious.”*

The final set of words, *“beautiful,” “spacious,”* is then used to construct the “unverifiable quality” index.

B.1. Assessing the face validity of the “unverifiable index”

To assess whether our procedure is doing a good job capturing unverifiable quality claims in the verbal descriptions, we examine the public remarks ranked in the top-five and bottom-five by our “unverifiable index.” We are satisfied that it is, as shown by the top-ranked and bottom-ranked descriptions in the San Diego data, reproduced below.

Public remark ranked highest by the unverifiable quality index

Views! Views!! Views!!! Welcome to this gorgeous 4 bedroom, 3 bathroom property located in the highly sought-after community of Bonita Ridge Estates. With panoramic city, mountain, and valley views throughout, this rare beauty offers complete privacy. With warm - yet refined - elegance, this incredible home has been upgraded to perfection. Spanning roughly 2600 sqft of comfortable living space, its single-story (top floor) layout boasts luxurious upgrades at every turn. Interior features include Brazilian cherry

wood flooring, high living room ceiling with new drywall, custom recessed lighting, new AC/Furnace and ducting, new toilets, vinyl wood-like flooring in bedrooms, new light fixtures and ceiling fans, gorgeous fire place, new paint throughout, huge updated kitchen with quartz countertops, custom cabinets, Thermador magnetic induction cooktop, custom storage areas, new windows, new blinds/window treatments, upgraded guest bathroom, 3-car attached garage, outdoor balcony with automatic awning, modern cable railing, and breathtaking views from every angle. Its beautiful master bedroom offers two spacious closets with custom organizers, sliding glass door to balcony with views, and automatic Hunter Douglas shades. The private master bath offers a rustic barn door, upgraded vanity with his and hers sinks, and a remodeled walk-in shower. Make your way downstairs to discover an entirely new living space with incredible possibilities. This area features a huge bonus room/living room/gym area, wet bar, fireplace, laundry room, and one spacious guest bedroom and bathroom. Step outside into a resort-like backyard on a spacious 12,197 sqft lot. Low-maintenance pebble paving, sparkling pool and spa, multiple lounge areas, fruit trees, beautiful landscaping, views throughout, and complete privacy make this dazzling outdoor space a true entertainer's delight. With both home solar and thermal pool solar, this completely move-in ready home is simply a masterpiece. Absolutely a must-see!!!

After extracting stop words and the intersection of the Bing sentiment list, what remains is this text:

breathtaking gorgeous sparkling generous upgraded meticulously leads bonus elegant warm cozy tops top butcher beautiful garbage upgraded elegant beautiful beauty luxury stunning refreshing gem

When estimating the value of these words, note that we are controlling flexibly for the length of the public description, the length of the remaining word list, and housing characteristics.

Public remark ranked lowest by the unverifiable quality index

Diamond in the Rough. Was a beautiful home when well decorated and cared for. Short sale subject to lender approval. Great home in Park Lane - gated community. Largest yard in complex. Near good schools, minutes to beach, EZ drive to freeway. Please bring your Vision.

And the words after extraction:

rough beautiful well great good

C. Additional Empirical Analysis

Table A.3: Toronto buyer survey homes versus Toronto MLS homes

Sample:	MLS (N=163583)		Survey (N=1925)	
Characteristic	Mean	SE	Mean	SE
A: Transaction outcomes				
Sales price/1000	418.15	0.431	420.67	3.92
Sales ratio	0.98	0.000	0.98	0.00
Days on market	31.30	0.075	27.06	0.62
Quick sale probability	0.18	0.001	0.20	0.01
B: Listing characteristics				
List price/1000	425.93	0.437	427.67	3.93
Just above threshold (%)	0.37	0.015	0.31	0.13
Exactly round (%)	0.36	0.015	0.31	0.13
Just below threshold (%)	11.43	0.079	11.22	0.72
C: House characteristics				
Number of bedrooms	3.37	0.002	3.36	0.02
Number of rooms	7.31	0.004	7.21	0.03
Number of washrooms	2.83	0.002	2.80	0.02
Lotsize	7398.85	41.090	5520.70	226.81
Fireplace	0.65	0.001	0.66	0.01
Detached	0.20	0.001	0.22	0.01
Finished Basement	0.64	0.001	0.70	0.01
Family room	0.51	0.001	0.52	0.01
Driveway	0.30	0.001	0.20	0.01
Gas heat source	0.93	0.001	0.96	0.00
Forced air	0.93	0.001	0.93	0.01
D: Agent characteristics				
Average sales ratio	0.98	0.000	0.98	0.00
Average days on market	33.54	0.028	31.90	0.26
Number of homes sold	123.27	0.519	138.18	5.27
E: Districts Covered				
# FSAs	100.00		100.00	

Sample consists of all transactions in the Greater Toronto Area from January 2007-December 2009. All prices are in Canadian dollars. FSA refers to Forward Sortation Area—the first three characters of a Canadian postal code.

Table A.4: Summary statistics: Toronto survey of buyers

	Mean	SE
Number of bidders	1.68	0.034
% of homes with 1 bidder	68.10	1.089
% of homes with 2 bidders	16.52	0.867
% of homes with 3 bidders	6.87	0.591
% of homes with >3 bidders	8.51	0.652
Buyer budget (CAD)	412,301.88	4,232.664

C.1. Empirical Results

This section presents additional empirical results using both the U.S. and Toronto data. We first report two additional heterogeneity analyses for the U.S. sample. We then estimate several extensions of equation (1) using the Toronto data, replicating our analysis of U.S. data presented in the main text. Specifically:

1. **Years (U.S. data):** Table A.5 estimates odd-pricing effects by time periods: 2008–2010, 2011–2014, and 2015–2018.
2. **Cities (U.S. data):** Table A.6 reports the odd-pricing effects across Chicago, Minneapolis, and San Diego.
3. **Threshold Type Effects (Toronto data):** Table A.7 examines how the odd pricing effect varies by type of round-number threshold: \$100K versus \$50K versus \$10K multiples.
4. **Threshold-Specific Effects (Toronto data):** Table A.8 estimates separate odd-pricing effects for each \$100K threshold ($\{200K, 300K, \dots, 1, 200K\}$).
5. **Time Effects (Toronto data):** Table A.9 investigates how the odd-pricing effect varies across years in the Toronto data.
6. **The Incidence of Odd Pricing Can’t Be Predicted by Agent Quality and Experience (Toronto data):** Table A.10 presents results for Toronto that mirror the Table 11 results for the US.
7. **\$1 bins (Toronto data):** Figure A.3 replicates Figure 4 by treating each list price as its own bin, partitioning prices within $[\tau - 15K, \tau + 15K]$ into \$1 intervals. In the Toronto data, the figure highlights prices ending in 8s with light blue markers, as these endings are considered auspicious among Chinese buyers—a significant sub-segment of the Greater Toronto Area (GTA) market. Interestingly, properties with these special endings exhibit worse sales outcomes compared to round-priced properties.

8. **Sensitivity analysis (Toronto data):** Table A.11 contains the sensitivity analysis for Toronto. Similar to the U.S. results, an omitted confounder would have to have twice the explanatory power on the outcome and treatment as all of our observed controls to overturn the result. Figure A.2 graphically presents the results.

Table A.5: Odd pricing effects by year (U.S. data)

Dependent Variables:	(log) Transaction Price	Sales Ratio	Days on Market	Quick Sale	Probability of Sale
Model:	(1)	(2)	(3)	(4)	(5)
<i>Variables</i>					
Odd Price in 2008-2010	-0.0040* (0.0021)	-0.0032** (0.0014)	10.95*** (2.727)	-0.0294*** (0.0075)	-0.0439*** (0.0109)
Odd Price in 2011-2014	-0.0069*** (0.0009)	-0.0047*** (0.0008)	6.478*** (1.401)	-0.0211*** (0.0050)	-0.0372*** (0.0074)
Odd Price in 2015-2018	-0.0068*** (0.0006)	-0.0047*** (0.0005)	6.554*** (1.031)	-0.0423*** (0.0049)	-0.0394*** (0.0050)
-Agent Controls	Yes	Yes	Yes	Yes	Yes
-House Controls	Yes	Yes	Yes	Yes	Yes
<i>Fixed-effects</i>					
Threshold-Year-county	Yes	Yes	Yes	Yes	Yes
Zip Code-Year	Yes	Yes	Yes	Yes	Yes
Agent	Yes	Yes	Yes	Yes	Yes
<i>Fit statistics</i>					
Observations	241,704	241,704	241,704	241,704	353,758
R ²	0.99387	0.42419	0.43729	0.29431	0.32166
Within R ²	0.33118	0.01157	0.01587	0.00442	0.00435
p-value for equality of coeffs.	0.3796	0.5564	0.2984	0.0110	0.8499

All columns report β estimates from OLS regressions of equation (1) while allowing those coefficients to vary by year. Standard errors, in parentheses, are clustered at the zipcode level. Stars denote significance at the 1% (***), 5% (**), and 10% (*) levels. The sample consists of all properties listed within \$15K of a \$100K threshold. House and agent controls are listed in Internet Appendix A.

Table A.6: Odd pricing effects by city (U.S. data)

Dependent Variables:	(log) Transaction Price	Sales Ratio	Days on Market	Quick Sale	Probability of Sale
Model:	(1)	(2)	(3)	(4)	(5)
<i>Variables</i>					
Odd Price in Chicago	-0.0059*** (0.0009)	-0.0043*** (0.0007)	8.533*** (1.636)	-0.0208*** (0.0046)	-0.0398*** (0.0070)
Odd Price in Minneapolis	-0.0061*** (0.0006)	-0.0046*** (0.0006)	7.673*** (0.8658)	-0.0478*** (0.0055)	-0.0452*** (0.0065)
Odd Price in San Diego	-0.0079*** (0.0015)	-0.0056*** (0.0012)	3.169** (1.581)	-0.0424*** (0.0095)	-0.0172*** (0.0062)
-Agent Controls	Yes	Yes	Yes	Yes	Yes
-House Controls	Yes	Yes	Yes	Yes	Yes
<i>Fixed-effects</i>					
Threshold-Year-County	Yes	Yes	Yes	Yes	Yes
Zip Code-Year	Yes	Yes	Yes	Yes	Yes
Agent	Yes	Yes	Yes	Yes	Yes
<i>Fit statistics</i>					
Observations	241,702	241,702	241,702	241,702	353,755
R ²	0.99392	0.42407	0.43721	0.29462	0.32187
Within R ²	0.33657	0.01139	0.01574	0.00490	0.00467
<i>p</i> -value for equality of coeffs.	0.5182	0.6327	0.0269	0.0005	0.0044

All columns report β estimates from OLS regressions of equation (1) while allowing those coefficients to vary by city. (Seattle is missing because as noted in footnote 5, most Seattle observations are eliminated after conditioning on non-missing agent controls and agent fixed effects.) Standard errors, in parentheses, are clustered at the Zip Code level. Stars denote significance at the 1% (***), 5% (**), and 10% (*) levels. The sample consists of all properties listed within \$15K of a \$100K threshold. House and agent controls are listed in Internet Appendix A.

Table A.7: Odd pricing effects by threshold type (Toronto data)

	(log) Sale price (1)	Sales ratio (2)	Days on market (3)	Quick sale probability (4)
Odd price at \$100K multiple	-0.0075*** (0.0014)	-0.0066*** (0.0012)	1.040*** (0.3143)	-0.0414*** (0.0068)
Odd price at \$50K multiple	-0.0061*** (0.0011)	-0.0057*** (0.0009)	0.2573 (0.2892)	-0.0292*** (0.0051)
Odd price at \$10K multiple	-0.0022*** (0.0005)	-0.0014*** (0.0005)	-1.622*** (0.2482)	0.0032 (0.0044)
Agent controls	✓	✓	✓	✓
Average:	-0.004*** (0.001)	-0.004*** (0.001)	-0.559*** (0.166)	-0.015*** (0.003)
House controls	✓	✓	✓	✓
R ²	0.99	0.39	0.28	0.21
Observations	623,625	623,625	623,625	623,625
Threshold-year fixed effects	✓	✓	✓	✓
FSA-year fixed effects	✓	✓	✓	✓
Agent fixed effects	✓	✓	✓	✓

All columns report OLS regressions of equation (1) while allowing those coefficients to vary by threshold type. Standard errors, in parentheses, are clustered at the FSA level. Stars denote significance at the 1% (***), 5% (**), and 10% (*) levels. The sample consists of all properties listed within \$5K of a \$100K, \$50K, or \$10K threshold. House and agent controls are listed in Internet Appendix A.

Table A.8: Odd pricing effects by threshold (Toronto data)

	(log) Sale price (1)	Sales ratio (2)	Days on market (3)	Quick sale probability (4)
Odd price at \$200K	-0.0329*** (0.0106)	-0.0245*** (0.0084)	-1.524 (2.850)	-0.0146 (0.0290)
Odd price at \$300K	-0.0134*** (0.0031)	-0.0112*** (0.0027)	0.8560 (1.289)	-0.0524* (0.0273)
Odd price at \$400K	-0.0131*** (0.0030)	-0.0113*** (0.0026)	1.358* (0.7729)	-0.0497*** (0.0187)
Odd price at \$500K	-0.0140*** (0.0033)	-0.0114*** (0.0030)	0.5942 (0.7644)	-0.0483*** (0.0176)
Odd price at \$600K	-0.0090*** (0.0025)	-0.0072*** (0.0023)	1.152 (0.7956)	-0.0650*** (0.0195)
Odd price at \$700K	-0.0126*** (0.0037)	-0.0131*** (0.0034)	0.9813 (0.9817)	-0.0806*** (0.0226)
Odd price at \$800K	-0.0134*** (0.0033)	-0.0125*** (0.0029)	1.720* (0.9895)	-0.0200 (0.0246)
Odd price at \$900K	-0.0052 (0.0058)	-0.0041 (0.0050)	0.7810 (1.190)	-0.0211 (0.0295)
Odd price at \$1,000K	-0.0213*** (0.0078)	-0.0167*** (0.0055)	3.044* (1.824)	-0.0509* (0.0259)
Odd price at \$1,100K	0.0026 (0.0033)	0.0017 (0.0027)	2.337** (1.110)	-0.0344* (0.0191)
Odd price at \$1,200K	-0.0030 (0.0042)	-0.0038 (0.0036)	2.258 (1.458)	-0.0756*** (0.0238)
Agent controls	✓	✓	✓	✓
House controls	✓	✓	✓	✓
R ²	0.99	0.48	0.36	0.29
Observations	214,078	214,078	214,078	214,078
Equality of coefs.:				
<i>p</i> -value	0.0001	0.0001	0.8496	0.5381
Threshold-year fixed effects	✓	✓	✓	✓
FSA-year fixed effects	✓	✓	✓	✓
Agent fixed effects	✓	✓	✓	✓

All columns report OLS regressions of equation (1) while allowing those coefficients to vary by threshold. Standard errors, in parentheses, are clustered at the FSA level. Stars denote significance at the 1% (***), 5% (**), and 10% (*) levels. The sample consists of all properties listed within \$15K of a \$100K threshold. House and agent controls are listed in Internet Appendix A.

Table A.9: Odd pricing effects by year (Toronto data)

	(log) Sale price (1)	Sales ratio (2)	Days on market (3)	Quick sale probability (4)
Odd price in 2007-2010	-0.0075** (0.0031)	-0.0084*** (0.0027)	1.774 (1.142)	-0.0683*** (0.0174)
Odd price in 2011-2014	-0.0074*** (0.0020)	-0.0075*** (0.0018)	1.519** (0.6405)	-0.0423*** (0.0122)
Odd price in 2015-2018	-0.0078*** (0.0021)	-0.0066*** (0.0018)	0.9058** (0.4522)	-0.0395*** (0.0110)
Agent controls	✓	✓	✓	✓
House controls	✓	✓	✓	✓
R ²	0.99	0.48	0.36	0.29
Observations	214,078	214,078	214,078	214,078
Equality of coefs.: <i>p</i> -value	0.9899	0.8305	0.6039	0.3677
Threshold-year fixed effects	✓	✓	✓	✓
FSA-year fixed effects	✓	✓	✓	✓
Agent fixed effects	✓	✓	✓	✓

All columns report OLS regressions of equation (1) while allowing those coefficients to vary by year. Standard errors, in parentheses, are clustered at the FSA level. Stars denote significance at the 1% (***), 5% (**), and 10% (*) levels. The sample consists of all properties listed within \$15K of a \$100K threshold. House and agent controls are listed in Internet Appendix A.

Table A.10: Predicting the incidence of odd pricing (Toronto data)

	Odd Price Indicator $\times 100$		
	(1)	(2)	(3)
Ave. Agent Asking Price	-0.7132*** (0.1593)	-0.0013 (0.2262)	0.0046 (0.2243)
Ave. Agent Days on Market	-0.0324** (0.0164)	-0.0124 (0.0112)	-0.0122 (0.0113)
Ave. Agent Sales/List Ratio	-3.636 (9.552)	-9.743 (11.11)	-9.419 (11.09)
Agent Experience (Num. of Sales)	0.7962* (0.4113)	-0.8561 (0.6960)	-0.8896 (0.6965)
Agent Experience ²	-0.0989 (0.0632)	0.0310 (0.0882)	0.0342 (0.0882)
Agent Experience ³	0.0021 (0.0022)	-0.0007 (0.0030)	-0.0008 (0.0030)
R ²	0.08	0.20	0.20
Observations	623,625	623,625	623,625
<i>Partial R²:</i>			
Agent Characteristics	0.001	0.0002	0.0002
Agent Fixed Effects		0.1251	0.1251
House Characteristics			0.0005
<i>Joint test:</i>			
Experience = 0 (<i>p</i> -value)	0.0097	0.0637	0.0576
Threshold-year fixed effects	✓	✓	✓
FSA-year fixed effects	✓	✓	✓
Agent fixed effects		✓	✓

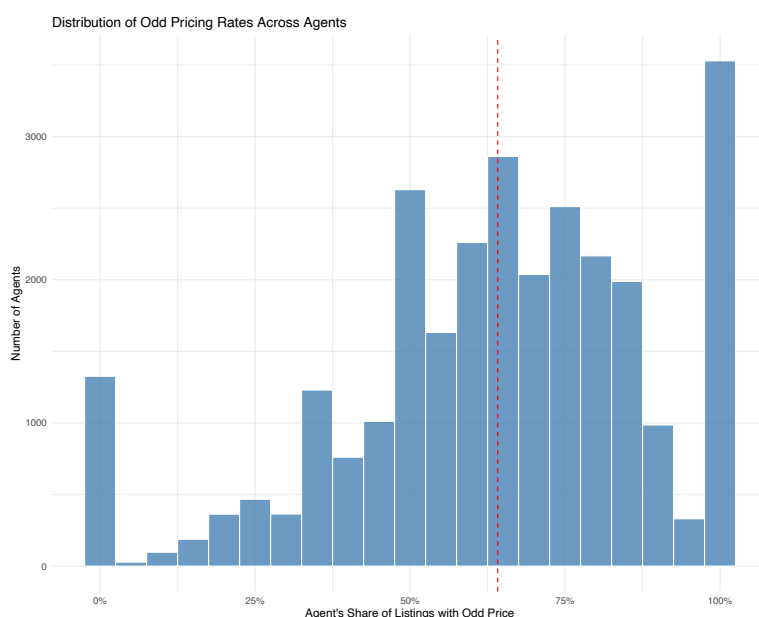
All columns report OLS regressions where the dependent variable is an indicator for odd pricing. Standard errors, in parentheses, are clustered at the agent level. Stars denote significance at the 1% (***), 5% (**), and 10% (*) levels. The partial R^2 values report the contribution of each set of variables to explaining variation in odd pricing. The joint test reports the *p*-value from an F-test of the null hypothesis that all coefficients on agent experience are equal to zero. Agent experience is scaled by 100 for presentation purposes. The sample is the 623,625-listing estimation sample described in Appendix 2.2. A detailed list of controls for housing and agent characteristics can be found in Appendix A.

Table A.11: Bounding the potential bias from confounders on the odd-pricing effect on sales ratio in Toronto

Estimate: -0.0075 (0.0013)					
Benchmark	Bias	Bias Bounds	95% CI	R_Y^2	R_D^2
All Controls	0.0017 (0.00001)	[-0.0092 – -0.0058]	[-0.0111 – -0.0039]	0.0121	0.0018
House Characteristics	0.0015 (0.00001)	[-0.0090 – -0.0060]	[-0.0109 – -0.0041]	0.0118	0.0014
Agent Controls	0.0001 (0.00000)	[-0.0077 – -0.0074]	[-0.0096 – -0.0055]	0.0004	0.0003

The top-line estimate of -0.0075 (0.0013) is the estimated odd pricing effect on sales ratio from column (5) of Table 6. |Bias| denotes the estimated absolute bias from omitting an unobserved confounder that explains R_Y^2 and R_D^2 proportions of the variances in the outcome and “treatment,” respectively. “Bias bounds” indicate the range of adjusted estimates after accounting for potential confounding; 95% CI provides the confidence interval for the adjusted estimate. The rows correspond to different sets of observed covariates in column (5) of Table 6: all controls, house characteristics, and agent controls.

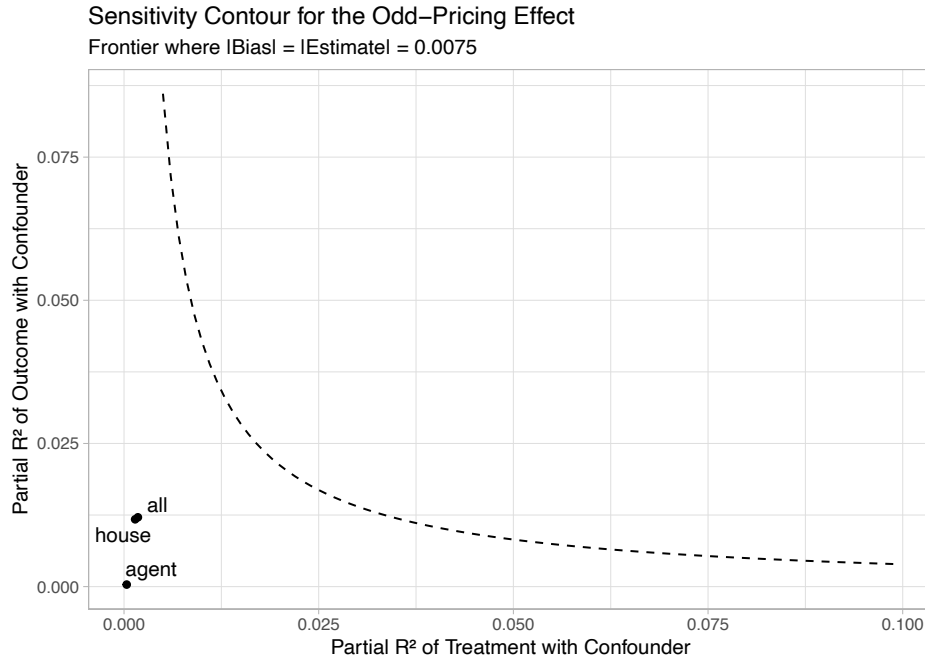
Figure A.1: Agent heterogeneity in use of odd pricing (Toronto Data)



This figure shows a histogram of odd pricing rates across agents in Toronto data. The distribution is extremely wide, with spikes at 0% (agents who never use odd pricing) and 100% (agents who always use odd pricing). At the same time, a substantial mass of agents use odd pricing for only a fraction of their listings. Overall, the figure shows that while some agents consistently follow a single pricing strategy, many alternate between odd and round pricing across listings.

Alt Text. The figure shows a histogram of odd pricing rates across agents in Toronto data, with the number of agents on the y-axis and the share of listings with odd prices (from 0% to 100%) on the x-axis. The distribution spikes at 0% and 100%, along with a substantial mass of agents across intermediate values. A vertical dashed line indicates the median odd-pricing share across agents, approximately 63%.

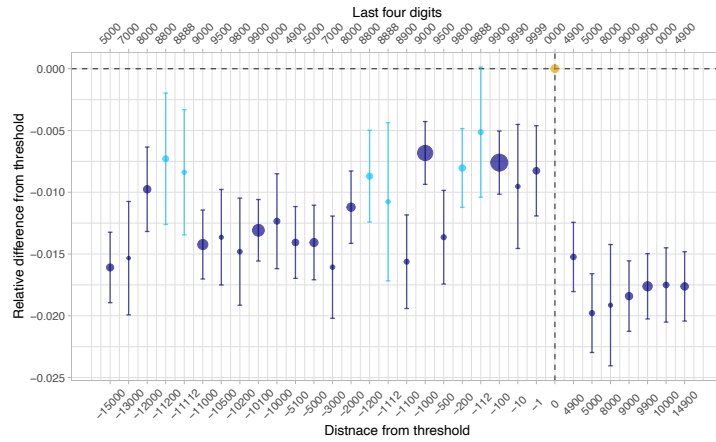
Figure A.2: Sensitivity Analysis of Omitted Variable Bias in the Estimated Odd-Pricing Effect on Sales Ratio in Toronto (based on Table A.11)



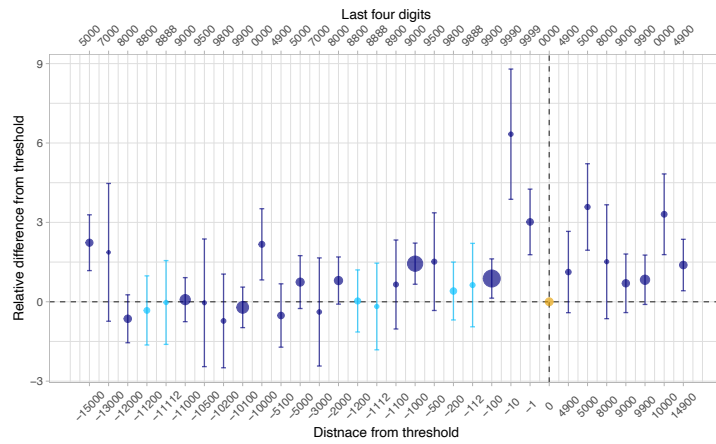
The horizontal axis shows the fraction of residual variation in the “treatment” explained by a potential unobserved confounder, while the vertical axis shows its influence on the outcome. The dashed contour represents the outer boundary of these confounder explanatory powers that would still preserve our estimated odd-pricing effect (the frontier where $|Bias|$ equals the estimated effect, 0.0075, assuming a worst-case scenario). Labeled points lying well within the frontier indicate that the explanatory powers of specific sets of observed covariates in column (5) of Table 6 do not approach this frontier.

Alt Text. This figure shows a downward-sloping contour plot with the partial R^2 of a confounder with the treatment on the horizontal axis and the partial R^2 with the outcome on the vertical axis, both ranging from 0 to approximately 0.10. Labeled points corresponding to observed covariates are plotted at low values of both axes, positioned below and to the left of the contour.

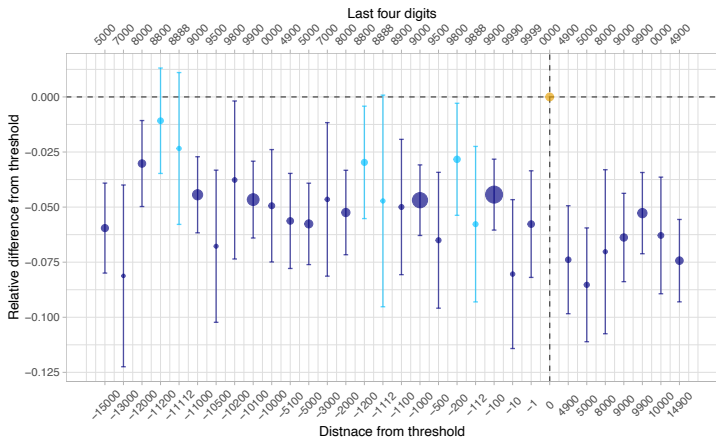
Figure A.3: Estimates of the odd-pricing effect in Toronto for \$1 bins



(a) Sales ratio



(b) Days on market



(c) Quick sale probability

This figure displays estimates of the odd-pricing effect for \$1 bins on: (a) sales ratio, (b) days on the market, and (c) quick sale probability. Houses listed exactly at a \$100K multiple are shown by an orange dot at 0. The top x-axis shows the last four digits of the list price and the bottom x-axis shows its distance from round numbers. For example, -1 on the bottom axis and 9999 on the top axis corresponds to list prices like \$299,999 and \$499,999. All prices in Canadian dollars.

Alt Text. The figure shows three panels with point estimates and confidence intervals plotted across \$1 price bins relative to a round price. The horizontal axis shows distance from the threshold, with a corresponding top axis indicating the last four digits of the price. The vertical axis shows relative differences for each outcome. Panel (a) displays sales ratio, panel (b) days on market, and panel (c) quick sale probability. Odd-priced listings underperform relative to round-priced listings priced \$1 apart.