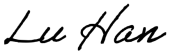
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Sincerely,



Lu Han

Corresponding Author

Signed on behalf of Sridhar Moorthy, Ben Sand and Yuwen Ji.

The Microstructure of Odd Pricing in Housing Markets

LU HAN, SRIDHAR MOORTHY, BEN SAND, and YUWEN JI*

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The Microstructure of Odd Pricing in Housing Markets

ABSTRACT

We examine home sales in a number of North American cities. Despite the high stakes, sellers often list at "odd prices"—prices just below round numbers, such as $499,800. While this strategy is known to increase demand for low-ticket consumer goods, it backfires in housing markets: odd-priced homes are 4 percentage points less likely to sell, sell for 0.7% less, and stay on the market 7 days longer than round-priced counterparts. These effects are robust across cities, price thresholds, and years, and cannot be explained as a spurious correlation. Rather, odd-priced houses appear to underperform because they attract fewer, lower willingness-to-pay buyers, and face more competition than round-priced houses.

Residential real estate transactions account for trillions of dollars in asset turnover each year across North America. Unlike centralized financial exchanges, however, housing transactions occur through a decentralized search process in which buyers must screen large numbers of potential properties before deciding which homes to inspect or bid on. This search process is mediated by digital platforms that organize and display house listings to prospective buyers. The design of these platforms is therefore a potentially important source of influence on the visibility of different transaction opportunities, with knock-on effects for the equilibrium outcomes of these markets.

This paper studies how small numerical features of listing prices interact with digital search interfaces to affect housing market outcomes. The central insight is that the round-numbered price thresholds embedded in digital platform filters can have a significant effect on the search process. Specifically, houses with list prices just below those thresholds—what we refer to as "odd prices" in this paper—run the risk of being screened out when buyers set minimum price filters to weed out properties that are unlikely to meet their quality requirements. The round-priced house's discrete advantage in visibility makes the demand function discontinuous. In turn, this influences bidding competition, and ultimately transaction outcomes for otherwise nearly-identical homes.

Odd pricing is, of course, a widely observed phenomenon in retail markets. Small-ticket consumer goods with prices such as \$1.99 and \$10.98—also referred to as "charm prices" and "just-below prices"—are a common sight in the places where individuals usually shop (Stiving and Winer 1997; Anderson and Simester 2003; Gaur and Fisher 2005; List et al. 2023). In those contexts, the principal justification for such a pricing strategy is "left-digit bias" on the part of buyers: they process price information from left to right, placing most attention to the left-most digit and progressively less attention to succeeding digits (Levy et al. 2020; Schindler and Wiman 1989).[1] The price appears smaller than it is,

[1]Even financial traders are apparently not immune to left-digit bias. In the stock market, Bhattacharya, Holden, and Jacobsen 2012 document "excess buying (selling) by liquidity demanders at all price points

boosting demand.[2] From the seller's point of view, even if a small fraction of buyers exhibit left-digit bias, the increase in demand is likely to far outweigh the margin hit, making odd pricing a dominant strategy (Basu 2006; Schindler and Kirby 1997).

But surely this logic can't apply to housing markets? The price of a single-family home typically runs into the six figures in North America, and for most households a house purchase is the largest financial transaction they will ever make, involving negotiation, deliberation, and professional intermediation. Under these conditions, one might expect list price heuristics to have a negligible effect, and realizing this, sellers would see little point in pursuing an odd pricing strategy.

It turns out that both conjectures are incorrect. To take the second first, our data, two million listings over a ten-year period from four major U.S. metropolitan areas—Chicago, Minneapolis, San Diego, and Seattle—as well as Toronto (Canada), show that odd pricing is alive and well in housing markets. Prices just below a round number occur between four and seven times more often than round prices (e.g., 51.5% vs. 7.2% in 2008–2009; 46.0% vs. 11.3% in 2016–2018). By contrast, listings with prices just above a round number are exceedingly rare—below 0.5%. Figure 1 shows this visually for the U.S. data. List prices are bunched just below round numbers throughout the distribution, from $100,000 at the lower end to $1,000,000 at the upper end.[3]

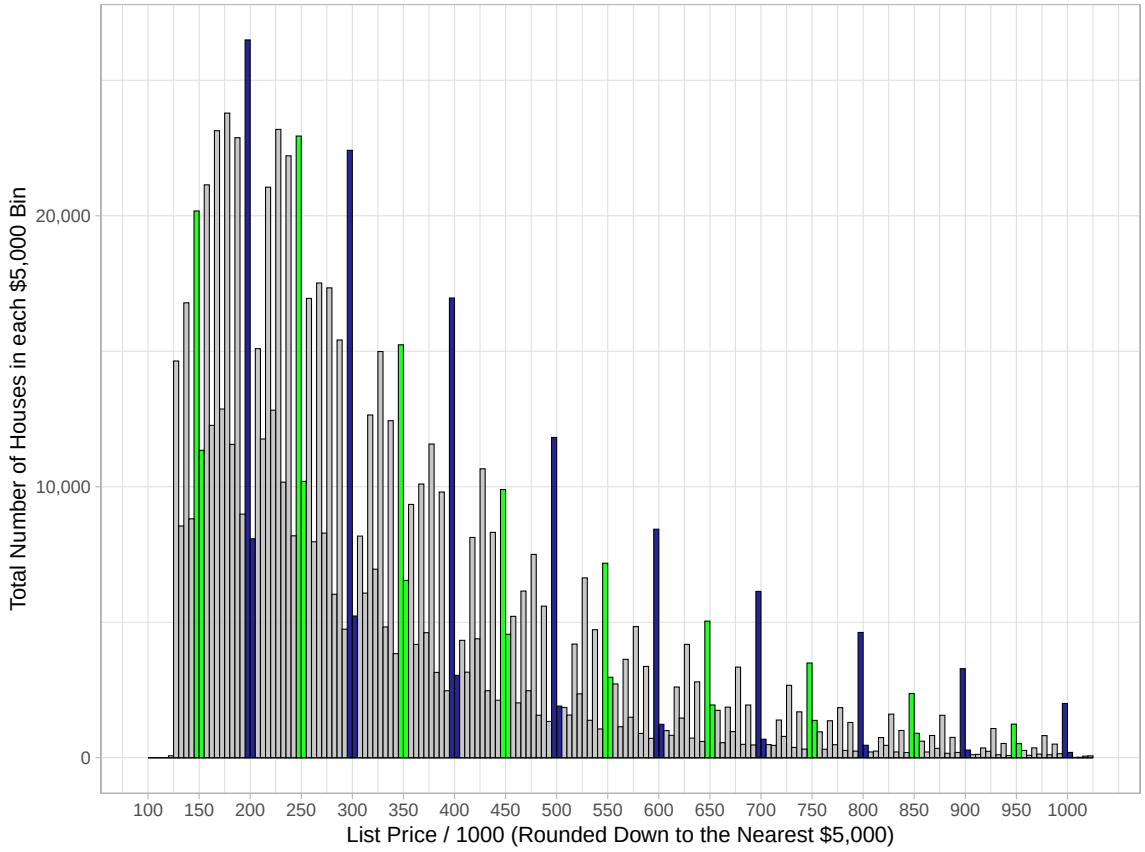
Coming to the first conjecture, it does make a difference whether a house is listed at a round price or at an odd price. Comparing observationally similar properties whose listing prices differ by as little as $1,000 around the same round-number threshold—such as $499,900 versus $500,000—we find that odd-priced homes are 4 percentage points less

one penny below (above) round numbers," and in the options market, Heraud and Page 2024 find that "the options' fundamental value is discontinuous around round numbers, indicating mispricing due to the left-digit bias."

[2]For example, Strulov-Shlain 2023 shows that grocery-store consumers respond to a one-cent decrease from a round price price as if it were more than a twenty-cent decrease.

[3]Other studies have reported similar patterns (Palmon, Smith, and Sopranzetti 2004; Pope, Pope, and Sydnor 2015; Repetto and Solís 2020; Mateen et al. 2023).

Figure 1. Histogram of list prices in our U.S. data. Each pair of identically-colored bars is centered on a round price, a multiple of \$10K, \$50K, or \$100K. If x is a round price, the left-hand bar represents the interval $[x - \$5K, x)$ and the right-hand bar represents the interval $[x, x + \$5K)$. The histogram is truncated at \$1 million for clarity.



likely to sell than their round-priced counterparts, and conditional on selling, sell for approximately 0.7% less *and* remain on the market roughly seven days longer. These effects are remarkably robust—across cities, price thresholds, and years. Odd pricing underperforms round pricing comprehensively in housing markets.

Does odd pricing *cause* odd-priced houses to underperform? We argue, theoretically and empirically, that it does. In our main regression—from which come the performance numbers cited above—we are controlling for house attributes, market conditions, and agent characteristics (agent experience and past performance); in addition, the specification

includes a rich set of fixed effects: threshold × year × county, postal code × year, and agent. In short, we are making local comparisons between two similar-looking houses selling in the same market environment and represented by the same agent, one of which is odd-priced and the other round-priced. This design, in conjunction with the fact that the dominant source of variation in the pricing heuristic arises within agent rather than between agents, sharply limits the scope for confounding variation. Effectively, what we have is quasi-experimental variation in list prices in a neighborhood of the same round number.

The large scale of our data—two million listings—ensures statistical power. We are able to estimate precisely small differences in transaction outcomes between nearly identical homes. The estimated effects are highly statistically significant and remarkably consistent across markets, thresholds, and time periods.

We subject our findings to an extensive set of robustness checks to rule out spurious correlation as a plausible explanation. As already mentioned, our main empirical specification includes controls for property characteristics, agent characteristics, and local market conditions. In supplementary regressions, we exploit the potentially rich information available in the text of the listings—for example, one seller advertising "crown moldings and Wolf appliances" while another says "seller moving, must sell"—which we analyze using text-mining techniques, to see whether including signals of unobserved quality and seller desperation/urgency in the regression changes our results. The answer is no.

Finally, we perform a sensitivity analysis along the lines of Cinelli and Hazlett 2019 and Chernozhukov et al. 2023. The idea is to estimate the potential magnitude of any residual omitted variables bias, and to assess whether it would be strong enough to overturn the estimated odd-pricing effects. This analysis shows that any confounder would need to have more than 1.5 times the explanatory power of *all* observed controls combined—on both the treatment (odd versus round pricing) and the sales outcome—to nullify the

odd pricing's estimated underperformance. This explanatory threshold is empirically implausible.

In short, there is strong empirical evidence that odd pricing itself negatively affects transaction outcomes. The question is how. In Section I we develop a theoretical framework to answer this. We show how the search process for homes can interact with the design of online real estate platforms to disadvantage odd-priced homes. It all starts with the basic observation that houses are highly differentiated commodities (Han and Strange 2015). Search is necessary but costly. Houses have a mix of attributes, some search, some experience. Search will therefore be a multi-stage process, involving, first, screening to winnow the houses available for sale into a consideration set, second, online evaluation of the search attributes of the houses in the consideration set to form a shortlist, and third, personal visits to the houses in the shortlist to inspect their experience attributes.

The design of online platforms comes into play at the first step. We present a simple model to argue that the screening step must involve upper *and* lower price bounds when quality is unobserved, but correlated with price. Perhaps recognizing this, all the major online platforms—realtor.com, Redfin, Zillow—offer maximum and minimum price filters. Moreover, those filters feature round numbers (Piazzesi, Schneider, and Stroebel 2020). As a result, odd-priced houses, but not round-priced houses, get screened out by buyers whose minimum price coincides with the adjacent round price. At the same time, whenever an odd-priced house is considered, so is its round-priced counterpart. Thus, round-priced houses are (a) more visible than odd-priced houses, (b) more likely to attract buyers with a greater willingness to pay, and (c) face less competition. These discrete advantages wend their way through the search process, ultimately delivering higher sales prices and shorter times on the market to round-priced houses.

We test this theory using several complementary sources of evidence. First, if online platform design is really playing such a crucial role in undermining odd-priced listings,

we should expect the odd-pricing effects to have strengthened over time, concomitant with the rising penetration of high-speed broadband internet in North America. Indeed, this is what we find when we parse the odd-pricing effect by year. Second, taking advantage of the variation in the lower price bounds suggested on realtor.com websites across cities and over time, we investigate whether those specific round prices have larger odd-pricing effects than other round prices. Using data from a digital archive of the internet ("The Wayback Machine"), we find that odd-priced houses that are adjacent to a suggested realtor.com round price sell at a one-third larger price discount, and take twice as long to sell, than odd-priced houses that are not adjacent to a suggested round price. Finally, using the Genesove and Han 2016 survey of home buyers in Toronto—whose purchases are represented in our MLS data—we find that self-reported buyer budgets in the Toronto survey display pronounced bunching at multiples of $50,000 and $100,000. Moreover, round-priced properties are 14.6% more likely to attract multiple bidders than observationally similar odd-priced houses; and buyers of those round-priced properties report having a higher initial budget than buyers of adjacent odd-priced properties.

The remaining piece of the puzzle is why sellers use odd prices when it is self-defeating. Following Backus, Blake, and Tadelis 2018, one might surmise that a list price serves as a "cheap-talk signal" to communicate something of value to the seller—for instance, that they are a "motivated seller."[4] However, for a cheap-talk signal to work with rational buyers, sellers must experience a trade-off deploying the signal. In Backus, Blake, and Tadelis's (2018) data, there is a trade-off: sellers listing at round prices get a lower price, but are more likely to sell, and faster, than sellers listing at neighboring non-round prices. In our real estate data, however, there are no trade-offs: round-priced sellers beat

[4]Backus, Blake, and Tadelis 2018 find evidence that in the eBay collectibles marketplace, a round asking price signals seller weakness. However, note that they are comparing round prices against neighboring "precise prices": non-round prices on *both* sides of the round price. By contrast, we are comparing odd prices—which are, by definition, "just-below"—against neighboring round prices. In their data, round prices are relatively more numerous; in our data, odd prices are relatively more numerous.

odd-priced sellers on probability of sale, sale price, and time on the market.

Thus it is hard to rationalize sellers' motivations for using odd prices. On the other hand, "behavioral" reasons can be entertained. For instance, home sellers may have faith in the left-digit bias of home buyers, notwithstanding rational arguments to the contrary. They may reflexively believe that an odd price will look more attractive to potential buyers than the adjacent, higher, round price. What lends credence to such beliefs is the relative inexperience of the average home seller selling anything[5]—much less real estate.[6] It is quite possible that the ubiquity of odd prices in the places where they usually buy things—grocery stores, department stores, amazon.com—leads them to believe that these marketing strategies work universally. Previous work has shown that such cognitive errors can persist even when the stakes are high and there is professional intermediation (Hirshleifer 2015; Barberis 2018).

This paper contributes to several strands of literature. First, we contribute to the literature on the microstructure of housing markets, which studies how decentralized trading institutions shape transaction outcomes (Han and Strange 2015). One example of such institutions is digital platforms and algorithmic tools that shape the information environment in which housing transactions occur (Buchak et al. 2020; Troncoso and Beas 2025). Another body of work emphasizes the role of search frictions and heterogeneous buyer consideration sets in determining housing market liquidity and prices. For example,

[5]Most individuals spend most of their lives as consumers rather than as sellers. And we know that consumers make sub-optimal decisions in a variety of financial domains, e.g., choice of a credit card (Shui and Ausubel 2004), mortgage refinancing (Agarwal, Rosen, and Yao 2016), spending decisions in response to predictable income changes (Jørring 2024); for a review see Agarwal, Chomsisengphet, and Lim 2017.

[6]Of course, they hire agents for that very reason (National Board of Realtors *op. cit.*). However, as Hirshleifer 2015 has noted in the context of professional investment advisors, "owing to conflict of interest, or to imperfect rationality ... employing agents is an imperfect remedy for ignorance and folly." Bucchianeri and Minson 2013 observe, for example, that agents' recommendations are often at variance with what is optimal for the seller: "although most professional advice recommends under-pricing, over-pricing one's home relative to any of several benchmarks used in our analyses results in a higher sale price, controlling for how long one waits to sell." Our odd-pricing effects are new to the literature and, arguably, even more subtle than the anchoring effect of above-market list prices; it shouldn't be surprising that perhaps agents are not aware of them. In Section IV.A we provide evidence that agent experience is no antidote to the use of odd prices.

Piazzesi, Schneider, and Stroebel 2020 show that housing markets are segmented because buyers search within limited sets of properties defined by location, amenities, and price ranges. Our work complements Piazzesi, Schneider, and Stroebel 2020 by showing how the round-numbered nature of those price ranges can interact with sellers' penchant for odd pricing to deliver suboptimal outcomes.

Second, our results connect to the broader market microstructure literature in finance, which studies how trading mechanisms and market design influence price formation and liquidity (O'Hara 1995; Duffie, Garleanu, and Pedersen 2005). A central insight of this literature is that market outcomes depend not only on fundamentals but also on the institutional structures through which buyers and sellers meet. Our results show that digital housing platforms effectively play a role analogous to market microstructure in financial markets: by organizing search through price filters and other interface features, platform design shapes listing visibility, buyer arrival rates, and the intensity of bidding competition.

Third, we contribute to research on the role of numerical salience in affecting market outcomes. Prior studies document clustering around salient price points in both consumer and financial markets, often attributing such patterns to behavioral biases among consumers or traders (Stiving and Winer 1997; Anderson and Simester 2003; Bhattacharya, Holden, and Jacobsen 2012; Heraud and Page 2024). The popularity of odd prices in retail markets is commonly attributed to left-digit bias, whereby consumers place disproportionate weight on the leading digit (Levy et al. 2020; Schindler and Wiman 1989; Strulov-Shlain 2023). By contrast, we find no evidence of buyers being handicapped by odd prices in housing markets; on the contrary, they are better off—paying lower prices than buyers of essentially equivalent round-priced houses. Oddly enough, it is the sellers of odd-priced houses who seem to be suffering from several behavioral biases. First, their faith in the left-digit bias of buyers is clearly misplaced. Second, their affinity to odd

pricing betrays a lack of understanding of how the search interface of online real-estate platforms might undermine the effectiveness of their preferred pricing strategy.

The rest of this paper is organized as follows. In Section I we present a conceptual framework for how odd pricing can interact with the microstructure of housing markets. Our data are described in Section II. Section III documents the adverse effects of odd pricing on sales outcomes in four U.S. cities and in Toronto.[7] In Section IV we investigate and rule out the possibility of spurious correlation accounting for our results. Section V presents evidence that odd-priced houses face a lower demand curve than observationally similar round-priced houses. Finally, Section VI concludes the paper. All prices are in U.S. dollars unless otherwise noted.

I. Conceptual Framework

This section describes a framework for thinking about how listing strategy, odd versus round pricing, can interact with the design of digital search platforms to affect housing market outcomes. The framework builds on canonical search models of housing markets (Wheaton 1990; Genesove and Han 2012) as well as recent work emphasizing segmented search and heterogeneous buyer consideration sets (Piazzesi, Schneider, and Stroebel 2020).

In decentralized housing markets, transactions occur when buyers and sellers locate each other through a stochastic search process. Houses differ in "search" attributes—price, location, number of bedrooms and bathrooms, etc.—and "experience" attributes: what the buyer sees (only) upon visiting the house—things like curb-appeal, layout, construction quality, state of repair, view, etc. While the former can be searched on an online platform such as realtor.com, the latter calls for personal inspection (Badarinza, Balasubramaniam, and Ramadorai 2023). This leads naturally to a three-stage search

[7]While Section III presents the headline results for Toronto alongside the U.S. results, many of its supplementary results are relegated to the Internet Appendix.

process: (i) screening the available listings to form a consideration set, (ii) perusal of the houses in the consideration set based on their search (listing) attributes, and (iii) physical inspection of shortlisted houses.

Screening by upper and lower price bounds. When quality is unobserved but price is, and expected to be correlated with quality, screening must involve upper *and* lower bounds on price (Gabor and Granger 1966). To see this, consider a buyer with utility function $U(q,p) = V(q) - p$, where q is quality, p is price, and $V(\cdot)$ is an increasing function mapping quality to reservation price. The buyer doesn't know the (q,p) pairs available in the market before search. The screening decision—whether to place a house listed at p into the consideration set—will be based on $\hat{V}(p)$, the buyer's *expected* reservation price for a house priced at p, and c, the cost of considering such a house—the expected search/deliberation cost to be incurred in the second and third stages on this house. We expect reservation price to be an increasing, concave function of price because we expect the quality-price relationship, $q(p)$, to be an increasing, concave function of price (Scitovszky 1944; Leavitt 1954; Gabor and Granger 1966).[8]

At the consideration stage, then, the buyer is evaluating $\hat{V}(p) - p - c$. To be worthy of consideration, a house must satisfy $\hat{V}(p) - p - c \geq 0$. Assume $\{p : \hat{V}(p) - p - c \geq 0\}$ is nonempty, i.e., there are houses worth considering. If $\hat{V}(p)$ has a slope greater than 1 at lower price levels and a slope less than 1 at higher price levels, then $\hat{V}(p) - c$ will intersect p at two points, $\underline{p}$ and $\bar{p}$, while it is above p in between.[9] Those intersection points are the buyer's lower and upper price bounds for consideration, subject to $\bar{p}$ satisfying $\bar{p} \leq B$, where B is the buyer's budget constraint. Effectively, $\bar{p}$ is the price above which a house would be considered too expensive and $\underline{p}$ is the price below which

[8]This formulation neatly encapsulates the role of a buyer's agent as educating the buyer about the price-quality relationship.

[9]For instance, if $\hat{V}(p) = ap^2 + bp$, with $a < 0$ and $b > 1$, then $\underline{p} = \left(-(b-1) - \sqrt{(b-1)^2 + 4ac}\right)/2a$ and $\bar{p} = \left(-(b-1) + \sqrt{(b-1)^2 + 4ac}\right)/2a$.

the expected quality would be unacceptably low.[10] The buyer's consideration set is thus $\mathcal{S} = \{j : \underline{p} \leq p_j \leq \min\{\bar{p}, B\}\}$.

The comparative statics of the lower and upper bounds with respect to c are illuminating. Assuming $\bar{p} < B$, $\underline{p}$ and $\bar{p}$ solve

$$\hat{V}(p) - p - c = 0.$$

Total differentiation with respect to c then yields

$$\left(\hat{V}'(p) - 1\right) \frac{dp}{dc} - 1 = 0.$$

If $\hat{V}'(p) > 1$, i.e., the bound in question is the lower bound, then $dp/dc > 0$; if $\hat{V}'(p) < 1$, i.e., the bound in question is the upper bound, then $dp/dc < 0$. As consideration costs increase, the buyer sets more stringent bounds, shrinking her consideration set.

Platform design and the microstructure of housing markets. When screening houses by upper and lower price bounds, buyers are likely to use round numbers. This is because: (a) round numbers are natural focal points, and (b) the online real-estate platforms make it easy to pick round numbers. With respect to the former, there is a large literature documenting the human tendency to use round numbers in a variety of contexts (Lynn, Flynn, and Helion 2013; Zinn and Würbach 2016; Argyle, Nadauld, and Palmer 2020; Kuo, Lin, and Zhao 2015). With respect to the latter, all major real-estate platforms in the U.S. and Canada feature drop-down menus of round-numbered minimum and maximum price filters. For example, on a recent visit to the Chicago realtor.com

[10] Piazzesi, Schneider, and Stroebel 2020 provide direct evidence of home buyers using lower and upper price bounds to screen properties. Their data come from the real-estate website trulia.com, where San Francisco Bay Area buyers had the opportunity to set e-mail alerts to be notified of new listings. They observe that 63% of buyers specify either a lower or an upper price bound (besides geographic location, which the site requires them to specify); of these, 52% specify a lower price bound. Guren 2018 finds a concave demand function that is upward-sloping at lower price levels in the same market (see also Cubbin 1974; Andersen et al. 2022).

website we saw "No min," \$90K, \$180K, \$250K, \$350K, \$450K, \$500K, and \$600K as possible mimimum prices and "No max," \$150K, \$300K, \$450K, \$600K, \$800K, \$900K, and \$1M as possible maximum prices, with "No min" and "No max" as the defaults. Taking those defaults—and imposing no other filters—would have meant looking at all 9,418 homes available for sale in Chicago; however, by selecting a lower bound of \$600,000 and an upper bound of \$800,000 from the drop-down menus, the number of listings went down by 92%.

Of course, buyers are not obligated to take a platform's suggestions; they can enter alternative bounds of their own choosing. But since round numbers are natural focal points, even those choices are likely to be round numbers.[11] Piazzesi, Schneider, and Stroebel's (2020) histograms of the minimum and maximum prices set by San Francisco Bay Area home buyers on the platform trulia.com confirms this. This platform pre-populated the minimum and maximum price boxes with "No min" and "No max," but didn't offer drop-down menus of suggested bounds; the user had to manually enter alternative bounds if they didn't want the defaults. Their data show that the bounds people enter are typically multiples of \$50,000, with particularly pronounced peaks at multiples of \$100,000.[12]

Round-numbered minimum and maximum price filters affect listing visibility as follows. Consider a buyer with a search range $[\underline{p}, \bar{p}]$, where $\underline{p}$ and $\bar{p}$ are round numbers. This buyer will filter out a house odd-priced at $\underline{p} - \epsilon$, but will consider a house adjacently round-priced at $\underline{p}$. On the other hand, if an odd-priced house falls in the interior of a search range—such as house priced at \$499,500 with respect to a buyer with a screening range of $[\$400,000, \$600,000]$—so that it is included in the buyer's consideration set, so will its round-priced counterpart. In other words, a round-priced house will make the cut when an odd-priced house does, but the reverse is not necessarily true. This also means

[11] This is important because mobile app versions of the real-estate platforms typically do not offer drop-down menus (very likely due to space constraints on a smartphone display).

[12] Our survey of Toronto buyers— discussed later—reveal similar patterns in those buyers' reported budgets (Figure A.II).

that an odd-priced house will always face more competition than an adjacent round-priced house.

Finally, since $\bar{p}$ and $\underline{p}$ are likely to be positively correlated—for one thing, because the former must necessarily be larger than the latter—the buyers for whom a round-priced house hits their lower bound will tend to have a higher reservation price than the buyers who consider an adjacent odd-priced house—because the latter must have a lower lower-bound, and hence likely a lower upper bound. This implies that the average buyer who considers a round-priced house will tend to have a higher reservation price than the average buyer who considers an adjacent odd-priced house.

In effect, when round-numbered lower and upper price bounds interact with the odd versus round pricing strategies of sellers, they engender a highly localized form of segmented housing search. This is in contrast to the broader search that results when buyers search geographical neighborhoods. Those need not be adjacent to each other (Piazzesi, Schneider, and Stroebel 2020).

Our data provide a rare opportunity to test the implications of round-numbered minimum and maximum price filters. On the one hand, we have comprehensive MLS data from multiple metropolitan areas with detailed listing characteristics and transaction outcomes. In addition, we have survey data from Toronto buyers providing information on their budgets and the number of competing bidders they faced. Combining these sources allows us to examine not only the market outcomes predicted by the framework, but also the underlying mechanism that might have led to those outcomes. The next section describes these data and the institutional features that make the empirical analysis possible.

II. Data

We have residential real-estate transaction data from the multiple-listing service (MLS) of five major metropolitan areas in North America: the U.S. cities of Chicago, Minneapolis, San Diego, and Seattle, and the Canadian city of Toronto.[13] In addition, we have survey data from a sample of buyers in Toronto recalling their buying experience. These data are described next.

II.A. MLS Data from the United States

These data were obtained from CoreLogic, a company that specializes in U.S. residential real estate data. Our main analysis focuses on listings from 2008–2018: 2,457,966 in total, comprising 1,717,393 that sold (69.87%) and 740,573 that didn't (30.13%). The vast majority (98.41%) are single-family homes; the rest (1.59%) are duplexes. From these we retain only original listings that: (a) are listed between \$124,999 and \$1,024,999 (2,195,040 observations or 89.30%), (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)).[14] Our U.S. MLS data set contains 1,403,602 listings, 953,759 sold (67.95% of sample) and 449,843 unsold (32.05% of sample).

Table I describes these data. Panel A shows that the U.S. housing market improved from 2008 to 2018: average home price rose from \$278,111 to \$342,357 (23%); sale to list price ratio rose from .97 to .99; days on the market fell from 17 to 11 weeks; and probability of a "quick" sale—selling within a week of listing—rose from .02 to .11.

[13] By definition, these are data for publicly-listed properties sold through an agent. Private sales, and homes sold by an owner without an agent, don't appear in the MLS. The buying and selling processes for homes are essentially the same in Toronto as in the U.S. cities.

[14] Of 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.

Panel B shows list price characteristics in relation to round numbers (i.e., $100K, $50K or $10K multiples). Of interest is what proportion of list prices are round, what proportion are just-below round, and what proportion are just-above round, where just-below and just-above are defined as list prices up to $1K away from round prices. Consistent with the histogram in Figure 1, list prices below a round number are substantially more common than round list 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.

Table I
Summary statistics (U.S. MLS data)

Round prices are defined as $100K, $50K, and $10K multiples, and just-below/just-above as prices in $1K intervals, below/above adjacent round prices. Some extreme values of sales ratio, days on the market, and living area square footage have been winsorized at the 1 and 99 percentiles; none of our analyses is sensitive to this adjustment.

Transaction 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	0.000	0.964	0.000	0.977	0.000	0.986	0.000
Days on market	118.773	0.256	112.958	0.218	92.339	0.138	75.208	0.120
Quick sale	0.024	0.000	0.031	0.000	0.047	0.000	0.109	0.000
Sales price/1000	278.111	0.536	311.479	0.427	330.490	0.319	342.357	0.279
Probability of Sale	0.527	0.001	0.700	0.001	0.699	0.001	0.693	0.001
B: Listing characteristics								
List Price/1000	0.298	0.000	0.321	0.000	0.345	0.000	0.367	0.000
Just above threshold (%)	0.448	0.018	0.463	0.014	0.379	0.009	0.341	0.008
Exactly round (%)	7.164	0.068	8.293	0.058	9.099	0.043	11.322	0.041
Just below threshold (%)	51.537	0.133	50.953	0.104	48.906	0.075	45.952	0.065
C: House characteristics								
Number of bedrooms	3.277	0.003	3.370	0.002	3.354	0.001	3.330	0.001
Number of washrooms	2.485	0.002	2.595	0.002	2.632	0.001	2.624	0.001
Living area square footage	2110.582	2.297	2147.838	1.850	2113.098	1.328	2079.997	1.178
Lotsize	46311.651	9255.475	39397.697	1202.499	36949.676	454.548	33459.656	397.394
Number of fireplaces	0.771	0.002	0.792	0.002	0.727	0.001	0.681	0.001
Number of parking space	0.053	0.001	0.342	0.002	0.502	0.002	0.617	0.002
Gas heat source	0.927	0.001	0.889	0.001	0.880	0.000	0.888	0.000
Forced air	0.021	0.000	0.072	0.001	0.055	0.000	0.066	0.000
D: Agent characteristics								
Average sales ratio	0.980	0.000	0.975	0.000	0.974	0.000	0.975	0.000
Average days on market	74.062	0.110	82.823	0.095	85.309	0.065	82.471	0.056
Number of homes sold	102.679	0.382	83.393	0.264	72.698	0.177	63.072	0.147

Finally, Panels C and D show that house and agent characteristics were relatively stable over our time period, with the sole exception of agent experience, which shows a decrease—the average agent selling 40 fewer homes in 2016–2018 than in 2008-2009—perhaps reflecting the arrival of new agents into the business.

II.B. MLS Data from Toronto

These data cover sales transactions in the Greater Toronto Area (GTA) from January 1, 2000 to November 30, 2018.[15] Years prior to 2007 do not contain information on housing characteristics, hence our main analysis focuses 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 \$1,224,999 (677,777 observations), (c) contain non-missing list price, sale price, days on the market, and agent name (677,426 observations), and (d) contain non-missing "district" and lot-size information (643,343 observations). Our Toronto MLS data set comprises 643,343 listings.

These data are summarized in Table II. Panel A shows that the Toronto real-estate market also improved substantially during our sample period. Average home price rose from \$418,000 to \$726,000 (72%), sales ratio increased from 0.98 to 1.02, and time on the market fell from 31 to 19 days. Panel B focuses on the prevalence of list prices near \$100K multiples. Just as in the U.S. data, homes listed just below a \$100K multiple (within \$1,000) represent a common and increasingly popular strategy, rising from 11.4% of listings in 2007–2009 to 23% in 2016–2017. By contrast, homes listed just above a round number are relatively rare. Finally, panel C shows relatively stable house characteristics and panel D shows agents increasing their sales ratios while decreasing their number of homes sold.

[15] Unlike the U.S. data, these data don't have unsold listings.

Table II
Summary statistics (Toronto MLS data)

Round prices are defined as \$100K, \$50K, and \$10K multiples, and "just-below"/ "just-above" as prices in adjacent \$1K intervals, below/above. Some extreme values of sales ratio, days on the market, and lotsize have been winsorized at the 1 and 99 percentiles; none of our analyses is sensitive to this adjustment. All prices are in Canadian dollars (CAD).

Transaction year:	2007-2009 (N=165508)		2010-2012 (N=170190)		2013-2015 (N=179832)		2016-2018 (N=158052)	
Characteristic	Mean	SD	Mean	SD	Mean	SD	Mean	SD
A: Transaction outcomes								
Sales ratio	0.98	0.000	0.99	0.000	1.00	0.000	1.02	0.00
Days on market	31.25	0.075	25.63	0.068	23.15	0.063	18.55	0.06
Quick sale	0.18	0.001	0.25	0.001	0.29	0.001	0.39	0.00
Sales price/1000	418.18	0.429	488.77	0.481	576.73	0.528	726.71	0.62
B: Listing characteristics								
List Price/1000	425.95	0.434	494.13	0.482	577.25	0.517	705.70	0.57
Just-above (%)	0.13	0.009	0.12	0.008	0.11	0.008	0.11	0.01
Exactly round (%)	2.63	0.039	3.43	0.044	4.77	0.050	7.32	0.07
Just-below (%)	63.98	0.118	65.91	0.115	65.78	0.112	66.45	0.12
C: House characteristics								
Number of bedrooms	3.37	0.002	3.37	0.002	3.35	0.002	3.29	0.00
Number of rooms	7.31	0.004	7.49	0.004	7.50	0.004	7.47	0.00
Number of washrooms	2.83	0.002	2.88	0.002	2.91	0.002	2.85	0.00
Lotsize	7375.92	40.686	8244.40	46.415	8614.54	45.969	8429.51	46.84
Fireplace	0.65	0.001	0.65	0.001	0.65	0.001	0.56	0.00
Detached	0.20	0.001	0.19	0.001	0.18	0.001	0.18	0.00
Finished Basement	0.64	0.001	0.65	0.001	0.68	0.001	0.45	0.00
Family room	0.51	0.001	0.54	0.001	0.57	0.001	0.51	0.00
Driveway	0.30	0.001	0.87	0.001	0.88	0.001	0.59	0.00
Gas heat source	0.93	0.001	0.93	0.001	0.92	0.001	0.83	0.00
Forced air	0.93	0.001	0.94	0.001	0.94	0.001	0.86	0.00
D: Agent characteristics								
Average sales ratio	0.98	0.000	1.05	0.026	1.26	0.061	1.52	0.10
Average days on market	32.05	0.026	30.91	0.027	29.64	0.027	27.69	0.03
Number of homes sold	177.00	0.691	170.94	0.702	189.40	0.853	158.32	0.83

II.C. Survey of Buyers in Toronto

We supplement the Toronto MLS data with data from a mail/phone survey of Toronto home buyers from 2006-2009, conducted by Genesove and Han 2016 (reported previously in Han and Strange 2016). Among other things, the survey asked buyers to report—within

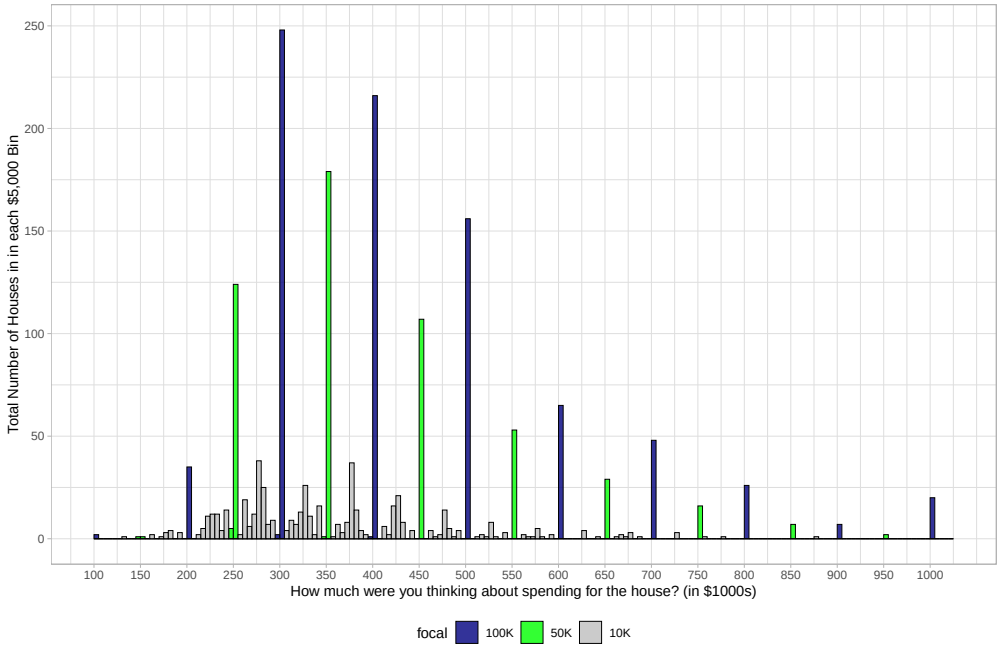
a year of purchase—their budget for the house and the number of other bidders on the property (if any). Importantly, these buyers' purchases can be identified in our MLS data, allowing us to connect their purchase process to the seller's listing strategy—something that is rare in the literature. (For example, while Piazzesi, Schneider, and Stroebel 2020 provide aggregate data on the search process, they can't relate individual search to individual outcomes.) We use this survey in Section V to test whether round-priced houses attract more and/or higher-budget buyers than observationally similar adjacently odd-priced houses.

To conduct the survey, Genesove and Han took a random sample of 18,789 single-family homes sold during 2006–2009 from the Toronto MLS: 4,021 from 2006, 4,580 from 2007, 6,909 from 2008, and 3,279 from the first three quarters of 2009. From the addresses of those properties, they obtained the names of the buyers from the Toronto Land Registry Office. Of these, 1,816 addresses were eliminated because they pertained to land transactions or to institutional buyers; the remaining 16,973 buyers were surveyed by mail and/or by telephone. Of the mail surveys, 351 were returned "household-moved" or "address unknown" by Canada Post. Ultimately, 3,193 surveys were completed, for an overall response rate of 19.2%. Table A.III shows that, for homes sold during 2007–2009, 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.

The Toronto survey provides individual-level information on the search and buying process for homes. Three particularly relevant questions are: "Were there other people actively bidding on the home when you submitted your first offer?"; "If yes, about how many other bidders were there?"; and "How much were you thinking about spending for the house?" As Table A.IV shows, 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 A.II

shows the histogram of reported budgets; the average budget is $412,302 CAD.

Figure 2. Histogram of self-reported buyer budget in the Toronto sample. Each pair of identically-colored bars is centered on a round price, a multiple of $10K, $50K, or $100K. If x is a round price, the left-hand bar represents the interval $[x - \$5K, x)$ and the right-hand bar represents the interval $[x, x + \$5K)$.



III. Odd Pricing and Sales Outcomes

We start by comparing odd-priced and adjacently round-priced properties on sales outcomes, house attributes, and agent characteristics. The first four columns of Table III display the means and standard deviations of these quantities 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,

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

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. See Internet Appendix II.B for additional details.

	Odd (N=1,004,367)		Round (N=399,235)		Difference	
Characteristic	Mean	SD	Mean	SD	Mean	t-statistic
A: Sales outcomes						
Sales ratio	0.977	0.000	0.981	0.000	0.004	45.504
Days on market	91.926	0.096	89.402	0.150	-2.524	-14.147
Quick sale	0.065	0.000	0.075	0.000	0.009	19.595
Sales price/1000	337.672	0.218	304.747	0.306	-32.925	-87.492
Probability of Sale	0.677	0.000	0.685	0.001	0.007	8.154
B: House characteristics						
Number of bedrooms	3.354	0.001	3.301	0.001	-0.053	-30.165
Number of washrooms	2.627	0.001	2.559	0.001	-0.067	-38.616
Living area square footage	2124.946	0.903	2053.633	1.353	-71.313	-43.839
Lotsize	39138.106	1969.644	33715.142	776.780	-5422.964	-2.561
Number of fireplaces	0.739	0.001	0.682	0.001	-0.057	-40.348
Number of parking space	0.514	0.001	0.388	0.002	-0.126	-56.903
Gas heat source	0.885	0.000	0.900	0.000	0.014	25.228
Forced air	0.064	0.000	0.046	0.000	-0.018	-42.653
C: Agent characteristics						
Average sales ratio	0.975	0.000	0.976	0.000	0.001	31.269
Average days on market	82.750	0.043	82.177	0.069	-0.573	-7.032
Number of homes sold	72.740	0.120	75.227	0.194	2.487	10.887

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 housing 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. Agent experience, proxied by number of homes sold before the current listing, is slightly lower for odd-priced listings, as is agent quality, proxied by sales ratio and average days on the market (of

properties sold before current listing).

The Toronto market shows strikingly similar comparisons in Table IV.

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

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. See Internet Appendix II.B for additional details.

	Odd (N=441,383)		Round (N=31,102)		Difference	
Characteristic	Mean	SD	Mean	SD	Mean	t-statistic
A: Transaction outcomes						
Sales ratio	1.00	0.000	1.01	0.000	0.008	18.68
Days on market	24.12	0.041	23.76	0.162	-0.357	-2.13
Quick sale	0.29	0.001	0.32	0.003	0.037	13.58
B: House characteristics						
Number of bedrooms	3.34	0.001	3.40	0.005	0.057	11.96
Number of rooms	7.44	0.003	7.60	0.011	0.164	14.29
Number of washrooms	2.86	0.002	2.93	0.006	0.076	12.05
Lotsize	8200.24	28.023	10083.54	131.519	1883.299	14.01
Fireplace	0.63	0.001	0.63	0.003	0.002	0.76
Detached	0.19	0.001	0.16	0.002	-0.025	-11.51
Finished Basement	0.61	0.001	0.59	0.003	-0.012	-4.11
Family room	0.53	0.001	0.56	0.003	0.027	8.82
Driveway	0.66	0.001	0.69	0.003	0.033	12.33
Gas heat source	0.91	0.000	0.88	0.002	-0.028	-14.29
Forced air	0.92	0.000	0.90	0.002	-0.021	-11.44
C: Agent characteristics						
Average sales ratio	1.25	0.041	1.25	0.157	-0.002	-0.03
Average days on market	29.84	0.017	29.23	0.064	-0.614	-2.98
Number of homes sold	172.38	0.466	200.96	2.144	28.578	1.22

III.A. Econometric Analysis

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 will estimate a local linear regression in a $15K neighborhood of round listing prices, defined as multiples of $100K between $200K

and \$1,000K.[16] Denote round list prices by $\tau \in \mathcal{T} \coloneqq \{200K, \ldots, 1000K\}$ and the 15K neighborhood corresponding to a τ by $N_\tau \coloneqq [\tau - 15K, \tau + 15K)$. The collection of all such neighborhoods is $\mathcal{N} \coloneqq \bigcup_\tau N_\tau$. If P_i^L denotes the list price of property i, our universe of observations is $\mathcal{I} \coloneqq \{i : P_i^L \in \mathcal{N}\}$.

Within each \$15K neighborhood, houses are assigned to \$1K bins. For $\tau \in \mathcal{T}$, define $\mathcal{R}_\tau \coloneqq [\tau, \tau + 1K)$ and $\mathcal{O}_\tau \coloneqq [\tau - 1K, \tau)$ as the round-priced and odd-priced bins, respectively, centered on τ.[17] Thus, we are defining list prices as odd when they are up to \$1K *below* a round price. The remaining \$1K bins in the neighborhood of τ are $\mathcal{B}_\tau^z \coloneqq [\tau + z, \tau + z + 1K)$ for $z \in \{-15K, \ldots, -2K, 1K, \ldots, 14K\}$.

For each property $i \in \mathcal{I}$, there exists a τ_i identifying the unique round price its list price is closest to. In the regressions below, we will use indicator variable $\texttt{Odd Price}_i$ to distinguish odd-priced houses from round-priced houses, and the 28×1 vector of indicator variables $\texttt{Bin}_i = (\texttt{Bin}_i^{-15K}, \ldots, \texttt{Bin}_i^{-2K}, \texttt{Bin}_i^{1K}, \ldots, \texttt{Bin}_i^{14K})$, to distinguish houses with other neighboring list prices from round-priced houses. $\texttt{Odd Price}_i$ and $\texttt{Bin}_i^z$ are defined as follows:

$$\texttt{Odd Price}_i = \begin{cases} 1 & \text{if } P_i^L \in \mathcal{O}_{\tau_i} \\ 0 & \text{if } P_i^L \in \mathcal{R}_{\tau_i} \end{cases}$$

$$\texttt{Bin}_i^z = \begin{cases} 1 & \text{if } P_i^L \in \mathcal{B}_{\tau_i}^z \\ 0 & \text{if } P_i^L \in \mathcal{R}_{\tau_i} \end{cases} \qquad \text{for } z \in \{-15K, \ldots, -2K, 1K, \ldots, 14K\}$$

Note that for every observation in the regression, either $\texttt{Odd Price}_i$ is equal to 1, or (exactly) one of the $\texttt{Bin}_i^z$ is equal to one, or both $\texttt{Odd Price}_i$ and all $\texttt{Bin}_i^z$ are equal to

[16] In Section III.B we will examine other definitions of round prices, such as multiples of \$50K and \$10K.

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

zero, in which case the list price is a round price. In short, round prices serve as the reference category in the regression.

We specify the regression as follows:

$$Y_i = \beta \cdot \texttt{Odd Price}_i + \texttt{Bin}_i'\boldsymbol{\beta}_{\mathcal{B}} + +\mathbf{X}_i'\boldsymbol{\alpha}_1 + \mathbf{Z}_i'\boldsymbol{\alpha}_2 + \boldsymbol{\gamma}_{\tau_i \times y_i \times c_i} + \boldsymbol{G}_{pc_i \times y_i} + \boldsymbol{A}_i + \epsilon_i \quad (1)$$

where Y_i denotes a sales outcome: whether the property sold or not, sale price, $\texttt{P}_i^S$, sales ratio, $\texttt{P}_i^S/\texttt{P}_i^L$, days on the market, and whether the house sold within a week of listing. The coefficient of interest is β; it captures the effect on outcomes of list prices in the odd-price bin $\mathcal{O}_{\tau_i}$ vis-a-vis houses in the round-price bin $\mathcal{R}_{\tau_i}$. The corresponding coefficients for list prices in the other neighboring bins $\texttt{Bin}_i^z$ are collected in the 28×1 vector $\boldsymbol{\beta}_{\mathcal{B}}$.[18]

To account for the possibility that odd-priced houses differ systematically from round-priced houses in ways that affect sales outcomes, we have a variety of covariates. These include $\mathbf{X}_i$, a vector of house characteristics (e.g., square footage, number of bedrooms, number of bathrooms, etc.), and $\mathbf{Z}_i$, a vector of agent characteristics that speak to agent experience (number of houses previously sold by the agent) and agent quality (previous average sales ratio and days on the market achieved by the agent); see Internet Appendix A for the full list of house and agent characteristics. Finally, to control for other unobserved variables that might vary by house location, year of sale, and listing threshold (e.g., a house priced around \$300K versus around \$400K), we include a variety of fixed effects: threshold-year-county fixed effects, denoted by $\boldsymbol{\gamma}_{\tau \times y \times c}$, and postal code-year fixed effects, denoted by $G_{pc \times y}$. Importantly, we also have agent fixed effects, denoted by $\boldsymbol{A}$, which absorb a key source of selection—agent proclivity to price in a certain way. Our most comprehensive specification, then, identifies β by comparing odd-priced and round-priced houses centered on the same round-numbered threshold, sold in the same year, located

[18] In Section IV.B we compare β and $\beta_{\mathcal{B}}$ to show that the odd-priced bin is indeed different from the other bins neighboring round prices.

in the same postal code, and sold by the same agent, while controlling for house and agent characteristics. In Section III.B, we examine heterogeneity by round-price threshold ($100K multiples), threshold type ($100K versus $50K versus $10K multiples), year, and city.

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

In column (1) we have threshold-year-county fixed effects only. This specification simply compares average transaction outcomes for odd-priced houses versus round-priced houses within each threshold-year-county, and then averages those comparisons over all threshold-year-counties. Given our definition of odd price, the comparisons in question involve houses with list prices that 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 listing 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 column (5), agent fixed effects as well. Including these additional controls slightly attenuates $\hat{\beta}$, with the largest such reduction happening to days on the market with the addition of Zip Code-year fixed effects. However, even with these expanded sets of controls, the basic result from column (1) remains: odd-priced houses underperform relative to their round-numbered counterparts on probability of selling, sale price, and time to sell. Specifically, in our most comprehensive specification (column (5)), odd-priced houses are

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

All columns report β estimates from OLS regressions of equation (1). Standard errors, in parentheses, are clusterd 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.

	Bin size = $1,000				
	(1)	(2)	(3)	(4)	(5)
A: Dependent variable: ***log(Sale price)***					
Odd Price	-0.0076***	-0.0077***	-0.0073***	-0.0070***	-0.0066***
	(0.0005)	(0.0004)	(0.0005)	(0.0005)	(0.0005)
R^2	0.991	0.991	0.992	0.992	0.994
B: Dependent variable: ***Sales ratio***					
Odd Price	-0.0058***	-0.0059***	-0.0055***	-0.0054***	-0.0046***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
R^2	0.159	0.200	0.249	0.262	0.424
C: Dependent variable: ***Days on the market***					
Odd Price	8.026***	7.429***	6.628***	7.006***	7.160***
	(0.6878)	(0.6766)	(0.6749)	(0.6827)	(0.8011)
R^2	0.192	0.226	0.269	0.284	0.437
D: Dependent variable: ***Quick sale probability***					
Odd Price	-0.0382***	-0.0373***	-0.0353***	-0.0355***	-0.0355***
	(0.0029)	(0.0029)	(0.0029)	(0.0030)	(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
E: Dependent variable: ***Probability of sale***					
Odd Price	-0.0549***	-0.0502***	-0.0469***	-0.0501***	-0.0394***
	(0.0037)	(0.0038)	(0.0037)	(0.0037)	(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
Fixed-effects					
Threshold-Year-County	Yes	Yes	Yes	Yes	Yes
ZIP Code-Year			Yes	Yes	Yes
Agent					Yes

less likely to sell by about 4 percentage points, and when they sell, they sell at a .66% discount and about a week later.

Table VI presents estimates of equation (1) in the Toronto market. For each dependent

variable, Columns 1–4 show results from specifications with progressively more control variables. Consistent with the U.S. findings, we observe that homes with odd prices consistently have worse transaction outcomes than their round-priced counterparts.

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

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.

	Bin size = $1,000				
	(1)	(2)	(3)	(4)	(5)
A: Dependent variable: ***log(Sale price)***					
Odd Price	-0.0050**	-0.0067***	-0.0079***	-0.0073***	-0.0078***
	(0.0020)	(0.0018)	(0.0015)	(0.0014)	(0.0015)
R^2	0.98	0.98	0.98	0.98	0.99
B: Dependent variable: ***Sales ratio***					
Odd Price	-0.0052***	-0.0068***	-0.0077***	-0.0071***	-0.0075***
	(0.0017)	(0.0015)	(0.0013)	(0.0012)	(0.0013)
R^2	0.17	0.25	0.36	0.37	0.48
C: Dependent variable: ***Days on the market***					
Odd Price	1.644***	2.644***	1.747***	1.278***	1.265***
	(0.4299)	(0.3625)	(0.3219)	(0.3100)	(0.3637)
R^2	0.06	0.16	0.23	0.25	0.36
D: Dependent variable: ***Quick sale probability***					
Odd Price	-0.0440***	-0.0520***	-0.0453***	-0.0398***	-0.0456***
	(0.0086)	(0.0083)	(0.0076)	(0.0074)	(0.0079)
R^2	0.06	0.10	0.14	0.16	0.29
House controls		Yes	Yes	Yes	Yes
Agent controls				Yes	Yes
Fixed-effects					
Threshold-year fixed effects	✓	✓	✓	✓	✓
FSA-year fixed effects			✓	✓	✓
Agent fixed effects					✓
Observations	230,640	220,910	220,910	214,078	214,078

III.B. Heterogeneity

In this section we examine how the odd-pricing effect varies by: (i) listing threshold, (ii) threshold type—whether the threshold in question is a \$100K multiple, or a \$50K multiple, or a \$10K multiple, (iii) year of sale, and (iv) city of sale.

Listing Threshold. Table VII shows the results of estimating (1) for the U.S. cities while allowing for a separate response for each \$100K threshold. With a few exceptions, for each of the five response variables, the main tendency is a heightening of the odd-price effect as list price increases. What is noteworthy is that even the smallest effects shows odd-priced houses underperforming their round-priced counterparts on probability of selling, sale price, and time to sell.

Threshold Type. In Table VIII we investigate whether the odd-pricing effect exists at round-number thresholds that are "less round" than \$100K multiples. In particular, we expand our regression to allow for separate threshold effects at \$50K multiples (that are not \$100K multiples) and \$10K multiples (that are not \$50K or \$100K multiples). Overall, there is a reduction in the magnitude of the odd-pricing effect, for all five response variables, as we go from \$100K multiples to less-round pricing thresholds.[19] The relative paucity of observations near uniquely \$50K and \$10K multiples makes those estimates relatively less precise.

Years. Table IX examines heterogeneity across year-bands. From 2008–2010 to 2011–2014, odd pricing's performance worsens on probability of sale, sale price, sales ratio, and probability of a quick sale, while it improves for days on the market; from 2011–2014 to 2015–2018, odd pricing's performance doesn't change much except in probability of a quick sale, which worsens.

Cities. In Table X, we report odd pricing effects for Chicago, Minneapolis, and San Diego. (Seattle is excluded because of missing data; see footnote 14.) While there is

[19] As we will discuss in Section V, this is consistent with our theory of the odd-pricing effect.

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

All columns report β estimates from OLS regressions of equation (1) while allowing those coefficients to vary by threshold. Standard errors, in parentheses, are clusterd 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.

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

some heterogeneity in the effect size, in each city odd-priced houses underperform their round-priced counterparts on each of our five performance measures.

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

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 clusterd at the zipcode 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.

Dependent Variables:	(log) Transaction Price	Sales Ratio	Days on Market	Quick Sale	Probability of Sale
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Odd Price at $100K multiple	-0.0060***	-0.0045***	6.656***	-0.0346***	-0.0365***
	(0.0004)	(0.0004)	(0.6974)	(0.0030)	(0.0038)
Odd Price at $50K multiple	-0.0035***	-0.0025***	2.407***	-0.0271***	-0.0263***
	(0.0004)	(0.0003)	(0.6671)	(0.0024)	(0.0030)
Odd Price at $10K multiple	-0.0045***	-0.0028***	1.228***	-0.0300***	-0.0006
	(0.0002)	(0.0002)	(0.3989)	(0.0020)	(0.0021)
-Agent Controls	Yes	Yes	Yes	Yes	Yes
-House Controls	Yes	Yes	Yes	Yes	Yes
Fixed-effects					
Threshold-Year-County	Yes	Yes	Yes	Yes	Yes
Zip Code-Year	Yes	Yes	Yes	Yes	Yes
Agent	Yes	Yes	Yes	Yes	Yes
Fit statistics					
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

IV. Explaining the Underperformance of Odd-Priced Houses, I: Spurious Correlation?

The regressions above show that odd-priced houses underperform their round-priced counterparts on all sales outcomes, and this result is robust across years, cities, listing thresholds, and threshold types, even after controlling for house and agent characteristics, and a rich set of fixed effects. What makes this interesting is that neither odd listing price nor round listing price commits the seller to sell at those prices (in fact, no list price does—Han and Strange 2016), nor does it oblige the buyer to buy at those prices (Pope,

Table IX
Odd pricing effects by year (U.S. data)

All columns report β estimates from OLS regressions of equation (1) while allowing those coefficients to vary by year. Standard errors, in parentheses, are clusterd 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.

Dependent Variables:	(log) Transaction Price	Sales Ratio	Days on Market	Quick Sale	Probability of Sale
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Odd Price in 2008-2010	-0.0040*	-0.0032**	10.95***	-0.0294***	-0.0439***
	(0.0021)	(0.0014)	(2.727)	(0.0075)	(0.0109)
Odd Price in 2011-2014	-0.0069***	-0.0047***	6.478***	-0.0211***	-0.0372***
	(0.0009)	(0.0008)	(1.401)	(0.0050)	(0.0074)
Odd Price in 2015-2018	-0.0068***	-0.0047***	6.554***	-0.0423***	-0.0394***
	(0.0006)	(0.0005)	(1.031)	(0.0049)	(0.0050)
-Agent Controls	Yes	Yes	Yes	Yes	Yes
-House Controls	Yes	Yes	Yes	Yes	Yes
Fixed-effects					
Threshold-Year-county	Yes	Yes	Yes	Yes	Yes
Zip Code-Year	Yes	Yes	Yes	Yes	Yes
Agent	Yes	Yes	Yes	Yes	Yes
Fit statistics					
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

Pope, and Sydnor 2015), yet this small pricing quirk—as small as $1,000 on houses selling for an average price of $300,000—has a significant economic effect on market outcomes.

There are two possible routes toward an explanation, direct and indirect, the direct posing the bigger challenge. The direct route would argue that odd pricing itself has a causal effect on demand or supply conditions that is ultimately manifested in the observed negative outcomes. Left-digit bias on the part of buyers would be such an explanation, except that it predicts a boost in demand from odd pricing, not the lower demand that we seem to be observing. Another direct explanation, but this one focusing on the supply side, would be Backus, Blake, and Tadelis's (2018) theory that round prices are a cheap-talk

Table X
Odd pricing effects by city (U.S. data)

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 14, 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.

Dependent Variables:	(log) Transaction Price	Sales Ratio	Days on Market	Quick Sale	Probability of Sale
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Odd Price in Chicago	-0.0059***	-0.0043***	8.533***	-0.0208***	-0.0398***
	(0.0009)	(0.0007)	(1.636)	(0.0046)	(0.0070)
Odd Price in Minneapolis	-0.0061***	-0.0046***	7.673***	-0.0478***	-0.0452***
	(0.0006)	(0.0006)	(0.8658)	(0.0055)	(0.0065)
Odd Price in San Diego	-0.0079***	-0.0056***	3.169**	-0.0424***	-0.0172***
	(0.0015)	(0.0012)	(1.581)	(0.0095)	(0.0062)
-Agent Controls	Yes	Yes	Yes	Yes	Yes
-House Controls	Yes	Yes	Yes	Yes	Yes
Fixed-effects					
Threshold-Year-County	Yes	Yes	Yes	Yes	Yes
Zip Code-Year	Yes	Yes	Yes	Yes	Yes
Agent	Yes	Yes	Yes	Yes	Yes
Fit statistics					
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
p-value for equality of coeffs.	0.5182	0.6327	0.0269	0.0005	0.0044

way to signal seller desperation. This, too, doesn't fit our data because round-priced home sellers fare better than odd-priced home sellers on all sales outcomes—probability of sale, sale price, and time on the market. In the next section we propose a direct search-based explanation that actually fits our data.

Meanwhile, in this section, we perform a series of tests to argue that spurious correlation cannot explain our results. First, we note that most of the variation in the incidence of odd pricing is absorbed by agent fixed effects—which also appear in our regressions

above. Second, we ask whether unobserved quality differences between odd- and round-priced houses can explain the former's underperformance. For this we (i) track how sales outcomes vary with list price and show that those outcomes are discontinuous *only* at round list prices (with the implication that this can't be due to unobserved quality because unobserved quality ought to vary continuously with list price), and (ii) include additional control variables in our regressions for verifiable quality signals present in our listings, in the verbal descriptions—phrases such as, "hardwood floors," "Wolf appliances," etc. Doing so doesn't dilute the odd-pricing effect. Third, we also control in our regressions for unverifiable quality claims ("charming," "perfection," etc.) and signals of seller desperation ("must sell," "asap," etc.) text-mined from the verbal descriptions, and find that they, too, don't undermine the odd-pricing effect. Finally, to address the possibility of confounders for which we lack data, we bound the potential magnitude of omitted-variable bias in the sensitivity-analysis framework of Cinelli and Hazlett 2019; Chernozhukov et al. 2023 and find that, even in a worst-case scenario, such bias would be too low to nullify the odd-pricing effect.

IV.A. Agent fixed effects absorb most of the variation in odd pricing

In Table XI we show regressions where the dependent variable is an indicator of odd pricing and the independent variables are various measures of agent quality—past performance on asking price, sale/list price ratio, and time on the market—agent experience (modeled flexibly), house characteristics, and various fixed effects.

Columns (2) and (3) show that in the U.S. markets, controlling for agent, their quality and experience explain essentially none of the variation in odd pricing (partial $R^2 \approx 10^{-16}$—effectively zero). By contrast, agent fixed effects alone account for 12–15% of the variation (partial $R^2 \approx 0.15$). Figure A.I in the Internet Appendix illustrates this visually: the predicted probability curves for agent characteristics are essentially flat.

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

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^2s report the explanatory power of specific sets of variables. House and agent controls are listed in Internet Appendix A.

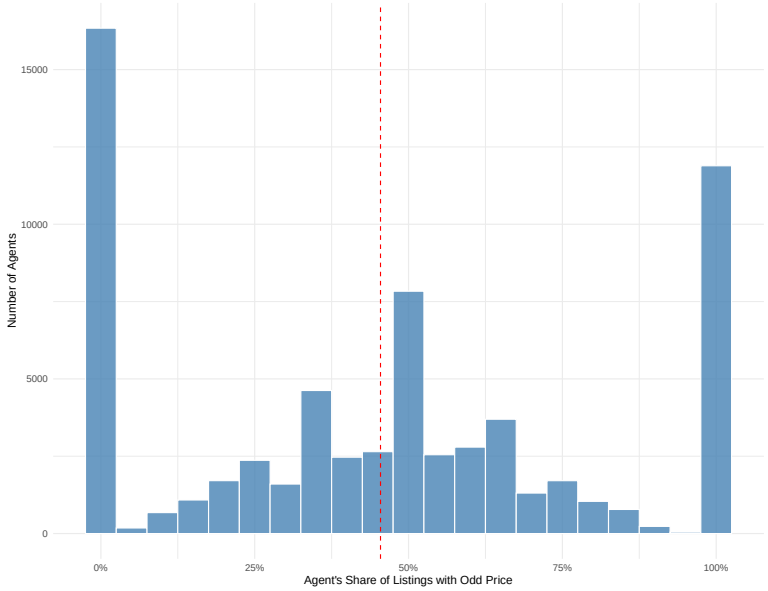
Dependent Variable:	Odd Price Indicator × 100		
Model:	(1)	(2)	(3)
Variables			
Ave. Agent Asking Price	0.1092	0.0968	0.1003
	(0.1437)	(0.1664)	(0.1667)
Ave. Agent Sales/List Ratio	-53.31***	-1.359	-1.186
	(7.637)	(5.930)	(5.930)
Ave. Agent Days on Market	-0.0274***	0.0030	0.0030
	(0.0037)	(0.0035)	(0.0035)
Agent Experience (Num. of Sales/100)	3.915***	-0.6268	-0.6663
	(0.6841)	(0.7899)	(0.7906)
Agent Experience^2	-1.092***	0.1054	0.1162
	(0.2994)	(0.2722)	(0.2721)
Agent Experience^3	0.0779***	-0.0076	-0.0083
	(0.0292)	(0.0248)	(0.0248)
Fixed-effects			
Threshold-Year-County	Yes	Yes	Yes
ZIP Code-Year	Yes	Yes	Yes
Agent		Yes	Yes
Fit statistics			
Observations	814,386	814,386	814,386
R^2	0.06913	0.20811	0.20835
Within R^2	0.00099	7.31×10^{-6}	0.00031
Partial R^2:			
Agent Controls	0.0010	0×10^{-16}	0×10^{-16}
Agent Fixed Effects		0.1493	0.149
House Controls			3e-04
Joint test: all experience effects = 0 (p-value)	0×10^{-16}	0.7777	0.7611

Figure 3 shows that the distribution of agents' odd-pricing shares—what percentage of their listings are odd-priced—is extremely wide. Significant numbers of agents either never odd-price or odd-price all the time. However, most agents are in the middle, odd-pricing some of the time, round-pricing at others. Since we have agent fixed effects in the most comprehensive regression of Table V, our odd-pricing effects can't be driven by the first two

groups. Rather, they are driven by the agents who toggle between odd pricing and round pricing, seemingly randomly. This makes agent fixed effects not an auxiliary robustness choice in our main estimation, but the central control needed to deal with selection into odd pricing.

Internet Appendix Table A.VIII and Figures A.III–A.IV show that Toronto data perform similarly.

Figure 3. Agent heterogeneity in use of odd pricing. This figure shows a histogram of odd pricing rates across agents.



IV.B. Unobserved House Quality

Is odd pricing picking out houses with lower unobserved quality? Unobserved quality is things that a buyer sees (and values) but which we analysts don't, e.g., curb appeal, ambiance, how "bright" the house is, amount of traffic in the neighborhood, etc. Could it be that odd-priced houses are systematically worse than round-priced houses on these unobserved attributes, and that is what is driving their relative underperformance? Right

off the bat, however, this doesn't sound very plausible: why would houses that are different enough in unobserved quality to make a meaningful difference to sale price be listed so close in price? Nevertheless, we perform a series of analyses to confirm this intuition.

Sales Outcomes as Functions of List Prices are Discontinuous Only at Round Prices. We establish this by re-estimating (1), but instead of partitioning $[\tau - 15K, \tau + 15K]$ into \$1K bins, we partition it into \$1 bins. Now, with round prices as the baseline, the β coefficients are telling us how selling outcomes vary with list price in a \$15K neighborhood of a round price, controlling for observables.

Figure 4 shows the results for probability of sale, sales ratio, days on the market, and probability of quick sale in the U.S. data. (Figure A.VI provides similar 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.

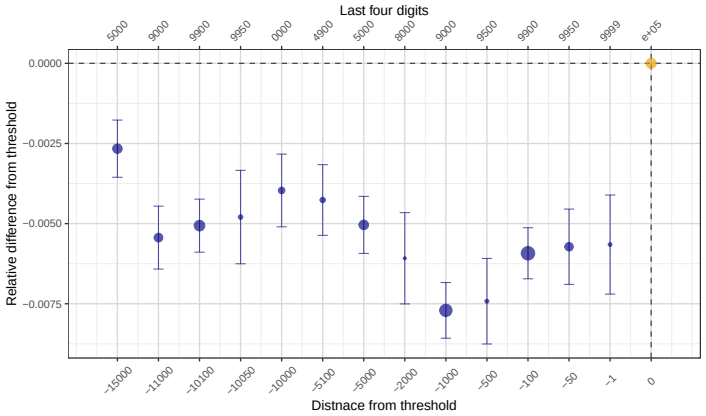
Note first that the yellow dot sits apart from all other points, consistently across the four outcome variables. For example, in the sales ratio plot, the dot immediately to the left of the yellow dot has a significantly lower sales ratio than the yellow dot (by about 0.6 percent), even though these houses are priced only \$1 apart. Second, going 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). Finally, further analysis (not reported here) shows that the \$1 odd-pricing effects observed here aren't observed for less salient round numbers, such as \$10K multiples, reprising our earlier observation that the odd-pricing effect is smaller at \$10K multiples (Table VIII).

Can houses priced \$1 apart differ significantly enough in unobserved quality to reduce sales ratio by .6 percent? And if so, how can it be that the difference in unobserved quality

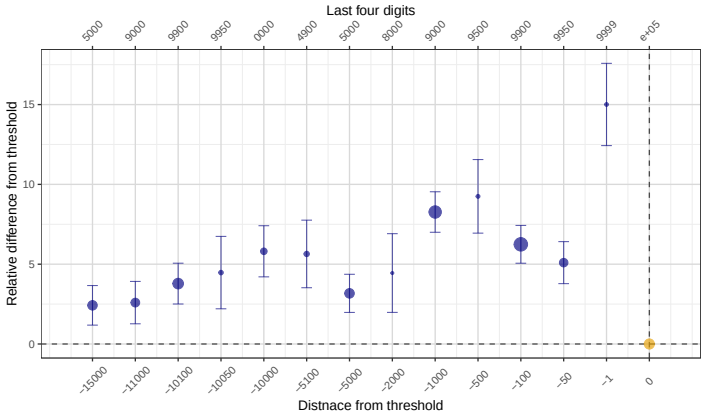
between houses priced $1 apart be the same as houses priced $1,000-$5,000 apart? And why does this relationship between list price and unobserved quality change discontinuously at a round number? Finally, based on the last observation in the preceding paragraph, why would a house priced at, say, $479,999 have the same unobserved quality as a house priced at $480,000, but a house priced at $499,999 have lower unobserved quality than a house priced at $500,000? In short, it is implausible that an underlying unobserved quality-list price correlation drives the underperformance of odd-priced houses.

Controlling for Proxies for Unobserved Quality in the Verbal Descriptions Doesn't Seem to Matter. In the U.S. MLS data (but not in the Toronto MLS data) we have a variable called "public remarks," which captures how properties are described verbally. (Section B.1 in the Internet Appendix provides two examples.) These descriptions are typically a combination of quality claims such as "Thermador magnetic induction cooktop" and "Hunter Douglas shades" that are verifiable upon inspection, puffery such as "rare beauty," and "gorgeous," and phrases suggestive of seller desperation, e.g., "motivated seller," "seller relocating."

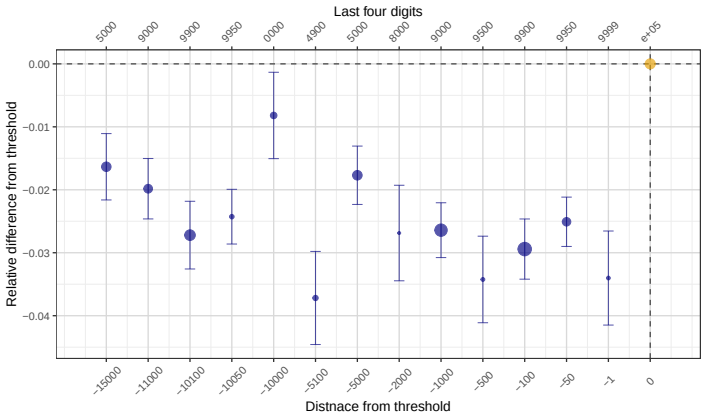
Figure 4. Estimates of the odd pricing effect for $1 bins (U.S. data). This figure displays estimates of the odd-pricing effect for $1 bins on: (a) sales ratio, (b) days on the market, (c) quick sale probability, and (d) sale probability. Houses listed exactly at a $100K multiple are shown by a yellow dot at 0. The bottom x-axis shows the price distance from round numbers, and the top x-axis shows the last four digits. For example, -1 on the bottom axis and 9999 on the top axis indicates pricing $1 below a round price like $500,000.



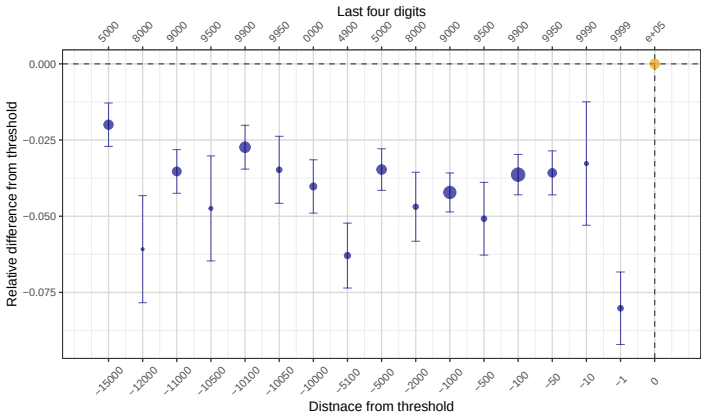
(a) Sales ratio



(b) Days on market



(c) Quick sale probability



(d) Probability of sale

We want to see whether controlling for verifiable quality claims in the regressions changes the odd-pricing effect. To do this, we parse the text of the verbal descriptions to construct: (1) indicator variables for features such as "crown molding," and "floor-to-ceiling windows" ("verifiable controls"), (2) a variable that counts the number of high-end kitchen elements such as "Wolf appliances" and "walk-in pantry" ("high-end features"), (3) indicators of premium building materials like "granite," and "mahogany" ("materials controls"), and (4) phrases such as "as is" and "move-in ready," indicative of the property's condition ("quality signals"). Table A.I lists the phrases considered in each of these categories.

As can be seen from columns (3) and (6) of Table XII, high-end features have a predictable effect on sales outcomes: probability of selling, sale price, and sales ratio go up, days on the market goes down. However, controlling for this and other measures of verifiable quality, such as "materials controls," does not eliminate the odd-pricing effect. In fact, the odd-pricing coefficients in Table XII are substantially the same as in Table V. This casts doubt on what other aspects of unobserved house quality there might be that could account for the observed odd-pricing effects.

IV.C. Advertising Strategy

By advertising strategy we mean verbose descriptions (large number of words), use of all-caps words and exclamation points, and puffery—unverifiable subjective descriptors like "charming," "fabulous," and "perfection."

To construct an index of unverifiable quality claims we proceed as follows. First we tokenize the public remarks and run each word through a filter to remove stop-words and sentiment-free words. We then take the most frequently-used words from those that remain and manually remove words that convey verifiable quality, such as the high-end features in Table A.I. The 200 "puffery" words that survive are shown in Table A.II of the

Internet Appendix. We then run a regression of the log sale price on a dummy for each of these words, all our observable housing controls, agent fixed effects, and flexibly specified controls for the length of the public remarks, number of all-caps words, and number of exclamation points. Importantly, we run this regression on a sample of data that is not used in our main analysis, i.e., we run this regression on houses that are *not* listed within \$15K of a round number. The estimated coefficients on the puffery words form the basis for our index of unverifiable quality.

Columns 5 and 6 of Table XII show that this index is positively associated with sales outcomes even in our main sample. However, crucially, it doesn't move the odd-pricing coefficient significantly—those coefficients remain more or less the same as in Table V. Controlling for advertising strategy also doesn't eliminate the odd-pricing effect.

IV.D. Seller Desperation and Urgency to Sell

We can't observe seller desperation or urgency to sell directly, but, again, the verbal descriptions provide clues. For example, a seller who is anxious to sell quickly might use phrases like "motivated seller" and "asap" in the verbal description.

So we proceed as follows. From the verbal descriptions we extract a count of such words, and include it in the regressions as the variable "urgency." Columns 4 and 6 of Table XII show that doing so doesn't change the odd-pricing effects significantly.

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

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.

Dependent Variable:			Bin size = $1000			
Model:	(1)	(2)	(3)	(4)	(5)	(6)
A: Dependent variable: ***log(Sale price)***						
Odd Price	-0.0066***	-0.0067***	-0.0066***	-0.0066***	-0.0068***	-0.0069***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
High-end features			0.0008***			0.0006**
			(0.0003)			(0.0003)
Urgency				0.00003		0.00007**
				(0.00003)		(0.00003)
Unverifiable Index					0.0020***	0.0018***
R^2	0.994	0.994	0.994	0.994	0.994	0.994
B: Dependent Variable: ***Sales ratio***						
Odd Price	-0.0046***	-0.0046***	-0.0046***	-0.0046***	-0.0046***	-0.0047***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0005)
High-end features			0.0008***			0.0007***
			(0.0002)			(0.0002)
Urgency				0.00003		0.00006**
				(0.00003)		(0.00003)
Unverifiable Index					0.0018***	0.0016***
					(0.0001)	(0.0001)
R^2	0.42498	0.42629	0.42535	0.42498	0.43113	0.43312
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
Fixed-effects						
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	236,934	236,934	236,934	236,934	229,121	229,121

(Continued)

Table XII—*continued*

Dependent Variable:			Bin size = $1000			
Model:	(1)	(2)	(3)	(4)	(5)	(6)
C: Dependent Variable: ***Days on the market***						
Odd Price	6.589***	6.559***	6.596***	6.589***	6.462***	6.420***
	(0.7981)	(0.7987)	(0.7986)	(0.7980)	(0.8093)	(0.8086)
High-end features			-1.029**			-0.8450*
			(0.5019)			(0.5077)
Urgency				0.2385***		0.1777***
				(0.0537)		(0.0548)
Unverifiable Index					-1.574***	-1.387***
					(0.2100)	(0.2102)
R^2	0.439	0.439	0.439	0.439	0.445	0.445
D: Dependent Variable: ***Quick sale probability***						
Odd Price	-0.0281***	-0.0279***	-0.0281***	-0.0281***	-0.0259***	-0.0257***
	(0.0034)	(0.0034)	(0.0034)	(0.0034)	(0.0035)	(0.0035)
High-end features			-0.0015			8.88×10^{-5}
			(0.0014)			(0.0014)
Urgency				0.0006***		0.0006***
				(0.0002)		(0.0002)
Unverifiable Index					0.0031***	0.0031***
					(0.0008)	(0.0008)
R^2	0.301	0.302	0.302	0.301	0.299	0.299
Observations	236,934	236,934	236,934	236,934	229,121	229,121
E: Dependent Variable: ***Probability of sale***						
Odd Price	-0.0390***	-0.0389***	-0.0391***	-0.0390***	-0.0347***	-0.0347***
	(0.0043)	(0.0043)	(0.0043)	(0.0043)	(0.0044)	(0.0044)
High-end features			0.0080***			0.0066***
			(0.0018)			(0.0018)
Urgency				-0.0004*		-2.06×10^{-5}
				(0.0002)		(0.0002)
Unverifiable Index					0.0175***	0.0164***
					(0.0011)	(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
Fixed-effects						
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

IV.E. Bounding the Potential Bias from Confounders

Our empirical strategy compares comparable houses listed within a $15K window around a round price, sold in the same year and postal code, and—crucially—represented by the same agent. This design absorbs a wide variety of potential confounders. In particular, the inclusion of agent fixed effects eliminates all stable differences among agents—in pricing style, bargaining ability, marketing quality, and clientele. In addition, we noted in Section IV.A that, controlling for those stable differences, time-varying characteristics of an agent, such as experience and past success, don't explain the use of odd pricing. Thus, any remaining confounder capable of biasing our estimated odd-pricing effect must operate within agent, at the level of specific house/listing, or the agent's time-varying effort.[20]

To assess the impact of such confounders, we use the sensitivity-analysis framework of Cinelli and Hazlett 2019, Chernozhukov et al. 2023, and Bach et al. 2025. Potential omitted-variable bias from confounders is represented as a function of two partial-R^2s: the explanatory power of a hypothetical confounder for the outcome (say, sales ratio) and the explanatory power of a hypothetical confounder for the treatment (odd versus round pricing), conditional on the full set of observables and fixed effects.[21] Those partial-R^2s

[20] Formally, in the regression specification, any confounder U_i that is constant for a given agent is absorbed by $\boldsymbol{A}_i$. Thus, for an omitted variable to bias β, it must satisfy $\mathrm{Cov}(U_i, \texttt{Odd Price}_i \mid \boldsymbol{A}_i, \boldsymbol{G}_{pc_i,y_i}, \boldsymbol{\gamma}_{\tau_i,y_i,c_i}) \neq 0$ and $\mathrm{Cov}(U_i, Y_i \mid \boldsymbol{A}_i, \boldsymbol{G}_{pc_i,y_i}, \boldsymbol{\gamma}_{\tau_i,y_i,c_i}) \neq 0$; that is, it must vary within agent-year-postal code-threshold neighborhoods. This sharply limits confounders to house-/listing-specific unobservables, or unobservable time-varying agent features.

[21] The formula is

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

where U is the latent confounder, $R^2_{Y\sim U|D,X}$ is the partial-R^2 of U with the outcome conditional on the treatment and controls, and $R^2_{D\sim U|X}$ 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.

are estimated on the basis of the observed partial-R^2s of the observables.

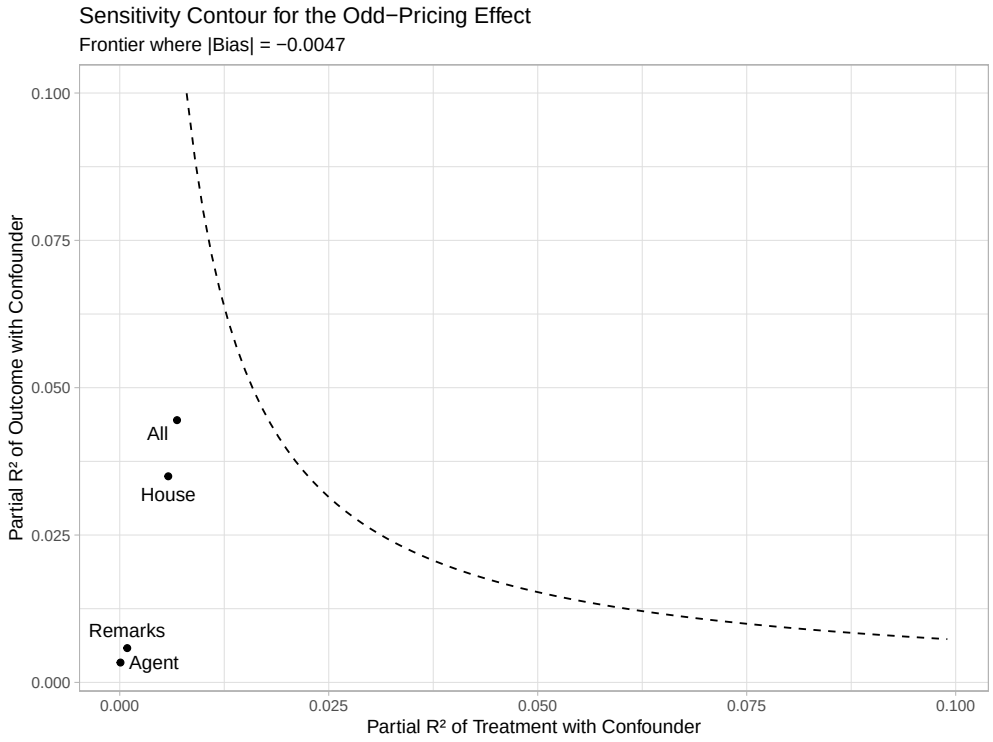
To implement this analysis, we focus on our most comprehensive model for the odd-pricing effect on sales ratio (column (6) of Panel B of Table XII). For this model we compute partial-R^2s for sets of observables that plausibly capture within-agent heterogeneity: (i) house characteristics, (ii) listing-level 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×year×county, postal code×year, and agent). As Table XIII 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^2s are even lower. We will use these partial-R^2s to benchmark potential bias from any unobserved confounders that could still be operating in our empirical setup.

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

The top-line estimate of −0.0047 (0.0005) is the odd pricing effect on sales ratio from column (6), Panel B, of Table XII. The column labeled |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).

	Estimate −0.0047 (0.0005)				
Benchmark	|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

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 ($|\text{Bias}| < -0.0047$) (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 XII do not approach this frontier.



The top row of Table XIII 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 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 XIII repeat the exercise for narrower sets of

within-agent observables. Even a confounder as strong as all house characteristics, or as strong as all public-remarks indicators, or as strong as the full set of time-varying agent controls, would generate a bias far too small to alter our qualitative conclusions.

Figure 5 provides a visual summary of these benchmarks. It shows a sensitivity contour that traces combinations of partial-R^2s for which a confounder would drive the odd-pricing effect to zero. All observed covariates lie well inside this frontier.[22] This analysis demonstrates the robustness of our estimates to confounders with explanatory power as strong as our extensive set of observed controls.

V. Explaining the Underperformance of Odd-Priced Houses, II: Buyers' Search Strategies

As discussed in Section I, an odd-priced house is likely to underperform relative to its round-priced counterpart because buyers are likely to use round-numbered lower and upper price bounds to screen properties. The underperformance is manifested in the following ways:

1. Whenever an odd-priced house is considered, so will its round-numbered counterpart, but not necessarily vice-versa. Thus, a round-priced house will attract a larger pool of prospective buyers than an odd-priced house.

2. The marginal buyers only considering a round-priced house are likely to have a higher upper bound, and thus a greater willingness-to-pay than buyers considering the adjacently odd-priced house. The winning bid for such a house will likely come

[22]The bounds reported in Table XIII assume a worst-case scenario of confounding paths aligning themselves in such a way ($|\rho| = 1$) as to yield the 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, bounds we report are deliberately conservative.

from these marginal buyers.

3. Finally, the odd-priced house faces more competition than its round-priced counterpart: whereas everyone considering the former also considers the latter, the latter has buyers who are not looking at an odd-priced house.

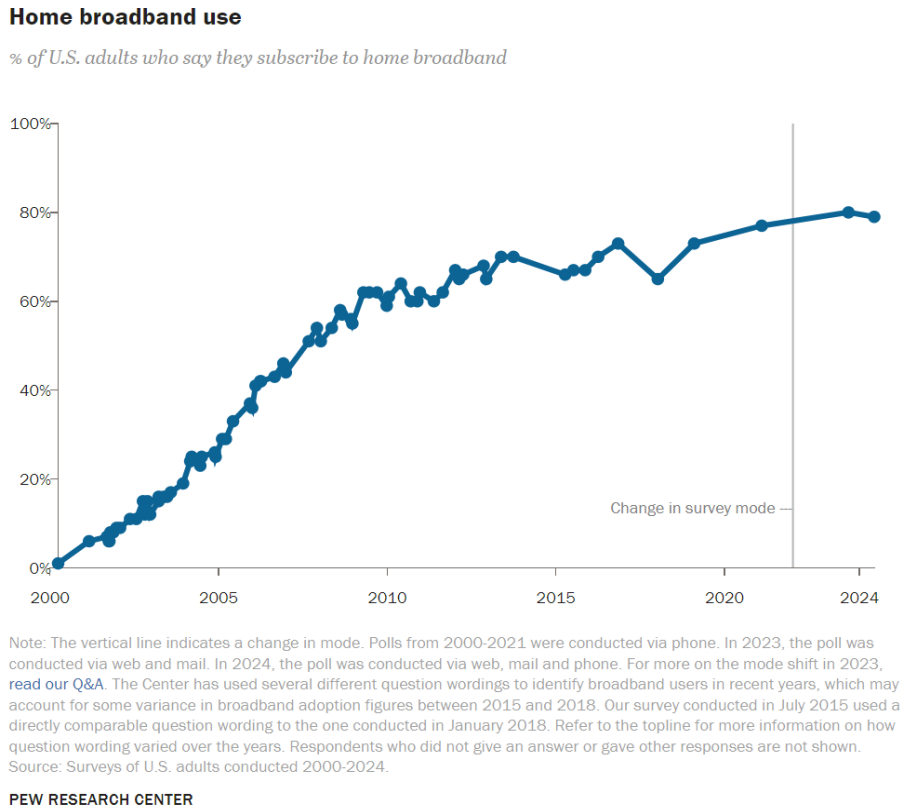
Together, these effects explain why round-priced houses outperform their adjacently odd-priced counterparts.[23]

The results in Table IX are already consistent with this story. They show a strengthening of the odd-pricing effect from 2008 to 2018—in line with the increasing penetration of broadband internet in the U.S. (Figure 6). For a more direct test of whether screening by round-numbered lower bounds on MLS websites is leading to the underperformance of odd-priced properties, we take advantage of the fact that these websites suggest *specific* round-numbered lower bounds, and those specific bounds vary across metros and over time. For example, the suggested lower and upper price bounds at realtor.com San Diego differ from the ones at realtor.com Chicago and Minneapolis (shown above). To capture the time variation, we use The Wayback Machine to determine what our U.S. metro MLS websites looked like at various past dates.[24] From these observations we record

[23]Repetto and Solís 2020 report a positive effect of odd pricing on sale price, with no adverse effect on selling time, in the Swedish real estate market. Why might their results be different from ours? There are several institutional differences between Swedish and North American real estate markets, including the one that Repetto and Solís 2020 emphasize, namely, the use of ascending-price auctions in the former, private negotiations in the latter. However, the crucial difference might be the absence of a dedicated buyer's agent in Sweden. There, the seller's agent is "required by law to operate in the best interest of both the seller and the buyer." Since a seller's agent enters the picture only if a buyer is interested in *that* seller's property, there is no real estate professional educating the buyer about the price-"quality" correlation in the local market. Absent this knowledge, Swedish buyers are unlikely to screen based on lower price bounds. Instead, they are more likely to screen based on the things they know—their budget, and what features they are looking for in a property (neighborhood, number of bedrooms and bathrooms, etc.). This means that odd-priced properties are just as likely as round-priced properties to pass the initial screen. At that point, odd-priced houses have an advantage, simply because their price is lower—resulting in a larger number of bidders showing up at odd-priced auctions. In short, both in the U.S./Canada as well as in Sweden, screening by list price explains the number of bidders on a property. The difference is that in the former, odd-priced houses are hurt in the screening process (because buyers use round-priced lower bounds), whereas in the latter they are not.

[24]The Wayback Machine is a digital archive of the internet; it provides snapshots of websites from the past.

Figure 6. Broadband Internet Penetration. Source: www.pewresearch.org/internet/fact-sheet/internet-broadband.



the suggested lower and upper price bounds in a vector $\mathbf{s}_{ct}$, where c denotes city and t denotes year. Our test involves comparing the odd pricing effect for round numbers that are suggested at a MLS website with the odd pricing effect for round numbers that are not suggested at a MLS website.[25] If our theory is correct, the former should be larger than the latter.

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 \$1K of a round price in $\mathbf{r}$. The dummy variable $\texttt{Odd Price}_i$ below identifies the

[25]We are grateful to Kosuke Uetake for suggesting this analysis.

odd-priced houses among them:

$$\texttt{Odd Price}_i = \mathtt{P}_i^L \in [\mathbf{r} - 1000, \mathbf{r}) \,.$$

Now we estimate the following regression:

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

The regression includes the same set of fixed effects as (1). Note that by including fixed effects for round price × year × county, and postal code × year, we are effectively controlling for time- and location-specific variations in suggested price bounds. β_1 measures the odd-pricing effect for round prices that are *not* suggested bounds at MLS websites; β_2 measures the *additional* odd-pricing effect for round numbers that *are* suggested bounds at MLS websites. We want to see whether β_2 is negative.

Table XIV contains the result of estimating equation (2) for each of our key transaction outcomes. All estimates include our complete set of controls. Consistent with our previous findings, the β_1 estimate shows odd-priced houses underperforming their round-priced counterparts on all of our outcome measures. The new finding is the estimate of β_2. It is negative and statistically significant: odd-priced houses whose list prices are adjacent to round prices that appear on MLS websites' menus seem to *suffer even more* than other odd-priced houses. This is consistent with our story that odd-priced houses have a higher probability of being excluded from prospective buyers' consideration sets and attracting lower willingness-to-pay buyers because buyers screen houses using round-numbered lower bounds.

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

All columns report OLS regressions of equation (1) while allowing the β_z coefficients to vary by threshold type. Standard errors, in parentheses, are clusterd 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.

Dependent Variables:	(log) Transaction Price	Sales Ratio	Days on Market	Quick Sale	Probability of Sale
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Odd Price	-0.0034***	-0.0017***	1.348***	-0.0237***	-0.0094***
	(0.0002)	(0.0002)	(0.4397)	(0.0021)	(0.0021)
Odd Price × Suggested Round	-0.0008***	-0.0013***	1.442***	-0.0064**	-0.0159***
	(0.0003)	(0.0003)	(0.4879)	(0.0027)	(0.0029)
-Agent Controls	Yes	Yes	Yes	Yes	Yes
-House Controls	Yes	Yes	Yes	Yes	Yes
Fixed effects					
Threshold-Year-County	Yes	Yes	Yes	Yes	Yes
Zip Code-Year	Yes	Yes	Yes	Yes	Yes
Agent	Yes	Yes	Yes	Yes	Yes
Fit statistics					
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

Buyers of Odd-Priced Listings Report Fewer Bidders. Our Toronto MLS data, coupled with Genesove and Han's (2016) survey of Toronto buyers, allows us to test directly whether buyers of odd-priced properties report fewer 'bidders" than buyers of adjacently round-priced properties. Two questions from the survey are relevant to this inquiry: "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?" Using the answers to these questions, we repeat the same empirical design as the main analysis, but now with the goal of trying to predict the probability of multiple bidders. The results are shown in columns (1)-(2) of Table XV. All else equal, properties that are odd-priced at $50K multiples are 14% less likely to attract more than one bidder and 31% less likely to attract

more than two bidders than their round-priced counterparts.

Table XV
The effect of odd pricing on number of bidders and buyers' budgets (Toronto data)

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.

	Bidders > 1 (1)	Bidders > 2 (2)	(log) Budget (3)
Odd price at $50K multiples	-0.1455	-0.3091**	-0.1714**
	(0.1481)	(0.1406)	(0.0833)
Agent controls	✓	✓	✓
House controls	✓	✓	✓
R^2	0.27	0.27	0.64
Observations	1,779	1,779	1,808
Threshold fixed effects	✓	✓	✓
FSA-year fixed effects	✓	✓	✓

Buyers of Odd-Priced Listings Have Lower Budgets. If buyers indeed use round-numbered lower price bounds to screen houses, then we should expect round-priced listings to attract higher willingness-to-pay buyers than their odd-priced counterparts. To test this, we use the answers to another question from the Toronto survey, "How much were you thinking about spending for the house?" Column (3) in Table XV shows that, all else equal, buyers of round-priced properties at $50K multiples indeed have a 17% higher initial budget than similar adjacently odd-priced properties.

VI. Conclusion

Using MLS data from the Chicago, Minneapolis, San Diego, Seattle, and Toronto housing markets, we show that sellers have a penchant for listing their houses at odd prices—prices "just below" round numbers. However, this pricing strategy doesn't live up to its

popularity: On average, odd-priced properties are about 4% less likely to sell (as originally listed), fetch 0.7% lower prices, and stay on the market seven days longer than their round-priced counterparts. These effects are seen across years, geographies, and price thresholds, and they are robust to an extensive set of controls: house attributes, agent characteristics, house quality and seller urgency descriptors, and a rich array of fixed effects: threshold-year-county, postal code-year, and agent.

What is interesting about these observations is that it doesn't cost anything more to list a house at a round price than at an odd price. Yet this costless maneuver has economically significant revenue implications. For example, the average house in our U.S. database sold for about $342,357, in 75 days, during 2016-2018. By odd-pricing instead of round-pricing, such an owner left $2,260 on the table, plus the opportunity costs of slowing the sale by 10%.[26]

We examine two leading explanations for why odd pricing may underperform round pricing: (i) omitted variable bias, and (ii) distortions introduced by the search process. We reject the first and find support for the second. In the process, we uncover a fundamental weakness of odd pricing in housing markets. Prospective buyers searching for a home are likely to screen properties using *round*-numbered upper *and* lower price bounds—the upper bound reflecting the buyer's budget, the lower bound reflecting the buyer's reservation quality. Odd-priced houses run the risk of being screened out by the lower bound, and attracting buyers whose willingness to pay is lower than those attracted to adjacently round-priced houses.

Thus our results stand in stark contrast to much of the odd pricing literature. That literature typically attributes the popularity of odd pricing to its success in exploiting the left-digit bias of buyers. While that may be true for low-ticket consumer goods in posted-price settings, it is hard to imagine home buyers succumbing to left-digit bias

[26]This is a conservative estimate because it doesn't take into account the lower probability of selling under odd pricing.

in the high-stakes, negotiated-price environment of real estate markets. Indeed, the underperformance of odd-priced houses shows that they don't. It suggests, instead, a subtle role-reversal: buyers behaving rationally while negating the behavioral gambits of naive sellers.

References

Agarwal, Sumit, Souphala Chomsisengphet, and Cheryl Lim, 2017, What shapes consumer choice and financial products? a review, *Annual Review of Financial Economics* 9, 127–146.

Agarwal, Sumit, Richard J. Rosen, and Vincent Yao, 2016, Why do borrowers make mortgage refinancing mistakes? *Management Science* 62, 3494–3509.

Andersen, Steffen, Cristian Badarinza, Lu Liu, Julie Marx, and Tarun Ramadorai, 2022, Reference dependence in the housing market, *American Economic Review* 112, 3398–3440.

Anderson, Eric T. and Duncan I. Simester, 2003, Effects of $9 price endings on retail sales: evidence from field experiments, *Quantitative Marketing and Economics* 1, 93–110.

Argyle, Bronson S, Taylor D Nadauld, and Christopher J Palmer, 2020, Monthly payment targeting and the demand for maturity, *The Review of Financial Studies* 33, 5416–5462.

Bach, Philipp, Victor Chernozhukov, Carlos Cinelli, Lin Jia, Sven Klaassen, Nils Skotara, and Martin Spindler, 2025, *Sensitivity analysis for causal ml: a use case at booking.com*. URL: http://arxiv.org/abs/2510.09109 (visited on 10/21/2025). Pre-published.

Backus, Matthew, Thomas Blake, and Steven Tadelis, 2018, On the empirical content of cheap-talk signaling: an application to bargaining, *Journal of Political Economy* 127, 1599–1628.

Badarinza, Cristian, Vimal Balasubramaniam, and Tarun Ramadorai, 2023, In Search of the Matching Function in the Housing Market. en, *SSRN Electronic Journal*.

Barberis, Nicholas C., 2018, Psychology-based models of asset prices and trading volume. In: Douglas Bernheim, Stefano DellaVigna, and David Laibson, eds., *Handbook of*

behavioral economics: applications and foundations, volume 1. Amsterdam: Elsevier / North-Holland, 79–175.

Basu, Kaushik, 2006, Consumer cognition and pricing in the nines in oligopolistic markets, *Journal of Economics & Management Strategy* 15, 125–141.

Bhattacharya, Utpal, Craig W. Holden, and Stacey Jacobsen, 2012, Penny wise, dollar foolish: buy–sell imbalances on and around round numbers, *Management Science* 58, 413–431.

Bucchianeri, Grace W. and Julia A. Minson, 2013, A homeowner's dilemma: anchoring in residential real estate transactions, *Journal of Economic Behavior & Organization* 89, 76–92.

Buchak, Greg, Gregor Matvos, Tomasz Piskorski, and Amit Seru, 2020, *Ibuyers: liquidity in real estate markets?* SSRN.

Chernozhukov, Victor, Carlos Cinelli, Whitney Newey, Amit Sharma, and Vasilis Syrgkanis, 2023, Long story short: omitted variable bias in causal machine learning. Pre-published.

Cinelli, Carlos and Chad Hazlett, 2019, Making sense of sensitivity: extending omitted variable bias, *Journal of the Royal Statistical Society Series B: Statistical Methodology* 82, 39–67.

Cubbin, John, 1974, Price, quality, and selling time in the housing market, *Applied Economics* 6, 171–187.

Duffie, Darrell, Nicolae Garleanu, and Lasse Heje Pedersen, 2005, Over-the-Counter Markets. en, *Econometrica* 73, 1815–1847.

Gabor, André and C. W. J. Granger, 1966, Price as an indicator of quality: report on an enquiry, *Economica* 33, 43–70.

Gaur, Vishal and Marshall L. Fisher, 2005, In-store experiments to determine the impact of price on sales, *Production and Operations Management* 14, 377–387.

Genesove, David and Lu Han, 2016, Measuring the thinness of real estate markets. Working Paper, University of Toronto,

Guren, Adam M., 2018, House price momentum and strategic complementarity, *Journal of Political Economy* 126, 1172–1218.

Han, Lu and William C. Strange, 2015, The microstructure of housing markets. In: Gilles Duranton, J. V. Henderson, and Strange, eds., *Handbook of regional and urban economics*. Vol. 5. Elsevier, 813–886.

Han, Lu and William C. Strange, 2016, What is the role of the asking price for a house? *Journal of Urban Economics* 93, 115–130.

Heraud, Florian and Lionel Page, 2024, Does the left-digit bias affect prices in financial markets? *Journal of Economic Behavior & Organization* 218, 20–29.

Hirshleifer, David, 2015, Behavioral finance, *Annual Review of Financial Economics* 7 (Volume 7, 2015), 133–159.

Jørring, Adam Tejs, 2024, Financial sophistication and consumer spending, *The Journal of Finance* 79, 3773–3820.

Kuo, Wei-Yu, Tse-Chun Lin, and Jing Zhao, 2015, Cognitive limitation and investment performance: evidence from limit order clustering, *Review of Financial Studies* 28, 838–875.

Leavitt, Harold J., 1954, A note on some experimental findings about the meanings of price, *The Journal of Business* 27, 205–210.

Levy, Daniel, Avichai Snir, Alex Gotler, and Haipeng (Allan) Chen, 2020, Not all price endings are created equal: price points and asymmetric price rigidity, *Journal of Monetary Economics* 110, 33–49.

List, John A, Ian Muir, Devin Pope, and Gregory Sun, 2023, Left-digit bias at lyft, *Review of Economic Studies* 90, 3186–3237.

Lynn, Michael, Sean Masaki Flynn, and Chelsea Helion, 2013, Do consumers prefer round prices? evidence from pay-what-you-want decisions and self-pumped gasoline purchases, *Journal of Economic Psychology* 36, 96–102.

Mateen, Haaris, Franklin Qian, Ye Zhang, and Tianxiang Zheng, 2023, The numbers game: effects of listing and counteroffer pricing format in housing bargaining, *SSRN Electronic Journal*.

O'Hara, M., 1995, *Market microstructure theory*. Blackwell Publishers.

Palmon, Oded, Barton Smith, and Ben Sopranzetti, 2004, Clustering in real estate prices: determinants and consequences, *Journal of Real Estate Research* 26, 115–136.

Piazzesi, Monika, Martin Schneider, and Johannes Stroebel, 2020, Segmented housing search, *American Economic Review* 110, 720–759.

Pope, Devin G., Jaren C. Pope, and Justin R. Sydnor, 2015, Focal points and bargaining in housing markets, *Games and Economic Behavior* 93, 89–107.

Repetto, Luca and Alex Solís, 2020, The price of inattention: evidence from the swedish housing market, *Journal of the European Economic Association* 18, 3261–3304.

Schindler, Robert M. and Patrick N. Kirby, 1997, Patterns of rightmost digits used in advertised prices: implications for nine-ending effects, *Journal of Consumer Research* 24, 192–201.

Schindler, Robert M. and Alan R. Wiman, 1989, Effects of odd pricing on price recall, *Journal of Business Research* 19, 165–177.

Scitovszky, Tibor, 1944, Some consequences of the habit of judging quality by price, *The Review of Economic Studies* 12, 100–105.

Shui, Haiyan and Lawrence M. Ausubel, 2004, Consumer time inconsistency: evidence from a market experiment in the credit card market. In: Econometric Society 2004 North American Summer Meetings.

Stiving, Mark and Russell S. Winer, 1997, An empirical analysis of price endings with scanner data, *Journal of Consumer Research* 24, 57–67.

Strulov-Shlain, Avner, 2023, More than a penny's worth: left-digit bias and firm pricing, *Review of Economic Studies* 90, 2612–2645.

Troncoso, Pablo and Diego Beas, 2025, *Credit renegotiations: characterization and determinants using population administrative data.* Rochester, NY. URL: https://papers.ssrn.com/abstract=5325500 (visited on 03/19/2026). Pre-published.

Zinn, S. and A. Würbach, 2016, A statistical approach to address the problem of heaping in self-reported income data, *Journal of Applied Statistics* 43, 682–703.

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 listing 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 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 listing 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 Section IV.D: "high-end features," "urgency," "word controls," "materials controls," and "verifiable controls." See Table A.I. In addition, we develop an Unverifiable Index as a measure of advertising puffery, also used in Section IV.D, 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.I 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 thrid-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 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.II below contains the list of puffery words used in this procedure.

Table A.I
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.II
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.I:** If words like "wrought" survive step two, they are manually removed if they are included in Table A.I, 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 of the U.S. data

D. Empirical Analysis of the Toronto data

Table A.III
Toronto buyer survey homes versus Toronto MLS homes

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.

Sample:	MLS (N=163583)		Survey (N=1925)	
Characteristic	Mean	SD	Mean	SD
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	

Figure A.I. Agent characteristics and probability of odd pricing (U.S. data) Each panel shows (i) the effect of a particular agent characteristic on the probability of odd pricing (top), and (ii) histogram of that characteristic (bottom). [Sridhar: 1. In the top left-hand panel, for the experience levels where the probability of odd pricing is relatively precisely estimated, it seems to be decreasing with experience—which is not conducive to our story. So we seem to be shooting ourselves in the foot with these figures. 2. Not clear which regression is producing these curves.]

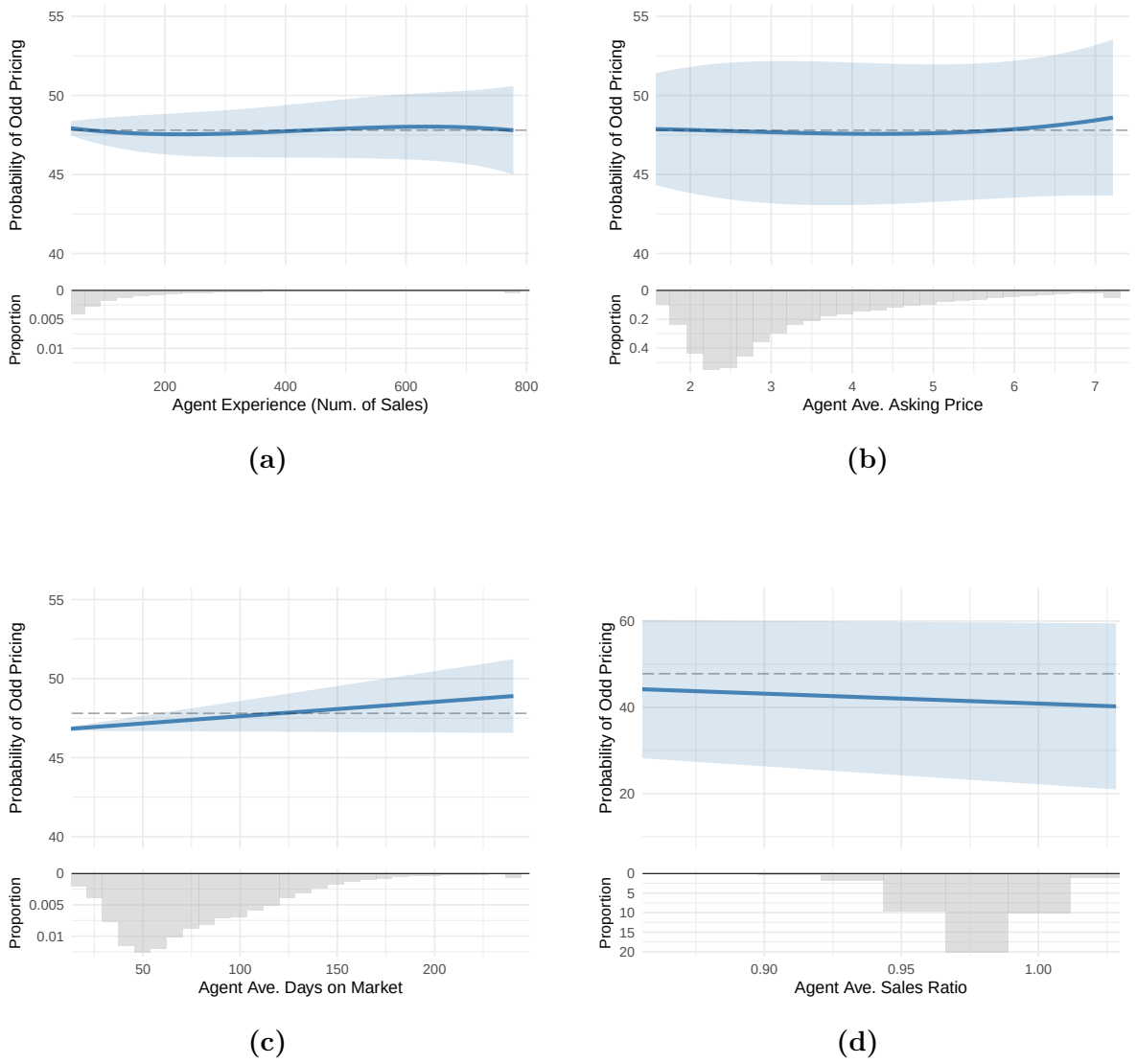


Table A.IV
Summary statistics: Toronto survey of buyers

	Mean	SD
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

Figure A.II. Histogram of buyers' reported budgets in the Toronto survey

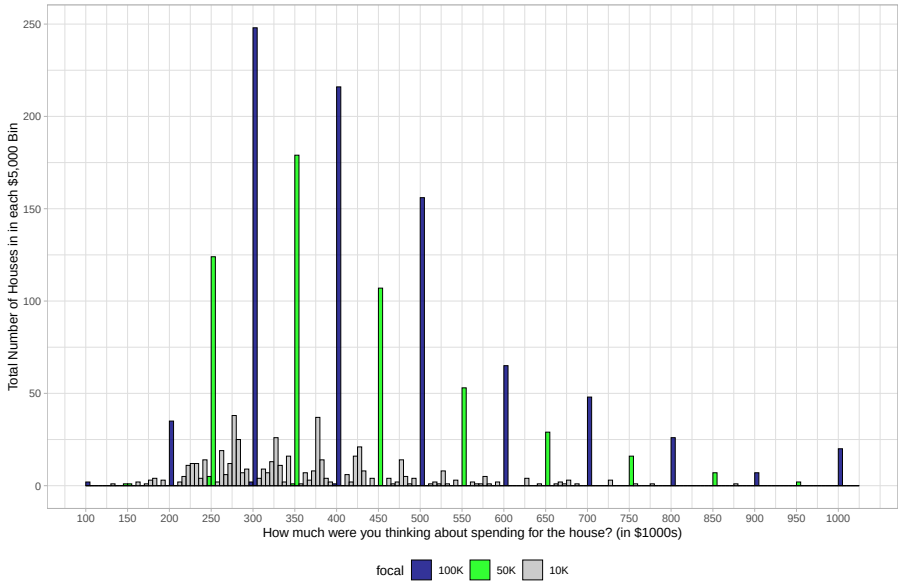


Table IV compares key transaction outcomes and property/agent characteristics for homes listed just above and just below $100K, 50K, and 10K thresholds, restricting the sample to listings within $1,000 of a threshold to align with our empirical analysis. The first four columns show means and standard deviations by listing type, while the last two columns report mean differences and t-statistics. The results indicate that homes listed just above thresholds have higher sales ratios, shorter days on market, and higher probabilities of a quick sale (sold within one week). These differences preview our empirical findings. Despite being similarly priced, house characteristics do show small, statistically significant differences between groups.

D.1. Empirical Results

In this section, we estimate several extensions of equation (1) using the Toronto data, replicating our analysis of U.S. data presented in the main text. Specifically:

1. **Threshold-Specific Effects:** Table A.V estimates separate odd-pricing effects for each $100K threshold ($\{200K, 300K, \ldots, 1,000K\}$).

2. **Threshold Type Effects:** Table A.VI examines how the odd pricing effect varies by type of round-number threshold: $100K versus $50K versus $10K multiples.

3. **Time Effects:** Table A.VII investigates how the above-threshold pricing effect varies across years in the Toronto data.

4. **The Incidence of Odd Pricing Can't Be Predicted by Agent Quality and Experience:** Table A.VIII presents results for Toronto that mirror the Table XI results for the US.

5. **$1 bins:** Figure A.VI 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.

6. **Sensitivity analysis:** Table A.IX 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.V graphically presents the results.

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

All columns report OLS regressions of equation (1) while allowing the β_z 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.

	(log) Sale price (1)	Sales ratio (2)	Days on market (3)	Quick sale probability (4)
Odd price at $200K	-0.0329***	-0.0245***	-1.524	-0.0146
	(0.0106)	(0.0084)	(2.850)	(0.0290)
Odd price at $300K	-0.0134***	-0.0112***	0.8560	-0.0524*
	(0.0031)	(0.0027)	(1.289)	(0.0273)
Odd price at $400K	-0.0131***	-0.0113***	1.358*	-0.0497***
	(0.0030)	(0.0026)	(0.7730)	(0.0187)
Odd price at $500K	-0.0140***	-0.0114***	0.5942	-0.0483***
	(0.0033)	(0.0030)	(0.7644)	(0.0176)
Odd price at $600K	-0.0090***	-0.0072***	1.152	-0.0650***
	(0.0025)	(0.0023)	(0.7956)	(0.0195)
Odd price at $700K	-0.0126***	-0.0131***	0.9813	-0.0806***
	(0.0037)	(0.0034)	(0.9817)	(0.0226)
Odd price at $800K	-0.0134***	-0.0125***	1.720*	-0.0200
	(0.0033)	(0.0029)	(0.9895)	(0.0246)
Odd price at $900K	-0.0052	-0.0041	0.7810	-0.0211
	(0.0058)	(0.0050)	(1.190)	(0.0295)
Odd price at $1,000K	-0.0213***	-0.0167***	3.044*	-0.0509*
	(0.0078)	(0.0055)	(1.824)	(0.0259)
Odd price at $1,100K	0.0026	0.0017	2.337**	-0.0344*
	(0.0033)	(0.0027)	(1.110)	(0.0191)
Odd price at $1,200K	-0.0030	-0.0038	2.258	-0.0756***
	(0.0042)	(0.0036)	(1.458)	(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
Threshold-year fixed effects	✓	✓	✓	✓
FSA-year fixed effects	✓	✓	✓	✓
Agent fixed effects	✓	✓	✓	✓

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

All columns report OLS regressions of equation (1) while allowing the β_z coefficients to vary by threshold type. Standard errors, in parentheses, are clustered at the FSA. 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.

	(log) Sale price (1)	Sales ratio (2)	Days on market (3)	Quick sale probability (4)
Odd price at $100K multiple	-0.0075***	-0.0066***	1.040***	-0.0414***
	(0.0014)	(0.0012)	(0.3143)	(0.0068)
Odd price at $50K multiple	-0.0061***	-0.0057***	0.2573	-0.0292***
	(0.0011)	(0.0009)	(0.2892)	(0.0051)
Odd price at $10K multiple	-0.0022***	-0.0014***	-1.622***	0.0032
	(0.0005)	(0.0005)	(0.2482)	(0.0044)
Agent controls	✓	✓	✓	✓
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	✓	✓	✓	✓

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

All columns report OLS regressions of equation (1) while allowing the β_z 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.

	(log) Sale price (1)	Sales ratio (2)	Days on market (3)	Quick sale probability (4)
Odd price in 2007-2010	-0.0075**	-0.0084***	1.774	-0.0683***
	(0.0031)	(0.0027)	(1.142)	(0.0174)
Odd price in 2011-2014	-0.0074***	-0.0075***	1.519**	-0.0423***
	(0.0020)	(0.0018)	(0.6405)	(0.0122)
Odd price in 2015-2018	-0.0078***	-0.0066***	0.9058**	-0.0395***
	(0.0021)	(0.0018)	(0.4522)	(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.:				
p-value	0.9899	0.8305	0.6039	0.3677
Threshold-year fixed effects	✓	✓	✓	✓
FSA-year fixed effects	✓	✓	✓	✓
Agent fixed effects	✓	✓	✓	✓

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

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^2s report the explanatory power of specific sets of variables. Internet Appendix A lists the house and agent characteristics.

Dependent Variable:	Odd Price Indicator × 100		
Model:	(1)	(2)	(3)
Variables			
Ave. Agent Asking Price	-0.6638***	-0.0160	-0.0014
	(0.1602)	(0.2689)	(0.2311)
Ave. Agent Days on Market	-0.0305*	-0.0126	-0.0126
	(0.0162)	(0.0106)	(0.0112)
Ave. Agent Sales/List Ratio	-6.341	-11.40	-9.589
	(9.618)	(10.89)	(11.13)
Agent Experience (Num. of Sales)	0.9109**	-0.5414	-0.7349
	(0.4145)	(0.6689)	(0.6986)
Agent Experience^2	-0.1207*	-0.0020	0.0126
	(0.0680)	(0.0866)	(0.0901)
Agent Experience^3	0.0029	0.0003	-4.16×10^{-5}
	(0.0025)	(0.0030)	(0.0031)
Fixed-effects			
centre-year	Yes	Yes	Yes
FSA-year	Yes	Yes	Yes
agent		Yes	Yes
Fit statistics			
R^2	0.08	0.19	0.20
Observations	652,609	652,609	623,625
Partial R^2:			
Agent Characteristics	0.0010	0.0001	0.0002
Agent Fixed Effecs		0.1228	0.1251
House Characteristics			0.0005
Joint test:			
Experience = 0 (p-value)	0.0098	0.0670	0.0600

Figure A.III. Agent characteristics and probability of odd pricing (Toronto Data). [Sridhar: Top panel left seems to show that inexperienced agents are the most likely to use odd pricing. Is this a message we want to convey?]Each panel shows (i) the effect of a particular agent characteristic on the probability of odd pricing (at the top), and (ii) histogram of that characteristic (at the bottom).

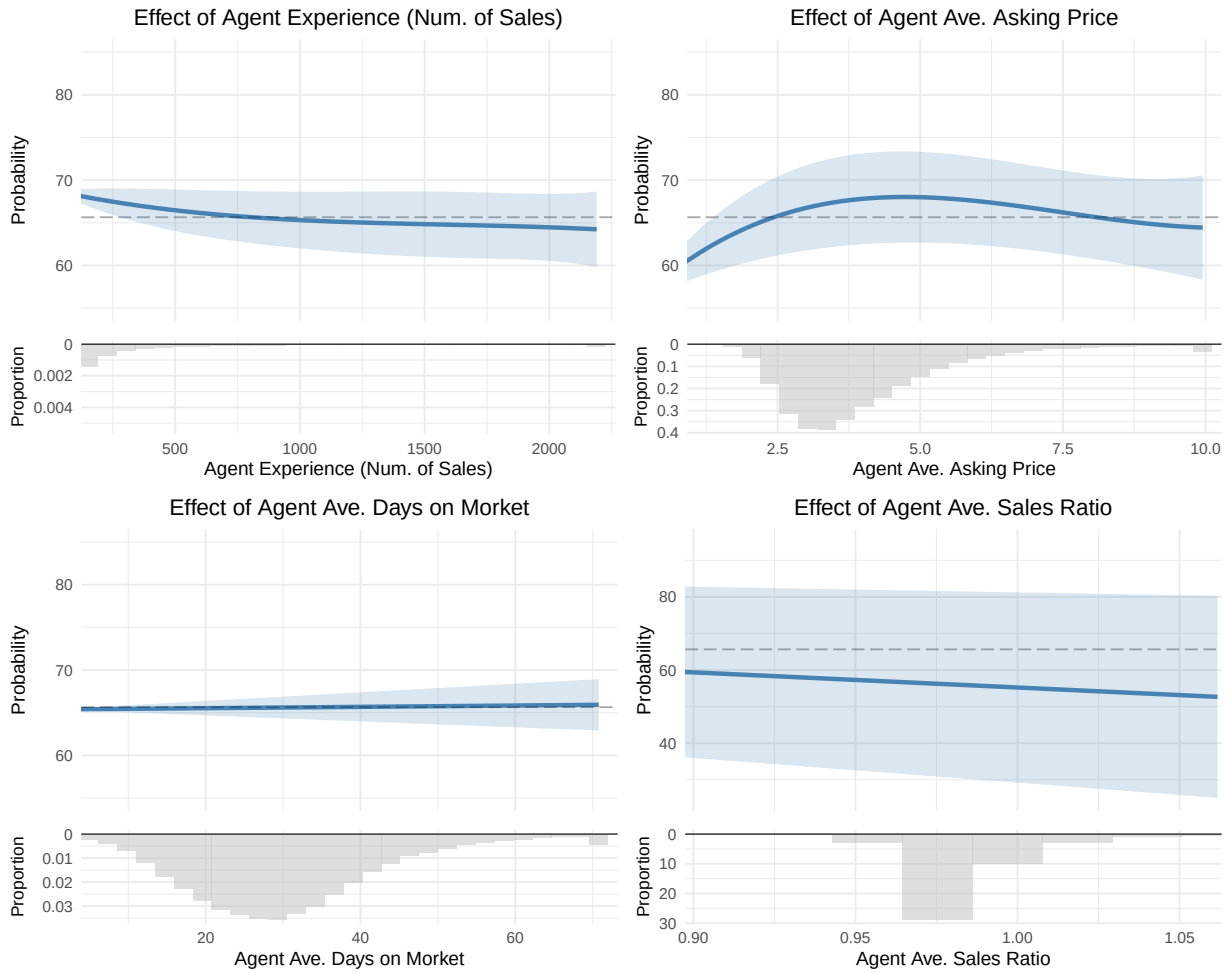


Figure A.IV. Agent heterogeneity in use of odd pricing (Toronto Data). This figure shows a histogram of odd pricing rates across agents.

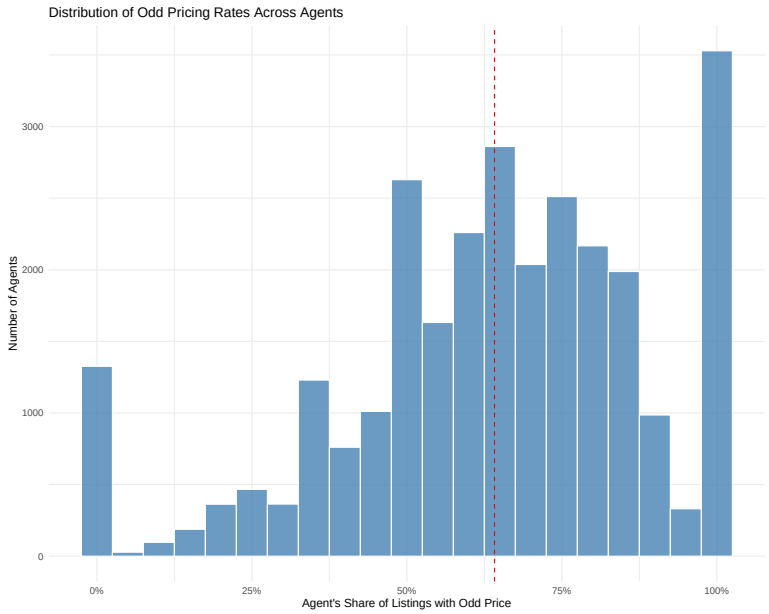


Table A.IX
Bounding the potential bias from confounders on the odd-pricing effect on sales ratio in Toronto

The top-line estimate of -0.0075 (0.0013) is the estimated odd pricing effect on sales ratio from column (4) of Table VI. |Bias| denotes the estimated absolute bias from omitting an unobserved confounder that explains R^2_Y and R^2_D 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 (4) of Table VI: all controls, agent controls, and house characteristics.

	Estimate: -0.0075 (0.0013)				
Benchmark	|Bias|	Bias Bounds	95% CI	R^2_Y	R^2_D
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

Figure A.V. Sensitivity Analysis of Omitted Variable Bias in the Estimated Odd-Pricing Effect on Sales Ratio in Toronto (based on Table A.IX). 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 ($|\text{Bias}| < -0.0075$) (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 (4) of from Table VI do not approach this frontier.

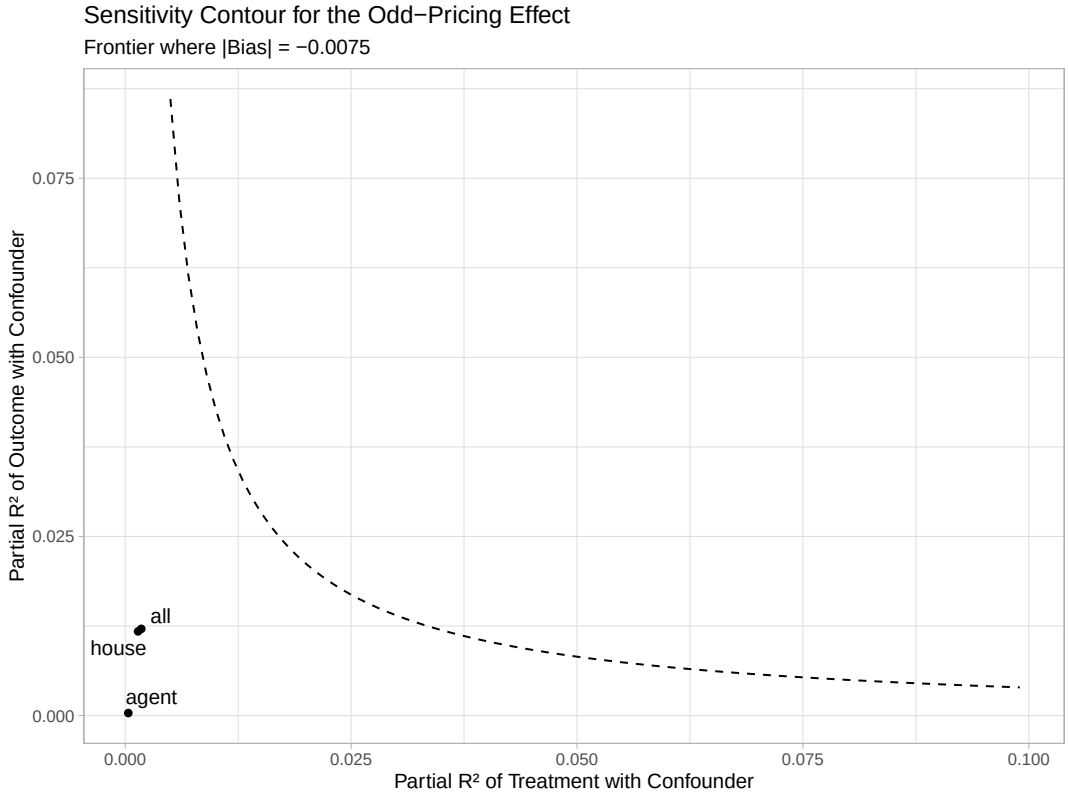
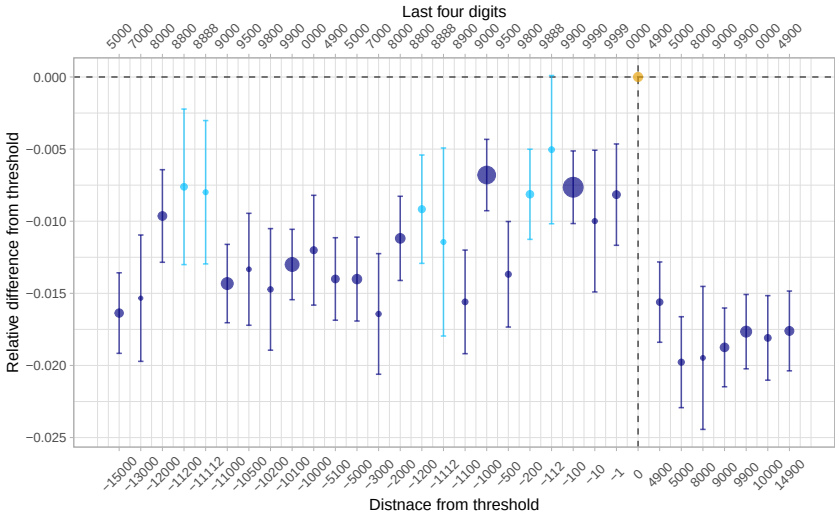
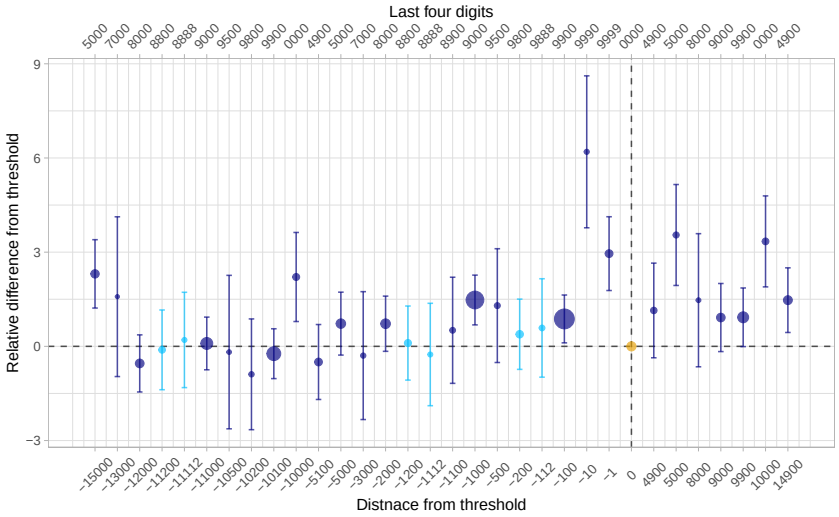


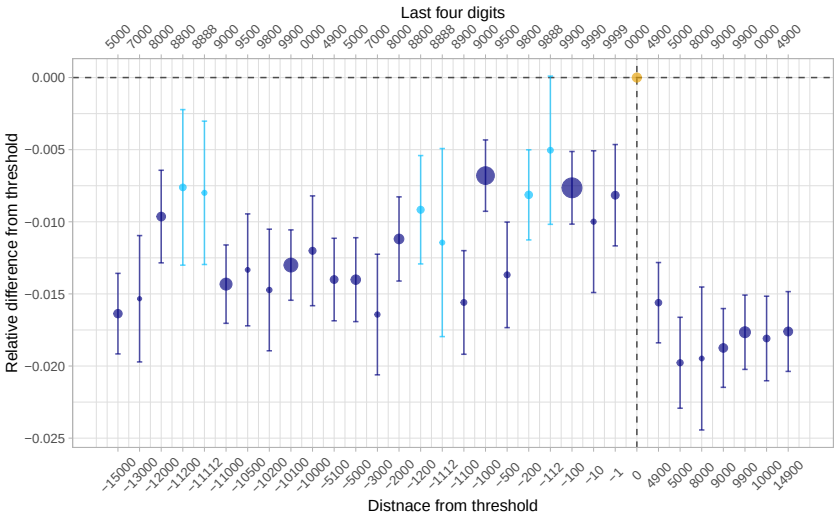
Figure A.VI. Estimates of the odd-pricing effect in Toronto for $1 bins. This figure displays estimates of the odd-pricing effect for $1 bins on: (a) sales ratio, (b) days on the market, and (c) quick sale probability. Houses listed exactly at a $100K multiple are shown by an orange dot at 0. The top 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.



(a) Sales ratio



(b) Days on market



(c) Quick sale probability