Odd Pricing and the Microstructure of Search in Housing Markets*

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ABSTRACT

Home sales data show that sellers often list their properties at "odd prices"—prices just below round numbers. 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, and cannot be plausibly explained as spurious correlation. Rather, odd-pricing seems to underperform because it interacts with the microstructure of online platforms to deliver fewer, lower willingness-to-pay buyers, and more competition to such houses.

Residential real estate transactions account for trillions of dollars 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 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.

This paper studies how small numerical features of listing prices interact with the search interfaces of housing platforms to affect market outcomes. The central insight is that houses with list prices just below round numbers—what we call "odd prices" in this paper—run the risk of being screened out, and being placed in a lower tier, when buyers set minimum price filters to weed out properties that are unlikely to meet their quality requirements. The round-priced house gets a discrete advantage in visibility and competition over its odd-priced counterpart, lifting its demand function, and resulting in better sales outcomes.

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 people 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 (Schindler and Wiman 1989; Levy et al. 2020).[1] The price appears smaller than it is, boosting demand.[2] From the seller's point of view, even if a small fraction of buyers

[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 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

exhibit left-digit bias, the increase in demand is likely to far outweigh the margin hit, making odd pricing a dominant strategy (Schindler and Kirby 1997; Basu 2006).

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.

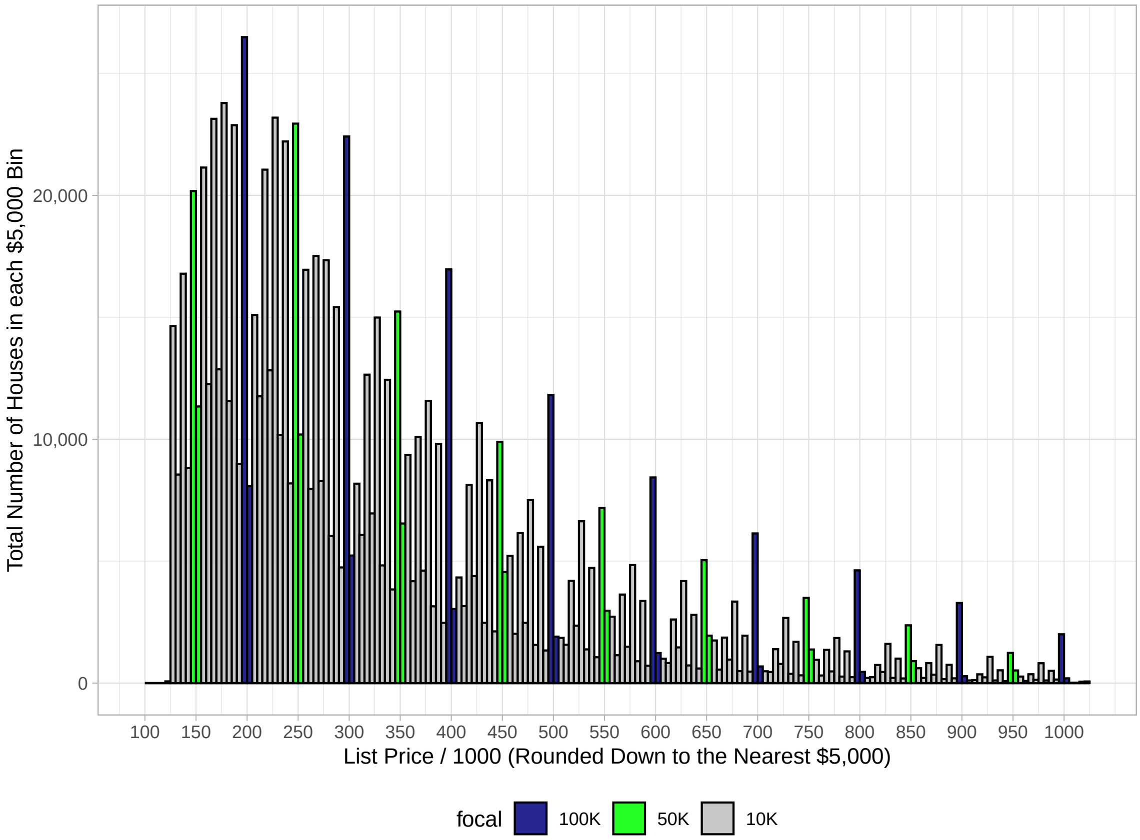
It turns out that both conjectures are incorrect. To take the second first, our data, consisting of two million houses listed in the Multiple Listing Service (MLS) of four major U.S. metropolitan areas—Chicago, Minneapolis, San Diego, and Seattle—as well as Toronto (Canada), show that odd pricing is 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 in the U.S. data). By contrast, listings with prices just above a round number are exceedingly rare—below 0.5%. Figure 1 shows this visually. 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 list prices differ by as little as $1,000 around the same round-number threshold—such as $499,000 versus $500,000—we find that odd-priced homes are 4 percentage points less 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

from a round 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.

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

effects are remarkably robust across cities, price thresholds, and years. Odd pricing simply underperforms round pricing in housing markets.

Does odd pricing *cause* odd-priced houses to underperform? We argue that it does. In our main regression—from which come the performance numbers cited above—we are controlling for house attributes, market conditions, and seller's agent characteristics (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 sharply limits the scope for confounding variation. 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 perform 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 such 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 1 we develop a conceptual framework to answer this. We argue that 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 search is costly in the housing market: there are many houses available for sale, and they can't all be visited (Han and Strange 2015). 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 show that the screening step must involve upper *and* lower list-price bounds when quality is unobserved, but correlated with list price. Perhaps recognizing this, all the major online platforms—realtor.com, Redfin, Zillow—offer drop-down menus to filter houses by maximum and minimum list prices. Crucially, these 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 lower price-bound 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 (a) appear in more consideration sets than odd-priced houses, (b) are more likely to attract higher willingness-to-pay buyers, and (c) face less competition. These discrete advantages wend their way through the search process, ultimately delivering higher sale 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 an important 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. Furthermore, buyers of those round-priced properties report having a higher initial budget, and 14.6% greater likelihood of encountering multiple bidders than observationally similar adjacently odd-priced houses.

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 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

[4] Backus, Blake, and Tadelis 2018 find evidence of a round asking price signaling seller weakness in the eBay collectibles marketplace. However, the alternative they are comparing round prices to is 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.

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 shop—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; Calder-Wang and Kim 2026). Another body of work emphasizes the role of search frictions and heterogeneous buyer consideration sets in determining housing market liquidity and prices. For example, Piazzesi, Schneider, and Stroebel 2020 show that the interaction between broad and narrow searchers can deliver an upward-sloping relationship

[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. 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 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 4.1 we provide evidence that agent experience is no antidote to the use of odd prices.

between inventory and search intensity across market segments within a city. Our work complements Piazzesi, Schneider, and Stroebel 2020 by showing how the round-numbered nature of search ranges—facilitated by the housing platform—can interact with the 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 how many potential buyers a house attracts, their willingness to pay, and the number of other houses those buyers consider.

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 (Stiving and Winer 1997; Anderson and Simester 2003; Bhattacharya, Holden, and Jacobsen 2012; Heraud and Page 2024), often attributing such patterns to left-digit bias, whereby consumers/traders place disproportionate weight on the leading digit (Bhattacharya, Holden, and Jacobsen 2012; Levy et al. 2020; Strulov-Shlain 2023; Heraud and Page 2024). 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 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 their preferred pricing strategy.

The rest of this paper is organized as follows. In Section 1 we present a conceptual framework for thinking about how odd pricing can interact with the microstructure of housing platforms to deliver unfavorable outcomes to odd-priced sellers. Section 2 describes our data and Section 3 estimates the effects of odd pricing on sales outcomes in four U.S. cities and Toronto.[7] In Section 4 we examine the possibility of spurious correlation accounting for our results. Section 5 presents evidence that odd-priced houses attract fewer, lower reservation price buyers, than observationally-equivalent round-priced houses. Finally, Section 6 concludes the paper. All prices are in U.S. dollars unless noted otherwise; supplementary tables and figures appear in an Internet Appendix.

1. Conceptual Framework

In housing markets, transactions occur when buyers and sellers find each other through a stochastic search process. Houses differ in "search" attributes—list price, location, number of bedrooms, etc.—and "experience" attributes: what the buyer sees *only* upon visiting the house—things like curb-appeal, layout, construction quality, etc. While the former can be searched on an online platform such as realtor.com, the latter calls for a personal visit. Since there are many houses for sale and they can't all be visited, considerable screening will be required. This leads naturally to a three-stage search process: (i) filtering the available listings on various search attributes to form a consideration set, (ii) examining the search attributes of houses in the consideration set to make a shortlist, and (iii) visiting shortlisted houses to examine their experience attributes (Badarinza, Balasubramaniam, and Ramadorai 2023).

Both the first and second stages are screening stages. Their job is to identify a subset of houses to pass on to the subsequent stage.[8] The difference between them is that whereas

[7]While Section 3 presents the headline results for Toronto alongside the U.S. results, many of its supplementary results are relegated to the Internet Appendix.

[8]The third stage can be thought of as a sequential search among heterogeneous distributions to identify the "optimal alternative" à la Weitzman (1979).

the first-stage screening is based on homogeneous priors—because all houses look alike before search[9]—the second-stage screening is based on heterogeneous priors: examining the houses in the consideration set reveals differences among them.

Screening by upper and lower price bounds in the first stage. The purpose of the first stage is to ease the search burden in the second and subsequent stages by weeding out houses that don't meet "minimal requirements." For example, a Chicago buyer may only want to consider houses in Hyde Park that have at least three bedrooms and two bathrooms. If she could, the buyer would also also like to screen for the quality of experience attributes, but those attributes will not be observed until the third stage. Experiential quality, however, is expected to be correlated with list price, so she can use list price not only to screen for affordability, but also to screen for acceptable quality (Gabor and Granger 1966; Piazzesi, Schneider, and Stroebel 2020). When list price-based screening serves these twin goals, it must involve upper *and* lower price bounds.

To see this, note that the first stage is effectively screening for houses whose expected utility is non-negative. Let $V(q) - p$ denote the buyer's utility function, where q is quality, p is transaction price, and $V(\cdot)$ is an increasing function mapping quality into reservation price. The buyer observes neither q nor p until the third stage, but she expects both to be positively correlated with list price.[10] Let $\hat{V}(p^\ell)$ and $\hat{p}(p^\ell)$ denote, respectively, the buyer's *expected* reservation and transaction prices for a house listed at p^ℓ; both $\hat{V}(\cdot)$ and $\hat{p}(\cdot)$ are expected to be increasing functions because of the underlying quality-price relationship.

To be worthy of consideration, a house must satisfy $\hat{V}(p^\ell) - \hat{p}(p^\ell) \geq 0$. Now it is easy to imagine $\hat{V}(\cdot)$ and $\hat{p}(\cdot)$ satisfying $\hat{V}(p^\ell) - \hat{p}(p^\ell) \geq 0$ if and only if $p^\ell \in [\underline{p}^\ell, \bar{p}^\ell]$.[11] This will

[9] This is one way house-hunting differs from shopping in a grocery store. In the latter, brand names are visible at the shelf. Since brand names can signal quality, consumers potentially have different priors for different brands.

[10] This formulation neatly encapsulates the role of a buyer's agent as educating the buyer about the price-quality relationship prevailing in the local market.

[11] For example, if $\hat{V}(p^\ell) = -a{p^\ell}^2 + (b+1)p^\ell - c$ and $\hat{p}(p^\ell) \equiv p^\ell$, with $a, b, c > 0$ and $b^2 - 4ac < 1$, then $\hat{V}(\cdot)$ is increasing for $p^\ell < (b+1)/2a$, and $\underline{p}^\ell = \left(b - \sqrt{b^2 - 4ac}\right)/2a$ and $\bar{p}^\ell = \left(b + \sqrt{b^2 - 4ac}\right)/2a$.

be the case if the buyer expects house quality to be too low given the expected transaction price, if list price is below $\underline{p}^\ell$, and the transaction price too high given the expected quality, if list price is above $\bar{p}^\ell$. Thus, $\underline{p}^\ell$ and $\bar{p}^\ell$ are the buyer's lower and upper price bounds for screening properties in the first stage, subject to $\hat{p}(\bar{p}^\ell) \leq B$, where B is the buyer's budget constraint. The buyer's consideration set is thus $\mathcal{S} = \{j : \underline{p}^\ell \leq p_j^\ell \leq \min\{\bar{p}^\ell, \hat{p}^{-1}(B)\}\}$.[12]

Platform design and odd versus round pricing. 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 provide round-numbered minimum and maximum price filters. 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; Kuo, Lin, and Zhao 2015; Zinn and Würbach 2016; Argyle, Nadauld, and Palmer 2020). 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 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, 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,

[12] 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 platform 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, which also suggests the existence of a lower price bound (see also Cubbin 1974; Andersen et al. 2022).

even those choices are likely to be round numbers.[13] 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 demonstrate 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 to take the defaults. Still, their data show that the bounds people enter are typically multiples of \$50,000, with particularly pronounced peaks at multiples of \$100,000.[14]

Round-numbered minimum and maximum price filters affect demand, and competition as follows. Consider a pair of houses, j and j', such that j is round-priced at p_j^ℓ and j' is odd-priced at $p_j^\ell - \epsilon$. Now imagine a buyer with a screening range $[\underline{p}^\ell, \bar{p}^\ell]$, where $\underline{p}^\ell$ and $\bar{p}^\ell$ are both round numbers with $\underline{p}^\ell < \bar{p}^\ell$, encountering these houses. If $\underline{p}^\ell > p_j^\ell$, then neither j nor j' is considered: both are screened out. However, if $\underline{p}^\ell = p_j^\ell$, then the round-priced house j makes the cut, but its odd-priced twin j' is filtered out. Finally, if $\underline{p}^\ell < p_j^\ell \leq \bar{p}^\ell$, then both j and j' are considered. In other words, whenever an odd-priced house is considered, so is its round-priced counterpart, but the reverse is not necessarily true. The potential demand for an odd-priced house is a strict subset of the potential demand for the adjacently round-priced house: $\left\{i : \underline{p}^{\ell i} \leq p_j^\ell - \epsilon \leq \bar{p}^{\ell i}\right\} \subset \left\{i : \underline{p}^{\ell i} \leq p_j^\ell \leq \bar{p}^{\ell i}\right\}$. This also means that an odd-priced house will always face competition from adjacently round-priced houses, whereas the round-priced house will not face competition from adjacently odd-priced houses for consumers in the set $\left\{i : \underline{p}^{\ell i} = p_j^\ell\right\}$. Finally, since $\bar{p}^\ell$ and $\underline{p}^\ell$ are likely to be positively correlated—because the former must necessarily be larger than the latter—the buyers in $\left\{i : \underline{p}^{\ell i} = p_j^\ell\right\}$ who consider j but not j' will tend to have a higher reservation price than the buyers who consider both houses (because the latter must have

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

[14]Our survey of Toronto buyers— discussed later—reveals similar patterns in those buyers' reported budgets (see Figure 2).

a lower lower-bound, and hence likely a lower upper bound). The winning bidder for a round-priced house is likely to come from these marginal higher reservation-price buyers.

2. Data

Our data provide a rare opportunity to test the implications of screening by round-numbered lower and upper price bounds. On the one hand, we have comprehensive MLS data from several major metropolitan areas in North America—the U.S. cities of Chicago, Minneapolis, San Diego, and Seattle, and the Canadian city of Toronto—with list prices, detailed listing descriptions, and transaction outcomes.[15] In addition, we have survey data from a subset of Toronto buyers reporting their budgets and the number of competing bidders they faced. Combining these sources allows us to examine not only the market outcomes predicted by our framework, but also the underlying mechanism that might have led to those outcomes.

2.1. MLS Data from the United States

These data cover 2,457,966 listings from 2008–2018, 1,717,393 of which 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)).[16] This leaves us with 1,403,602 listings, 953,759 sold (67.95% of sample) and 449,843 unsold (32.05% of sample).

[15]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.

[16]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.

Table 1 describes these data. Panel A shows that the U.S. housing market improved from 2008 to 2018: average home price increased from $278,111 to $342,357 (23%); sale to list price ratio rose from .97 to .99; days on the market fell from 17 to 11 weeks; and probability of selling within a week of listing went up from .02 to .11. Panels C and D show that house and agent characteristics were relatively stable, with the sole exception of agent experience—the average agent selling 40 fewer homes in 2016–2018 than in 2008-2009.

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 versus just-below/just-above round, where just-below and just-above are defined as 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 prices, ranging from 51.54% versus 7.16% in the 2008-2009 period to 45.95% versus 11.32% in the 2016-2018 period. On the other hand, listing just above a round number is relatively rare.

2.2. MLS Data from Toronto

These data cover sales transactions in the Greater Toronto Area (GTA) from January 1, 2000 to November 30, 2018.[17] Years prior to 2007 do not contain information on housing characteristics, so we focus on the 2007–2018 period, comprising 1,197,837 listings. From these observations, we retain only transactions that: (a) are coded as housing type "semi detached" or "single family house" (733,318 observations), (b) are listed between $124,999 and $1,224,999 (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). This leaves us with 643,343 listings.

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

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

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: List price characteristics								
List Price/1000	0.298	0.000	0.321	0.000	0.345	0.000	0.367	0.000
Round (%)	7.164	0.068	8.293	0.058	9.099	0.043	11.322	0.041
Odd (%)	51.537	0.133	50.953	0.104	48.906	0.075	45.952	0.065
Just above (%)	0.448	0.018	0.463	0.014	0.379	0.009	0.341	0.008
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

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

The data are summarized in Table 2. Panel A shows that the Toronto real-estate market also improved substantially during our sample period. Average home price rose from $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 C shows relatively stable house characteristics and panel D shows agents increasing their sales ratios while decreasing their number of homes sold. Finally, Panel B shows that, just as in the U.S. data, listing at odd prices is a common and increasingly popular strategy in Toronto, rising from 11.4% of listings in 2007–2009 to 23% in 2016–2017. By contrast, listing just above a round number occurs rarely.

2.3. 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 (and used previously in Han and Strange 2016). Among other things, the survey asked buyers to report—within a year of purchase—various details about their purchase process, such as their budget and the number of other bidders on the property if any. 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.[18] We use this survey in Section 5 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. 1,816 buyers were eliminated because they bought land or because they were

[18]For example, while Piazzesi, Schneider, and Stroebel 2020 provide aggregate data on the search process, they can't relate individual search to individual sales outcomes.

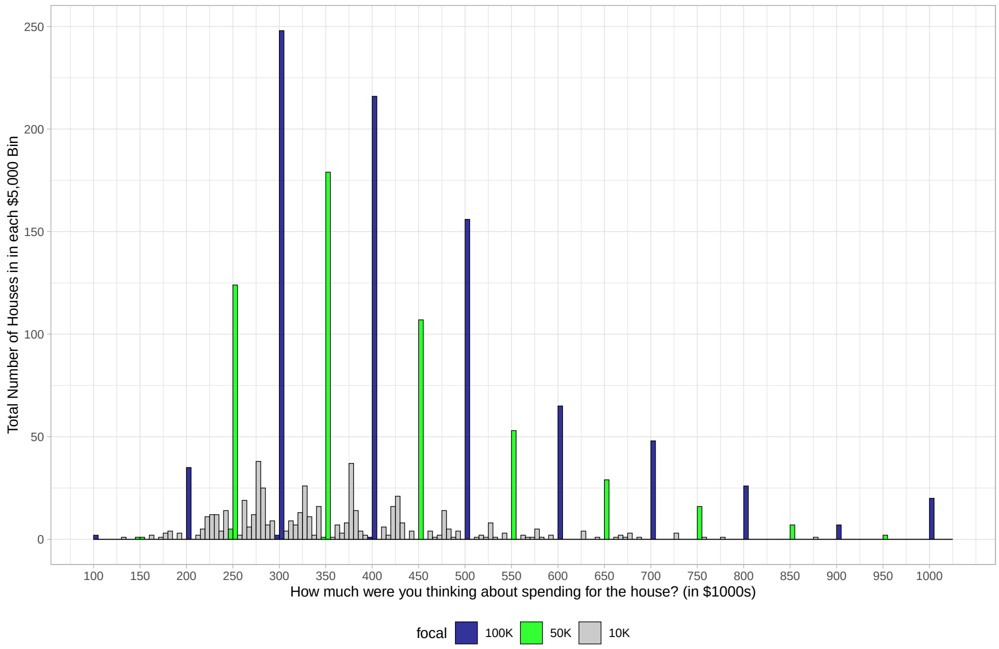
Table 2: Summary statistics (Toronto MLS data)

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: List price characteristics								
List Price/1000	425.95	0.434	494.13	0.482	577.25	0.517	705.70	0.57
Round (%)	2.63	0.039	3.43	0.044	4.77	0.050	7.32	0.07
Odd (%)	63.98	0.118	65.91	0.115	65.78	0.112	66.45	0.12
Just above (%)	0.13	0.009	0.12	0.008	0.11	0.008	0.11	0.01
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

Round prices are defined as $100K, $50K, and $10K multiples, and “odd/just above” as prices in $1K intervals, below/above adjacent round prices. Sales ratio is sale price/list price, and “quick sale” refers to the probability of selling within a week of listing. Some extreme values of sales ratio, days on the market, and 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).

institutions; 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.3 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.

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 $[x, x + \$5K)$.

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

The Toronto survey provides individual-level information on the search and buying process for homes. Three particularly relevant questions are: “How much were you thinking about spending for the house?” “Were there other people actively bidding on the home when you submitted your first offer?” and “If yes, about how many other bidders were there?” Figure 2 shows the histogram of reported budgets. They are predominantly $100K and $50K multiples; the average budget is $412,302 CAD. Table A.4 (in the Appendix), shows that just over two-thirds of buyers report only one bidder, while about one-sixth report two bidders, and slightly less than half as many report three bidders. Notably, about nine percent of buyers report more than three bidders.

3. 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 3 display the means and standard deviations of these quantities in the U.S. data by list-price type, and the last two columns show the differences between those means and the associated t-statistic.

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

	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

Sample consists of all properties listed within $1K of a $100K, $50K, or $10K threshold. "Odd" refers to homes listed in the interval $[z - 1K, z)$ and "Round" refers to homes listed in the interval $[z, z + 1K)$, where z is a $100K, $50K, or $10K multiple. Sales ratio is sale price/list price, and "quick sale" refers to the probability of selling within a week of listing.

Panel A shows statistically significant differences in sales outcomes, with odd-priced houses showing a lower probability of sale, lower sales ratio, more days on the market, and a lower probability of a quick sale than houses listed at the adjacent round number, previewing our regression results to follow. Since these homes are all priced within \$1K of the same \$100K, \$50K, or \$10K multiple, one might expect them to be fairly similar in house attributes, and Panel B bears this out—for the most part. On some house characteristics there are statistically significant differences; when there are such differences, it is notable that, in general, they favor odd-priced houses. For example, odd-priced houses have more bedrooms, more washrooms, and more square footage than their round-priced counterparts. Finally, Panel C compares selling agent characteristics. 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 similar comparisons in Table 4.

3.1. 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 estimate a local linear regression in a \$15K neighborhood of each round list price, where round price is defined as a multiple of \$100K between \$200K and \$1,000K.[19]

Within each neighborhood, we partition list prices into \$1K bins. For a given round price τ, let $\mathcal{O}_\tau := [\tau - 1K,\ \tau)$ denote the *odd-price bin*—the \$1K interval immediately below τ—and let $\mathcal{R}_\tau := [\tau,\ \tau + 1K)$ denote the *round-price bin.*[20] For each property i, let τ_i denote the nearest round price. We define $\texttt{Odd Price}_i$ as an indicator equal to one when property i's list price falls in the odd-price bin $\mathcal{O}_{\tau_i}$, and define $\texttt{Bin}_i^z$ as an indicator for each

[19]The \$15K bandwidth balances statistical power against local comparability; because the bin indicators flexibly absorb any residual price-outcome relationship within each neighborhood, results are not sensitive to this choice. In Section 3.2 we examine other definitions of round prices, such as multiples of \$50K and \$10K, where we use the entire sample.

[20]We call $[\tau, \tau + 1K)$ a round-priced bin because it is effectively the singleton set $\{\tau\}$. As noted in Table 1, there are very few houses priced just above a round number. Later, in Section 4.2, we will examine \$1 bins; then the round-number bins will contain nothing but round numbers.

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

	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

Sample consists of all properties listed within \$1K of a \$100K, \$50K, or \$10K threshold. “Odd” refers to homes listed in the interval $[z - 1K, z)$ and “Round” refers to homes listed in the interval $[z, z + 1K)$, where z is a \$100K, \$50K, or \$10K multiple. Sales ratio is sale price/list price, and “quick sale” refers to the probability of selling within a week of listing.

of the 28 remaining \$1K bins in the neighborhood ($z \in \{-15K, \ldots, -2K,\ 1K, \ldots, 14K\}$). The round-price bin $\mathcal{R}_{\tau_i}$ serves as the omitted category.

We specify the regression as follows:

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

where Y_i denotes a sales outcome: whether the property sold, sale price ($\mathtt{p}_i^s$), the sale-to-list price ratio ($\mathtt{p}_i^s / \mathtt{p}_i^\ell$)—“sales ratio,” hereafter—days on the market, or whether the house sold within a week of listing. The coefficient of interest is β: the effect on outcomes of listing in the odd-price bin $\mathcal{O}_{\tau_i}$ versus listing in the adjacent round-price bin $\mathcal{R}_{\tau_i}$. The coefficients on the other 28 neighboring bins are collected in the vector $\boldsymbol{\beta}_{\mathcal{B}}$.[21]

To account for the possibility that odd-priced houses differ systematically from round-priced houses, we include two sets of controls: $\mathbf{X}_i$, a vector of house characteristics (square footage, bedrooms, bathrooms, etc.), and $\mathbf{Z}_i$, a vector of agent characteristics capturing agent experience (number of houses previously sold) and agent quality (previous average sales ratio and days on market); see Internet Appendix A for the full list. To absorb unobserved heterogeneity, we include threshold×year×county fixed effects ($\boldsymbol{\gamma}_{\tau\times y\times c}$), postal code×year fixed effects ($\boldsymbol{G}_{pc\times y}$), and agent fixed effects ($\boldsymbol{A}_i$). The agent fixed effects are particularly important for our identification strategy: they absorb the persistent tendency of certain agents to favor odd pricing (see Figure 3). Our most comprehensive specification therefore identifies β by comparing odd-priced and round-priced houses centered on the same threshold, sold in the same year, located in the same postal code, and listed by the same agent, while controlling for variations in house and agent characteristics. In Section 3.2, we examine heterogeneity by threshold level ($100K multiples), threshold type ($100K versus $50K versus $10K multiples), year, and city.

Table 5 presents our baseline estimates of (1) for the U.S. markets. Panels A–E correspond to our five outcome measures: sale price, sales 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

[21]In Section 4.2 we compare β and $\boldsymbol{\beta}_{\mathcal{B}}$ to show that the odd-priced bin is indeed different from the other bins neighboring round prices.

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

	Bin size = $1,000				
	(1)	(2)	(3)	(4)	(5)
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

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.

is that houses listed at odd prices *underperform* relative to their round-priced counterparts on all five performance measures.

Of course, homes with very similar list prices within a threshold-year-county may still differ in ways that have a bearing on sales outcomes. To mitigate those concerns, we add additional controls: in column (2), house characteristics, in column (3), in addition, Zip Code-year fixed effects, in column (4), in addition, agent characteristics, and finally, in 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 round-priced counterparts on probability of selling, sale price, and time to sell. Specifically, in our most comprehensive specification (column (5)), odd-priced houses are less likely to sell by about 4 percentage points, and when they sell, they sell at a 0.66% discount and stay on the market about a week longer.

Table 6 presents estimates of equation (1) in the Toronto market. Consistent with the U.S. findings, we observe that homes listed at odd prices consistently have worse sales outcomes than their round-priced counterparts.

3.2. 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 7 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 listing threshold increases. What is noteworthy is that even the smallest effects show odd-priced houses underperforming their round-priced counterparts.

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

	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

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.

Threshold Type. In Table 8 we investigate whether the odd-pricing effect exists at round-number thresholds that are "less round" than $100K multiples. 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 as we go from $100K multiples to

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

Dependent Variables:	(log) Transaction Price	Sales Ratio	Days on Market	Quick Sale	Probability of Sale
Model:	(1)	(2)	(3)	(4)	(5)
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

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.

less-round pricing thresholds.[22] The relative paucity of observations near uniquely \$50K and \$10K multiples makes those estimates relatively less precise.

[22] As we will discuss in Section 5, this is consistent with our theory of the odd-pricing effect.

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

Dependent Variables:	(log) Transaction Price	Sales Ratio	Days on Market	Quick Sale	Probability of Sale
Model:	(1)	(2)	(3)	(4)	(5)
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

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 (i.e. within \$5K of a \$100K, 50K, or 10K threshold). House and agent controls are listed in Internet Appendix A.

Years. Table 9 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 10, we report odd pricing effects for Chicago, Minneapolis, and San Diego. (Seattle is excluded because of missing data; see footnote 16.) While there is 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 9: Odd pricing effects by year (U.S. data)

Dependent Variables:	(log) Transaction Price	Sales Ratio	Days on Market	Quick Sale	Probability of Sale
Model:	(1)	(2)	(3)	(4)	(5)
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

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.

4. Explaining the Underperformance of Odd Pricing: Spurious Correlation?

The regressions above show that odd-priced houses underperform their round-priced counterparts on all five of our 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 result interesting is that neither odd list price nor round list 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, 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.

Table 10: Odd pricing effects by city (U.S. data)

Dependent Variables:	(log) Transaction Price	Sales Ratio	Days on Market	Quick Sale	Probability of Sale
Model:	(1)	(2)	(3)	(4)	(5)
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

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 16, 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.

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 the opposite of what we are observing—odd pricing overperforming, rather than underperforming. Another direct explanation, but this one focusing on the supply side, would be Backus, Blake, and Tadelis's (2018) theory that round prices (versus non-round prices) are a cheap-talk way to signal seller weakness (see footnote 4). 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 indirect explanations based on spurious correlation cannot plausibly account for our results. First, we note that a significant amount of variation in the incidence of odd pricing is absorbed by the presence of agent fixed effects in our regressions, and what remains looks essentially random. Second, we ask whether unobserved quality differences between odd- and round-priced houses can explain the former's underperformance. For this we perform a series of tests: (i) we track how sales outcomes vary with list price and show that those relationships are discontinuous *only* at round list prices (with the implication that if an unobserved quality-list price correlation is really driving the odd pricing effect, why is that relationship abruptly changing from continuous to discontinuous only at round prices), and (ii) include additional control variables in our regressions for verifiable quality signals present in the verbal descriptions of our listings—phrases such as, "hardwood floors," "Wolf appliances," etc—and show that 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 omitted-variable bias from confounders for which we lack data, we bound the potential magnitude of such bias using the sensitivity-analysis framework of Cinelli and Hazlett 2019; Chernozhukov et al. 2023. This analysis reveals that even in the worst-case scenario of such confounders being correlated with the outcomes and the "treatment" as strongly as *all* of our observed covariates *combined*, such bias would be too low to nullify the odd-pricing effect.

4.1. Given Agent Fixed Effects in (1), What Drives the Odd Pricing Effect is Essentially Random Within-Agent Variation in the Incidence of Odd Pricing

Here we investigate whether the incidence of odd pricing is predictable in the presence of agent fixed effects. Table 11 shows regressions where the dependent variable is an indicator of odd pricing and the independent variables are various measures of agent quality—past asking prices, sales ratios, and times on the market—agent experience (modeled flexibly), house characteristics, and fixed effects. Columns (2) and (3) show that in the U.S. markets, controlling for agent, neither their quality nor their experience, nor house characteristics, explain much 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 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 5, 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.8 and Figure A.1 show that Toronto data behave similarly.

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

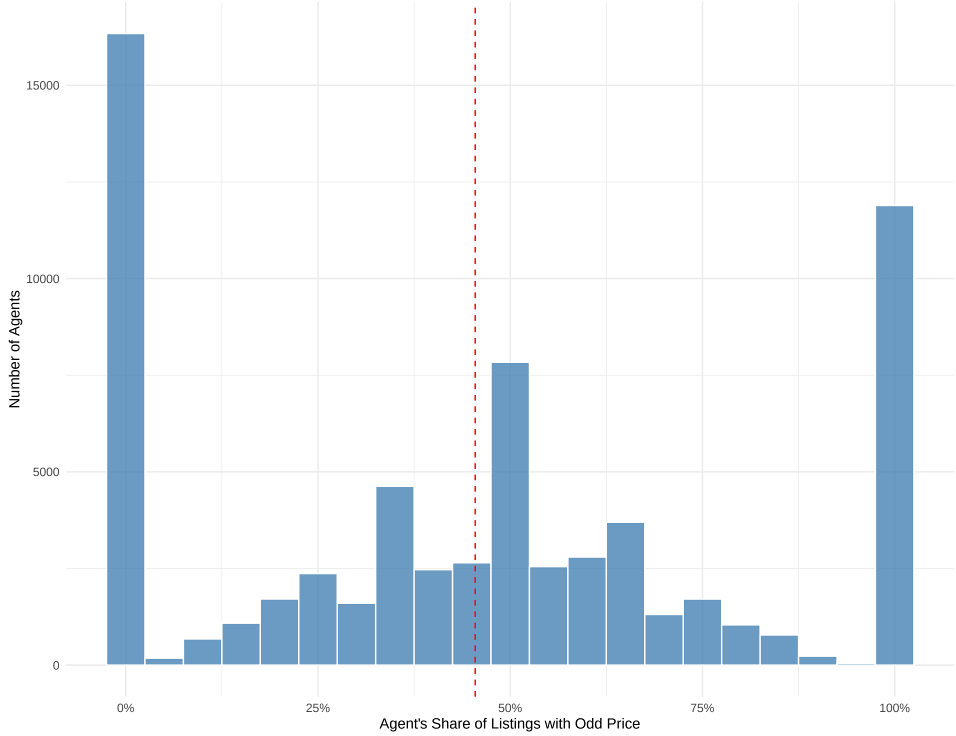
Dependent Variable:	Odd Price Indicator × 100		
Model:	(1)	(2)	(3)
Variables			
Ave. Agent Asking Price	0.1092	0.0968	0.1003
	(0.1437)	(0.1664)	(0.1667)
Ave. Agent Sales/List Ratio	-53.31***	-1.359	-1.186
	(7.637)	(5.930)	(5.930)
Ave. Agent Days on Market	-0.0274***	0.0030	0.0030
	(0.0037)	(0.0035)	(0.0035)
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

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.

4.2. 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, construction quality, 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

Figure 3: Agent heterogeneity in use of odd pricing



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

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

their relative underperformance? Right off the bat, however, this doesn't sound very plausible: why would houses 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.

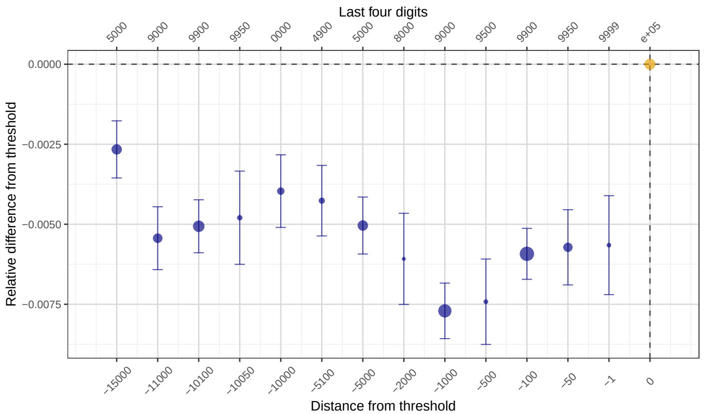
Figure 4 shows the results for probability of sale, sales ratio, days on the market, and probability of quick sale in the U.S. data. (Figure A.3 provides similar evidence for Toronto.) Houses priced exactly at \$100K multiples are marked by a yellow dot at 0 on the bottom x-axis; they form the reference 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 reported 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 8).

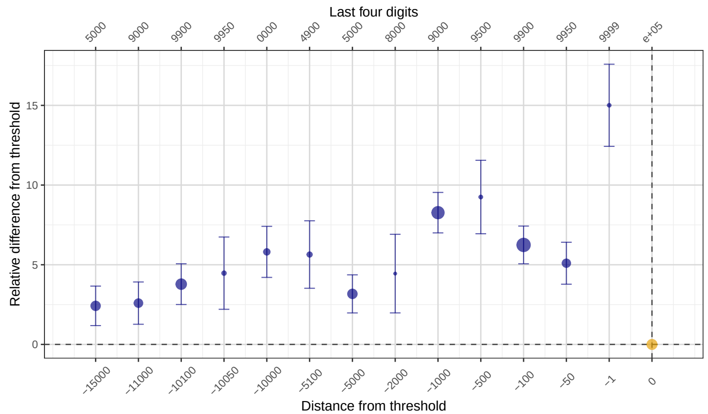
Can houses priced \$1 apart differ significantly enough in unobserved quality to reduce sales ratio by .6 percent? And if so, how can it be that the difference in unobserved quality between houses priced \$1 apart be the same as the difference in unobserved quality between houses priced \$1,000-\$5,000 apart? Next, 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, the relationship between list price and unobserved quality seems continuous except at \$100K multiples.

We conclude that it is implausible that an underlying unobserved quality-list price correlation drives the underperformance of odd-priced houses.

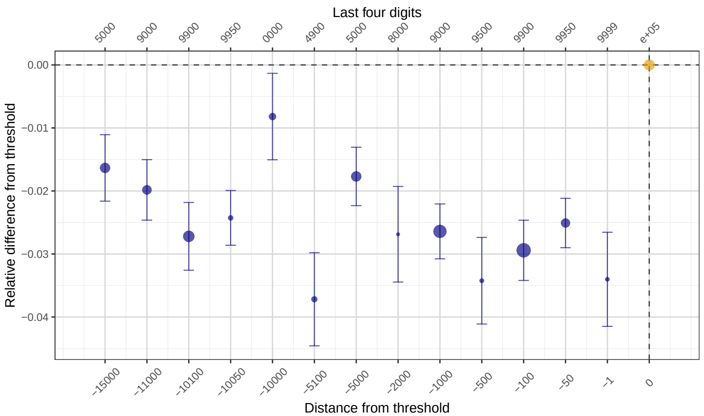
Figure 4: Odd-pricing effects as a function of list price (U.S. data).



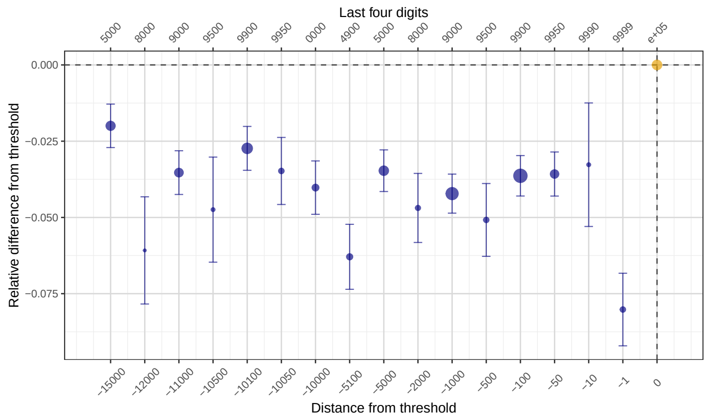
(a) Sales ratio



(b) Days on market



(c) Quick sale probability



(d) Probability of sale

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.

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

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."

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.1 lists the phrases considered in each of these categories.

As can be seen from columns (3) and (6) of Table 12, 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 12 are substantially the same as in Table 5. This casts doubt on what other aspects of unobserved house quality there might be that could account for the observed odd-pricing effects.

4.3. Controlling for Advertising Strategy Doesn't Seem to Matter

By advertising strategy we mean verbose descriptions (large number of words), use of all-caps words and exclamation points, and puffery such as "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.1. The 200 "puffery" words that survive are shown in Table A.2 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 12 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 5. Controlling for advertising strategy also doesn't eliminate the odd-pricing effect.

4.4. Controlling for Signals of Seller Desperation and Urgency Doesn't Seem to Matter

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.

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

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
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
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 12—*continued*

Dependent Variable:			Bin size = $1000			
Model:	(1)	(2)	(3)	(4)	(5)	(6)
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

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.

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 12 show that doing so doesn't change the odd-pricing effects significantly.

4.5. The Potential Bias from Confounders Will Need to be Implausibly Large to Overturn the Odd Pricing Effects

Our empirical strategy compares comparable houses listed within a \$15K window around a round price, sold in the same year and postal code, and 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 4.1 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.[23]

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.[24] Those partial-R^2s

[23]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 $\mathrm{Cov}(U_i, \texttt{Odd Price}_i \mid \boldsymbol{A}_i, \boldsymbol{G}_{pc_i,y_i}, \gamma_{\tau_i,y_i,c_i}) \neq 0$ and $\mathrm{Cov}(U_i, Y_i \mid \boldsymbol{A}_i, \boldsymbol{G}_{pc_i,y_i}, \gamma_{\tau_i,y_i,c_i}) \neq 0$; 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.

[24]The formula is

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

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

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

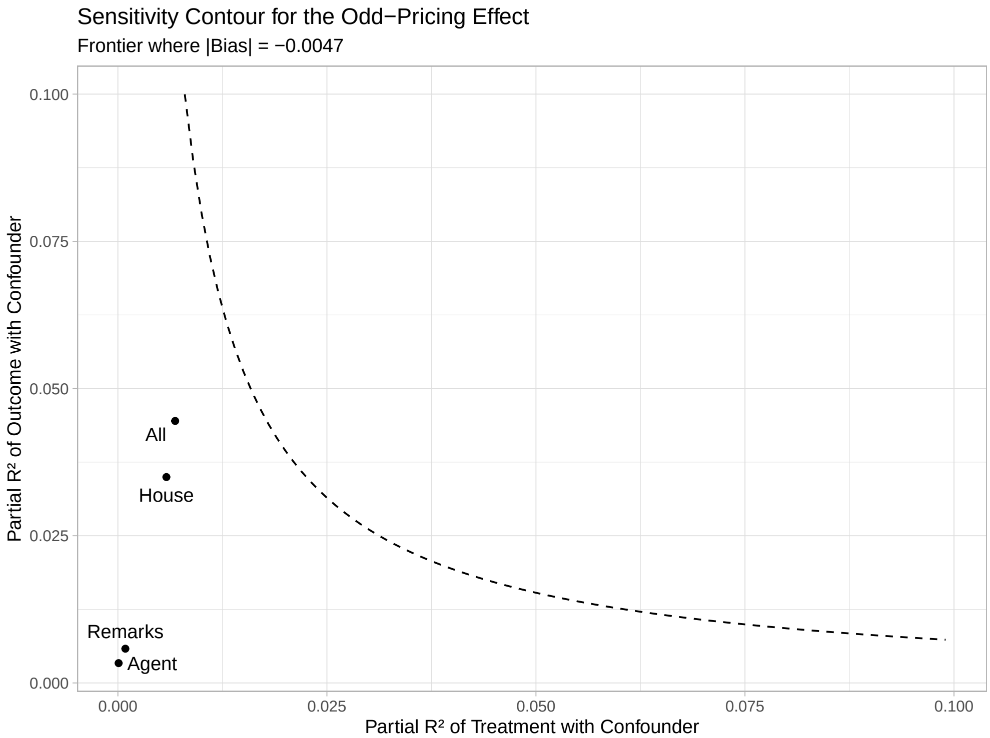
	Estimate -0.0047 (0.0005)				
Benchmark	|Bias|	Bias Bounds	95% CI	R^2_Y	R^2_D
All	0.0029	[-0.0075 – -0.0018]	[-0.0083 – -0.0010]	0.0445	0.0068
House Characteristics	0.0023	[-0.0070 – -0.0023]	[-0.0078 – -0.0016]	0.0350	0.0058
Agent Controls	0.0001	[-0.0047 – -0.0046]	[-0.0055 – -0.0038]	0.0034	0.0001
Public Remarks	0.0004	[-0.0050 – -0.0043]	[-0.0058 – -0.0035]	0.0058	0.0009

The top-line estimate of -0.0047 (0.0005) is the odd pricing effect on sales ratio from column (6), Panel B, of Table 12. The column labeled |Bias| reports the maximal absolute bias implied by a hypothetical confounder that explains R^2_Y of the residual variation in the outcome and R^2_D 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).

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 12). 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 13 shows, the full set of observables—house characteristics, agent controls, and public remarks—explains approximately 4.5% of the remaining variation in the sales ratio and less than 1% of the variation in odd pricing; for smaller subsets, the partial-R^2s are even lower. We will use these partial-R^2s to benchmark potential bias

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.

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 12 do not approach this frontier.

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

from any unobserved confounders that could still be operating in our empirical setup.

The top row of Table 13 shows that a hypothetical confounder as strongly associated with both treatment and outcome as all observables combined would generate a maximal absolute bias of only 0.0029. Therefore, to drive our odd-pricing effect of -0.0047 to zero, a within-agent confounder would need to be more than 1.5 times as predictive of both sales ratio and odd-pricing incidence as the entire set of observed house, agent, and listing controls. Even in this worst-case scenario, the bias-corrected 95% confidence interval excludes zero. The remaining rows of Table 13 repeat 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.[25] This analysis demonstrates the robustness of our estimates to confounders with explanatory power as strong as our extensive set of observed controls.

5. How Odd Pricing Interacts With the Microstructure of Search to Deliver Adverse Outcomes

In Section 1 we outlined a simple framework to explain why buyers are likely to use round-numbered lower and upper price bounds to screen properties on online real-estate platforms, and how this microstructure will interact with odd pricing to produce the following effects:

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.

[25]The bounds reported in Table 13 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.

2. The marginal buyers considering a round-priced house (but not its odd-priced counterpart) are likely to have a higher upper bound, and thus a greater willingness-to-pay than buyers considering its odd-priced counterpart. The winning bid for such a house will likely come from these marginal buyers.

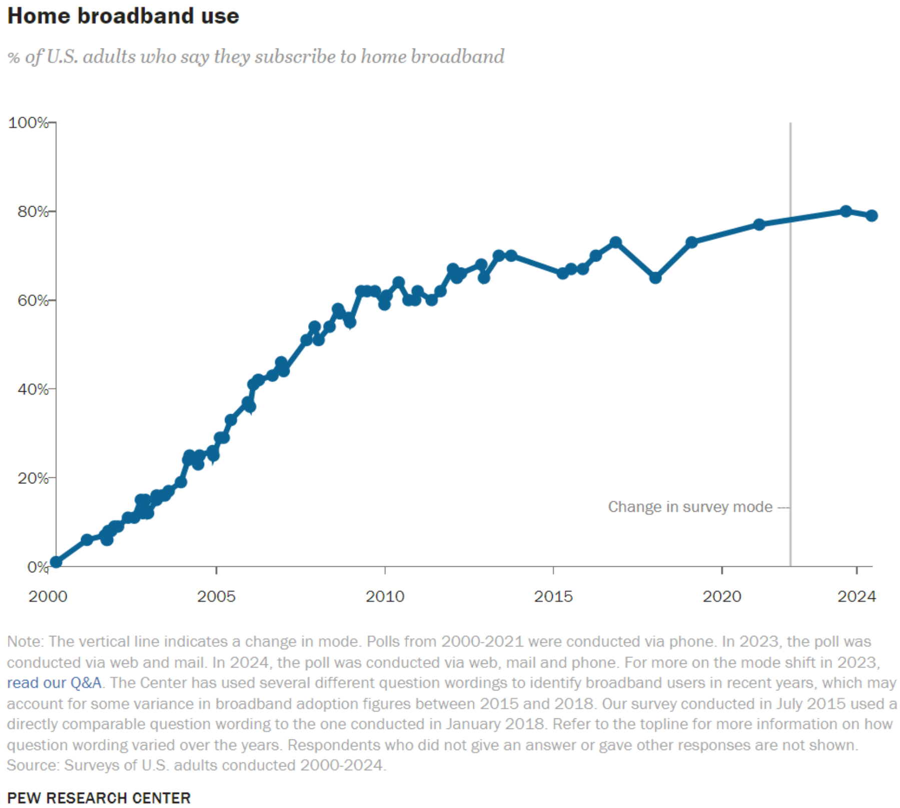
3. Finally, the odd-priced house faces more competition than its round-priced counterpart: whereas everyone considering the former also considers the latter, the latter has buyers who are not looking at an adjacently odd-priced house.

Together, these effects can explain why odd-priced houses underperform their round-priced counterparts.[26]

The results in Table 9 are already consistent with this story. They show a strengthening of the odd-pricing effect from 2008 to 2018—in line with the increasing use of online platforms engendered by the growth of high-speed broadband internet (Figure 6). For a more direct test of whether screening by round-numbered lower bounds on real-estate platforms 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

[26]The same framework can explain Repetto and Solís's (2020) apparently contradictory results in the Swedish real estate market. They report odd pricing having a positive effect on sale price, with no adverse effect on selling time. Why might their results be different? 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, sorting houses from low to high price leaves odd-priced houses with a visibility advantage, resulting in a larger number of bidders showing up at those houses' auctions. In short, both in the U.S./Canada as well as in Sweden, screening by list price explains the number of bidders at odd- versus round-priced properties. The difference is that in the former, that screening takes place at the first stage, hurting odd-priced houses (because buyers use round-priced lower bounds), whereas in the latter that screening takes place in the second stage, which helps odd-priced houses.

Figure 6: Broadband Internet Penetration



The figure plots the share of U.S. adults reporting home broadband subscription from 2000 to 2024. Source: www.pewresearch.org/internet/fact-sheet/internet-broadband.

Alt Text. This plot shows the percentage of U.S. adults reporting home broadband use from 2000 to 2024. The horizontal axis indicates survey years, and the vertical axis shows percentages from 0% to 100%. Broadband internet penetration rises steadily over time, with growth slowing in more recent years, and levels stabilizing at around 80%.

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.[27] From these observations we record 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

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

pricing effect for round numbers that are not suggested at a MLS website.[28] 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 odd-priced houses among them:

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

Now we estimate the following regression:

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

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 14 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

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

Table 14: Odd pricing effect interactions with suggested round-priced bounds on realtor.com (U.S. data)

Dependent Variables:	(log) Transaction Price	Sales Ratio	Days on Market	Quick Sale	Probability of Sale
Model:	(1)	(2)	(3)	(4)	(5)
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

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.

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.

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 faced 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 in columns (1)-(2) of Table 15. All else equal, odd-priced properties 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 15: The effect of odd pricing on number of bidders and buyers' budgets (Toronto data)

	Bidders > 1 (1)	Bidders > 2 (2)	(log) Budget (3)
Odd price at $50K multiples	-0.1455	-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	✓	✓	✓

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.

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 15 shows that, all else equal, buyers of round-priced properties at $50K multiples indeed have a 17% higher initial budget than buyers of similar adjacently odd-priced properties.

6. 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 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 results is that it doesn't cost anything more to list a house at a round price rather 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%—without even taking into account the lower probability of selling as originally listed.

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 affordability concerns, the lower bound reflecting the buyer's reservation quality. Odd-priced houses run the risk of being screened out by the lower bound, thus attracting more competition, fewer buyers, and buyers whose willingness-to-pay is lower than those attracted to adjacently round-priced houses.

Our results thus 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 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.

Calder-Wang, Sophie and Gi Heung Kim, 2026, Algorithmic Pricing in Multifamily Rentals: Efciency Gains or Price Coordination?

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.

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.

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.

Weitzman, Martin L., 1979, Optimal search for the best alternative, *Econometrica* 47. ArticleType: research-article / Full publication date: May, 1979 / Copyright © 1979 The Econometric Society, 641–654.

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 list price of all homes sold by the agent prior to the current transaction. In equation (1) we include these linearly, along with a third-order polynomial in the number of houses sold by the agent in our data prior to the current transaction. There are 102,305 individual agents identified in our data when we include agent fixed effects.

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

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

B. Text Analysis of the Listing Descriptions

In the U.S. MLS data, we use the variable "public remarks" that provides a verbal description of each listing. From these descriptions, we construct several control variables for use in the regressions reported in Section 4.4: "high-end features," "urgency," "word controls," "materials controls," and "verifiable controls." See Table A.1. In addition, we develop an Unverifiable Index as a measure of advertising puffery, also used in Section 4.4, through the following steps:

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

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

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

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

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

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

1. **Remove stopwords:** Exclude common words such as "this," "has," "a," and "and," leaving: *"house," "walnut," "cupboards," "wrought," "beautiful," "kitchen," "spacious," "yard."*

2. **Filter using the Bing sentiment lexicon:** From the remaining words, retain only those that appear in the Bing lexicon, such as: *"wrought,","beautiful," "spacious."* Words like "walnut," "cupboards," "house," "kitchen," and "yard" are excluded because they are not part of the Bing lexicon.

3. **Manually remove words listed in Table A.1:** If words like "wrought" survive step two, they are manually removed if they are included in Table A.1, leaving: *"beautiful," "spacious."*

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

B.1. Assessing the face validity of the "unverifiable index"

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

Public remark ranked highest by the unverifiable quality index

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

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

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

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

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

Public remark ranked lowest by the unverifiable quality index

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

And the words after extraction:

> rough beautiful well great good

C. Empirical Analysis of the Toronto data

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

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	

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

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

	Mean	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

Table 4 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.

C.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.5 estimates separate odd-pricing effects for each \$100K threshold ($\{200K, 300K, \ldots, 1,000K\}$).

2. **Threshold Type Effects:** Table A.6 examines how the odd pricing effect varies by type of round-number threshold: \$100K versus \$50K versus \$10K multiples.

3. **Time Effects:** Table A.7 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.8 presents results for Toronto that mirror the Table 11 results for the US.

5. **\$1 bins:** Figure A.3 replicates Figure 4 by treating each list price as its own bin, partitioning prices within $[\tau - 15K, \tau + 15K]$ into \$1 intervals. In the Toronto data, the figure highlights prices ending in 8s with light blue markers, as these endings are considered auspicious among Chinese buyers—a significant sub-segment of the Greater Toronto Area (GTA) market. Interestingly, properties with these special endings exhibit worse sales outcomes compared to round-priced properties.

6. **Sensitivity analysis:** Table A.9 contains the sensitivity analysis for Toronto. Similar to the U.S. results, an omitted confounder would have to have twice the explanatory power on the outcome and treatment as all of our observed controls to overturn the result. Figure A.2 graphically presents the results.

Table A.5: Odd pricing effects by threshold (Toronto data)

	(log) Sale price (1)	Sales ratio (2)	Days on market (3)	Quick sale probability (4)
Odd price at $200K	-0.0329***	-0.0245***	-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	✓	✓	✓	✓

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.

Table A.6: Odd pricing effects by threshold type (Toronto data)

	(log) Sale price (1)	Sales ratio (2)	Days on market (3)	Quick sale probability (4)
Odd price at \$100K multiple	-0.0075***	-0.0066***	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	✓	✓	✓	✓

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.

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

	(log) Sale price (1)	Sales ratio (2)	Days on market (3)	Quick sale probability (4)
Odd price in 2007-2010	-0.0075**	-0.0084***	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	✓	✓	✓	✓

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.

Table A.8: Predicting the incidence of odd pricing (Toronto data)

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

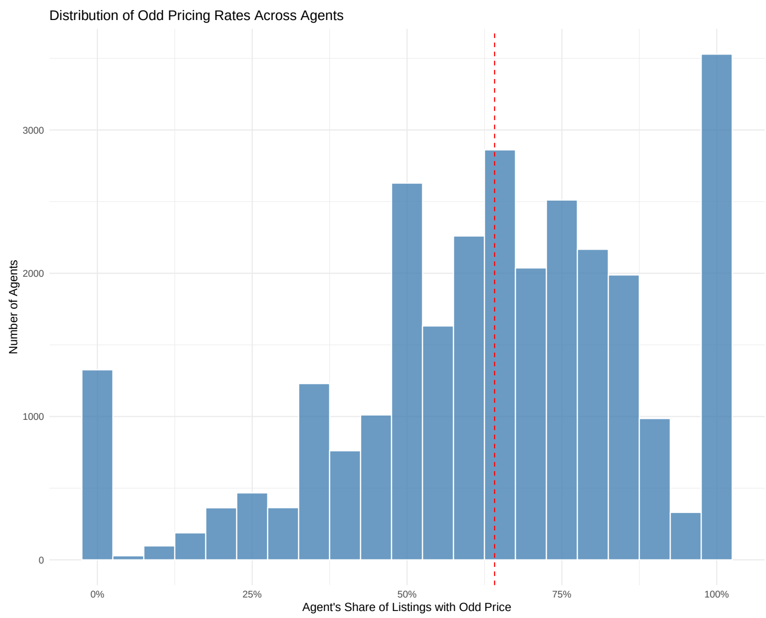
All columns report OLS regressions where the dependent variable is binary, taking the value 100 for an odd-priced house, 0 otherwise. Agent experience is scaled by 100 for presentation purposes. Sample consists of completed transactions only. Standard errors, in parentheses, are clustered at the agent 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.

Table A.9: Bounding the potential bias from confounders on the odd-pricing effect on sales ratio in Toronto

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

The top-line estimate of -0.0075 (0.0013) is the estimated odd pricing effect on sales ratio from column (4) of Table 6. |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 6: all controls, agent controls, and house characteristics.

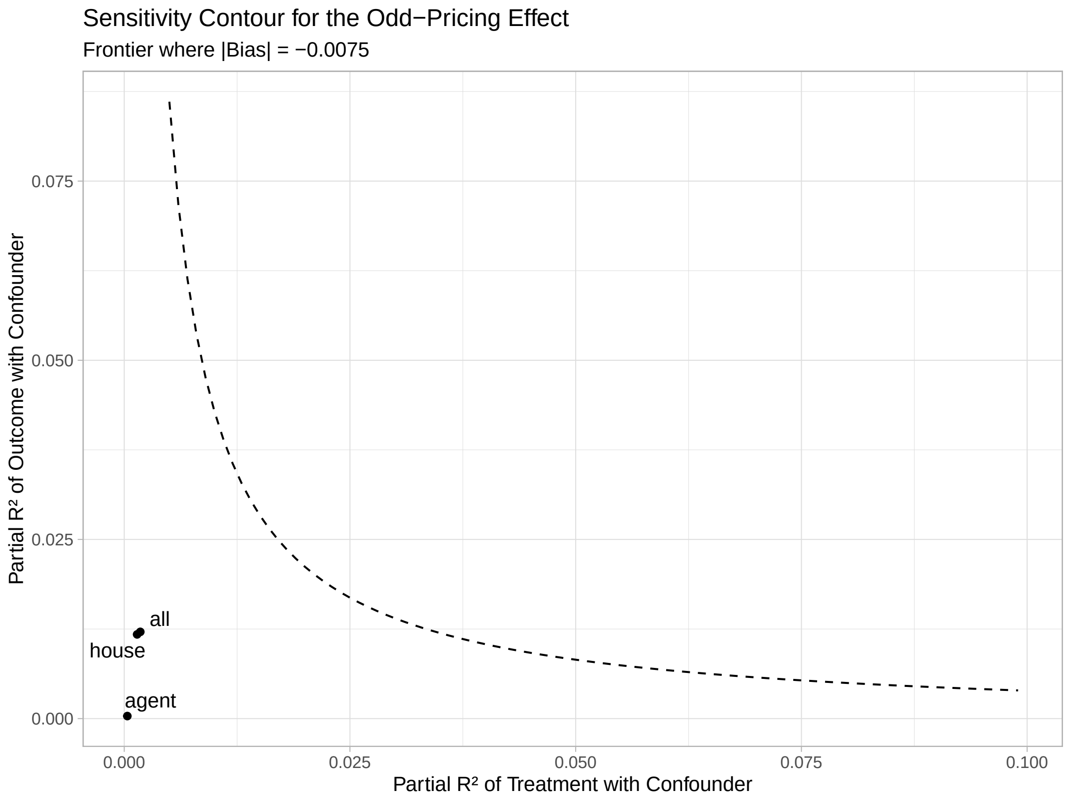
Figure A.1: Agent heterogeneity in use of odd pricing (Toronto Data)



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

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

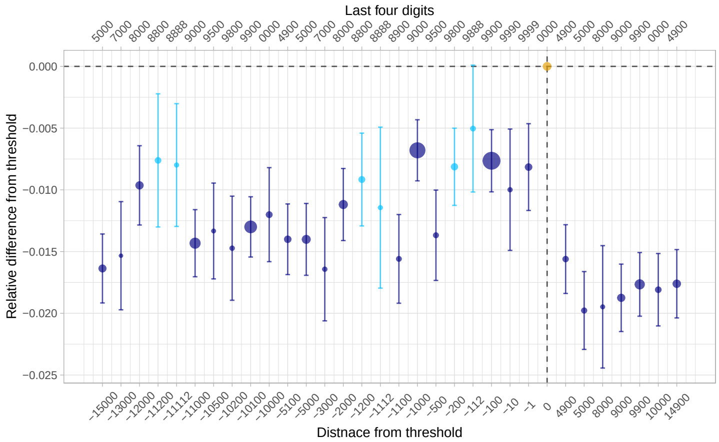
Figure A.2: Sensitivity Analysis of Omitted Variable Bias in the Estimated Odd-Pricing Effect on Sales Ratio in Toronto (based on Table A.9)



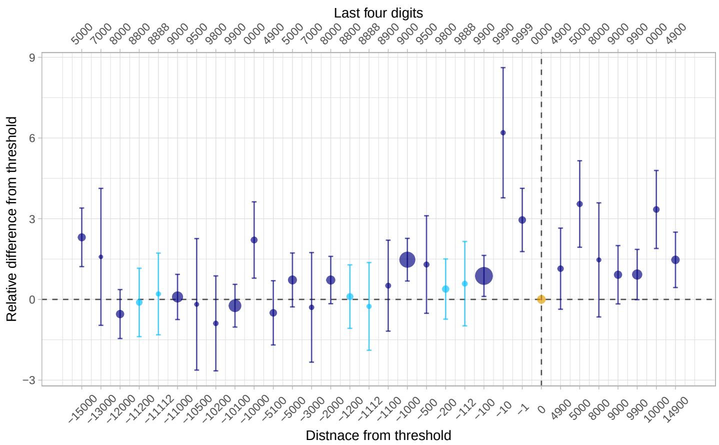
The horizontal axis shows the fraction of residual variation in the "treatment" explained by a potential unobserved confounder, while the vertical axis shows its influence on the outcome. The dashed contour represents the outer boundary of these confounder explanatory powers that would still preserve 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 6 do not approach this frontier.

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

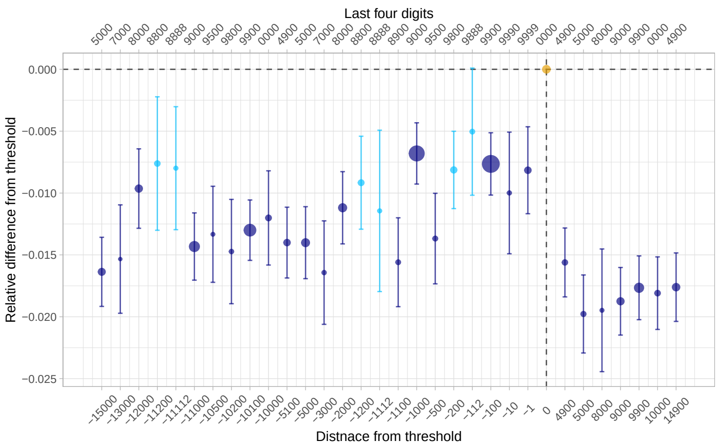
Figure A.3: Estimates of the odd-pricing effect in Toronto for $1 bins



(a) Sales ratio



(b) Days on market



(c) Quick sale probability

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

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