Breaking the Charm: How Odd Pricing Fails in Housing Markets*

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Abstract

We analyze home sales in Chicago, Minneapolis, San Diego, Seattle, and Toronto (2008–2018) and find that odd pricing backfires. Despite high stakes, many sellers list homes just below round numbers to exploit buyers' left-digit bias, but odd-priced homes sell for 0.7% less and stay on the market seven days longer than their round-priced counterparts. These effects persist across locations, price thresholds, cycles, and cannot be explained by omitted variable sorting. Rather than benefiting sellers, odd pricing reduces demand by limiting visibility in searches and attracting lower willingness-to-pay buyers. Instead of inattentive consumers, rational buyers counteract naive sellers' behavioral strategies.

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I. INTRODUCTION

Prices just below round numbers, such as \$0.99 or \$15.98, variously referred to as "odd prices," "just-below prices," and "charm prices," are a common occurrence in our everyday lives. They have been observed in many product categories: canned tuna and yogurt (Stiving and Winer 1997), women's clothing (Anderson and Simester 2003), toys (Gaur and Fisher 2005), "collectibles" (Backus et al. 2018), ride-sharing services (List et al. 2023), real estate (Allen and Dare 2004; Palmon et al. 2004; Pope et al. 2015; Repetto and Solís 2020). And in a variety of settings: brick-and-mortar stores (Stiving and Winer 1997; Gaur and Fisher 2005; Levy et al. 2020; Strulov-Shlain 2023), mail-order catalogs (Anderson and Simester 2003), online retailers (Hackl et al. 2014), negotiated prices (Allen and Dare 2004; Palmon et al. 2004; Pope et al. 2015), auctions (Repetto and Solís 2020).

Theories abound for why odd pricing is popular. Perhaps the foremost is "left-digit bias" on the part of buyers: consumers process price information from left to right, paying most attention to the leftmost digit and progressively less attention to succeeding digits (Levy et al. 2020; Strulov-Shlain 2023). The price appears smaller than it is, boosting demand. For example, Schindler and Wiman (1989) report that when consumers are asked to recall prices shown two days earlier (on products ranging in price from \$9.98 to \$570), "odd-ending prices are less likely than even-ending prices to be recalled accurately and that expressing a price as an odd-ending price increases the likelihood that it will be underestimated when it is recalled."[1] Strulov-Shlain (2023) estimates a structural model of demand on 3500 products sold in 25 U.S. grocery chains and shows that "consumers respond to a one-cent increase from a ninety-nine ending price as if it were more than a twenty-cent increase."

With a few exceptions,[2] the prevalence of odd pricing, and its effects, have been studied in relatively small-ticket product categories in posted-price settings, where the sellers are large commercial enterprises and the buyers are individuals.[3] When prices are small, left-digit bias on the part of buyers can be justified as boundedly-rational behavior (Basu 2006). And for sellers, even if only a small fraction of buyers exhibit left-digit bias, the resulting boost in demand is

[1] In a similar vein, Levy et al. (2020) find that "consumers have difficulty noticing higher prices if they are 9-ending, or noticing price-increases if the new prices are 9-ending because 9-endings are used as a signal for low prices."

[2] The exceptions are the real-estate studies cited above.

[3] For example, in Strulov-Shlain's (2023) study, the sellers were large U.S. grocery chains like Safeway and Wal-Mart, and the products in question were consumer packaged goods with an average posted price of \$4.27.

likely to far outweigh the margin hit, making odd pricing a dominant strategy.[4]

This paper examines a completely different scenario: real estate, specifically, residential real estate in North American markets, where a typical single-family home sells for several hundred thousand dollars. Sellers in these markets are usually households, not businesses; prices are negotiated off of a list price, not posted as take-it-or-leave-it offers; and, for both sellers and buyers, a house sale/purchase is probably the single most important financial transaction they will ever make. If buyer inattention or cognitive limitations are indeed driving left-digit bias, one shouldn't expect to see it here—people don't make snap judgments on buying houses, and offers to buy are formal, written documents, over which buyers presumably deliberate before signing off. Moreover, the seller is not looking to move large quantities of product; s/he has, typically, only a single house to sell. Under these circumstances, it would seem, odd pricing shouldn't have much purchase with consumers, and, realizing this, sellers shouldn't feel any particular attraction to it.

[FIGURE I HERE]

Our data, however, tell a different story. For example, consider the histograms of list and sale prices for the U.S. metros in our data set—Chicago, Minneapolis, San Diego, and Seattle—over the period 2008-2018 (Figure I). There are two interesting patterns here. First, the histogram of list prices shows that odd pricing is a popular pricing strategy: there is significant bunching just below round numbers relative to the adjacent round numbers, throughout the range of list prices—even at $1,000,000, the top of the price range. This is true for houses listed at multiples of $10,000 (such as $310,000), multiples of $50,000 (such as $350,000), as well as multiples of $100,000 (such as $300,000). Nor is this a peculiarity of the U.S. markets; our Toronto data show similar bunching.[5] Second, in contrast to list prices, sale prices show a relatively smooth distribution, as shown in the bottom panel of Figure I. (Again, our Toronto data show a similar pattern.) In other words, whatever is happening on the list price side is not getting transmitted to the sale price side. In particular, there is little evidence that buyers are snapping up odd-priced houses at list prices because of left-digit bias.

[4]The only caveat to this logic might be if the odd price does "first-order collateral damage." For example, if price signals quality and left-digit bias makes the biased price signal a lower quality, a seller may not want to adopt an odd price. However, for established products/brands, especially when the odd price is positioned as a "sale price" rather than as a regular price, this concern is likely to be minimal (Cubbin 1974; Stiving 2000; Anderson and Simester 2003).

[5]Several previous studies of real estate markets report similar patterns (Palmon et al. 2004; Pope et al. 2015; Repetto and Solís 2020). Thomas et al. (2010) is the only real-estate study to report bunching at round numbers, but their definition of round numbers is more expansive than most papers in the literature. For example, they consider $456,000 a round price.

What does odd-pricing accomplish for our sellers? We examine three outcome measures: sale price, sale price-to-list price ratio ("sales ratio"), and time to sell (proxied by days on the market and probability of selling within a week of listing). Presumably, sellers would like to sell faster, at higher prices. To make an apples-to-apples comparison, we compare properties listed at odd prices (such as $499,000) with properties listed at the adjacent round number ($500,000), while controlling for house, agent, and market characteristics—number of bedrooms/bathrooms, amenities (e.g., private driveway), location, agent experience and previous success, year of sale, etc.—and fixed effects for round number-year-county, postal code-year, and agent. In other words, we are comparing pairs of houses that look essentially the same in listing attributes, sold in the same year, in the same neighborhood, by the same agent, one of which is round-priced and the other correspondingly odd-priced—houses whose list prices differ by $1,000 at most. What we find is that properties listed at odd prices sell at a significant discount, and take longer to sell, than their round-priced counterparts. For example, in the U.S. metros, they sell at a 0.7% lower price and take 7 days longer to sell. These effects are seen across years, price thresholds, and cities. Strikingly, even houses listed $1 below a round price, sell at a significant price discount and take longer to sell.[6]

Why might odd-priced houses fare worse on the market than their round-numbered counterparts? One might speculate that this is because odd-priced houses differ meaningfully from their round-priced counterparts in ways that we haven't accounted for in our regressions. For example, it could be that odd-priced houses are worse in unobserved house quality[7] or involve sellers who are desperate to sell. Leveraging the unusually rich data at our disposal, we find no evidence that sorting along any of these dimensions could be driving our results. Indeed, applying the methods of Cinelli and Hazlett (2019) and Chernozhukov et al. (2023), our results indicate that an unobserved variable would need to have more than 1.5 times the explanatory power on both the outcome and the "treatment," as all observed controls combined, in order to overturn our findings.

We propose instead that odd pricing has a direct negative effect on demand. Houses priced this way are more likely to be excluded from prospective buyers' consideration sets. This is

[6]These results differ from Repetto and Solís's (2020) findings in the Swedish housing market, where properties are sold by (ascending-price) auction. There, odd-priced apartments sell at a higher price than their round-priced counterparts, with no difference in selling time. In Section V we discuss why the Swedish results might be different from North American results.

[7]Unobserved house quality pertains to house attributes that don't appear in our data but are seen by prospective buyers before they buy a house. These includes things like curb appeal, "charm," how "bright" the house is, the amount of traffic in the neighborhood, etc.

because potential buyers looking to buy a house can't possibly inspect every house on the market; they will need to do some screening to keep the cost of personal inspection manageable. Such screening is likely to involve upper *and* lower bounds on price,[8] the upper bound tied to the buyer's "budget"—the maximum price they can afford—and the lower bound dictated by "minimum acceptable quality" considerations: houses priced below that number deemed unworthy of further consideration (Gabor and Granger 1966). These upper and lower bounds are likely to be round numbers. Odd-priced houses thus run the risk of not making the cut on the lower bound, reducing potential demand. Furthermore, prospective buyers who do consider them, are likely to have a lower willingness to pay than those considering round-priced houses. Together, these two effects shift the demand curve down, with predictable consequences for sale prices and time to sell.

We test this explanation in several ways. First, using the Genesove and Han (2016) survey of home buyers in Toronto, whose purchases are also represented in our Toronto MLS data, we find that round-priced properties are 14.6% more likely to attract multiple bidders than observationally similar odd-priced houses; as well, buyers of those round-priced properties report having a higher initial budget than their odd-priced counterparts. Second, since online real-estate platforms such as realtor.com facilitate buyers screening by round-number price ranges, we expect the estimated odd-pricing effects to have strengthened over time, as high-speed broadband has penetrated more U.S. and Canadian homes.[9] Indeed, this is what we find. Finally, we investigate whether the *specific* lower bound values suggested on realtor.com websites—which varied across metro areas and over time—have an effect on estimated odd-pricing effects. Using data from a digital archive of the internet ("The Wayback Machine"), we find that odd-priced houses that are adjacent to a suggested round price sell at a one-third larger price discount, and take twice as long to sell, than odd-priced houses not adjacent to a suggested round price.

The remaining piece of the puzzle is why sellers use odd prices. Backus et al. (2018) have suggested that odd prices may serve as a "cheap-talk signal" to communicate something substantive about the seller, such as, that they are desperate to sell. However, for a cheap-talk signal to work with rational buyers, sellers must experience a trade-off sending the signal. In their own data on

[8]The MLS websites in most cities offer drop-down menus of suggested lower and upper price bounds; the defaults are "No min" and "No max," respectively. Taking the defaults simply returns a list of all houses available for sale. For example, on a recent search at the Chicago realtor.com website, we saw 10,825 homes listed at the default settings.

[9]According to the Pew Research Center, broadband internet penetration in the U.S. has increased from about 50% in 2008 to about 70% by 2018.

collectibles' sales at eBay, Backus et al. (2018) do observe a trade-off: products listed at odd prices fetch a higher price but take longer to sell than their round-priced counterparts. In our real estate data, however, we see no trade-offs: round-priced listings beat odd-priced listings on both sale price and time-to-sell.

In short, it is hard to rationalize sellers' motivations for listing at odd prices. On the other hand, "behavioral" reasons can be entertained. For instance, home sellers may have faith in the left-digit bias of home buyers, notwithstanding our 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—much less real estate.[10] It is quite possible that the ubiquity of odd prices in the places where they usually buy things—grocery stores, department stores, amazon.com—leads them to believe that these marketing strategies work universally.

Real-estate markets thus exhibit an interesting role reversal compared to consumer goods markets: whereas sellers in the latter behave rationally by exploiting buyers' behavioral biases, buyers in real estate markets behave rationally while negating the behavioral stratagems of sellers.

Our study contributes to multiple strands of literature. First, we provide evidence for the popularity of odd pricing in real estate markets that are several orders of magnitude pricier than the markets in which odd pricing is typically documented. Second, in contrast to much of the literature, which posits an increase in demand from odd pricing due to buyers' left-digit bias, we provide evidence for a decrease in demand from odd pricing due to prospective buyers being more likely to exclude such houses from their consideration sets. Third, we present evidence of sub-optimal behavior on the part of sellers: they embrace odd pricing over round pricing even though odd-priced houses sell for less, and take longer to sell, than comparable round-priced houses. Thus our study contributes to the growing body of literature documenting instances of seller irrationality and behavioral constraints, such as reference dependence (Andersen et al. 2022), loss aversion (Genesove and Mayer 2001), partial knowledge and optimization (Strulov-Shlain 2025), lagged seller response (Genesove and Han 2012).[11]

The rest of this paper is organized as follows. We describe our data in Section II. Section III

[10] Of course, they hire agents for this very reason. However, given the ubiquity of odd prices, it is unclear whether real estate agents know any better. After all, the present paper is the first to our knowledge to document the adverse effects of odd pricing in real estate.

[11] Other studies include using round numbers as anchors due to cognitive biases or coarse valuation grids in non-fungible-token (NFT) markets (Rosen and Spaenjers 2024).

documents the adverse effects of odd pricing on sales outcomes in the U.S. cities; similar results for Toronto appear in the Online Appendix. In Section IV we investigate and rule out the possibility of omitted variables accounting for our results. In Section V we provide evidence for how odd-priced houses face a lower demand curve because of (a) their greater likelihood of being screened out in the search process, and (b) attracting lower willingness-to-pay buyers. Section VI concludes the paper. All prices are in U.S. dollars unless indicated otherwise.

II. DATA

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

II.A. MLS Data from the United States

MLS transaction data for Chicago, Minneapolis, San Diego, and Seattle were obtained from CoreLogic, a company that specializes in U.S. residential real estate data. Our main analysis focuses on sales during 2008–2018, which comprises 1,716,370 transactions for single-family homes (99.40% of sample) and 10,245 transactions for duplexes (0.6%). From these we retain only transactions that: (a) are listed between \$124,999 and \$1,024,999 (1,524,672 observations or 88.83%), (b) are not real estate-owned (REO) sales or short sales (1,328,364 observations or 87.12% of (a)), (c) contain a non-missing listing price, sale price, days on the market, agent name (963,061 observations or 72.49% of (b)), and (d) contain non-missing geographic, housing attributes and lot-size information (944,759 observations or 98.10% of (c)). Our final U.S. MLS data set contains 944,759 transactions.

[TABLE I HERE]

Table I describes these data. Panel A summarizes transaction outcomes. As can be seen, the U.S. housing market improved from 2008 to 2018. Sales price of an average home rose from \$271,330 to \$339,130 (about 25%); sales ratio (sale price to listing price) rose from .97 to .99; days on the market fell from about 15 weeks to 8 weeks; and probability of a "quick sale"—selling within a week of listing—rose from .03 to .14.

Panel B shows list price characteristics in relation to $100K multiples. Of interest is what proportion of list prices are round (i.e., a $100K multiple), what proportion are just-below round, and what proportion are just-above round, where just-below and just-above are defined as list prices up to $1K away from round prices. Consistent with the histogram in Figure I, listing a home just below a $100K multiple is substantially more common than listing at a round number, ranging from 8.38% versus 1.27% in the 2008-2009 period to 7.79% versus 1.82% in the 2016-2018 period. On the other hand, listing just above a round number is relatively rare.

Finally, Panels C and D show substantially stable house and agent characteristics over our time period, with the sole exception of agent experience, which shows a decrease—the average agent selling 70 fewer homes in 2016–2018 than in 2006-2009—perhaps reflecting the arrival of new agents into the business.

II.B. MLS Data from Toronto

Besides U.S. MLS data, we also have MLS data from Canada covering transactions in the Greater Toronto Area (GTA) from January 1, 2000 to November 30, 2018. Years prior to 2007 do not contain information on housing characteristics, hence our main analysis focuses on the 2007–2018 period, comprising 1,197,837 observations. From these observations, we retain only transactions that: (a) are coded as housing type "semi detached" or "single family house" (733,318 observations), (b) are listed between $124,999 and $1,224,999 (677,777 observations), (c) contain non-missing list price, sale price, days on the market, and agent name (677,426 observations), and (d) contain non-missing "district" and lot-size information (643,343 observations). Our final Toronto MLS data set contains 643,343 transactions.

[TABLE II HERE]

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

and decreasing number of homes sold.

II.C. Survey of Buyers in Toronto

We supplement the Toronto MLS transaction data with data from a mail/phone survey of Toronto home buyers from 2006-2009, conducted by Genesove and Han (2016) (used also in Han and Strange (2016)). Among other things, the survey asked buyers to report—within a year of purchase—their initial budget and the number of other bidders on the property (if any). We will use this data to test whether round-priced houses attract more and/or higher-budget bidders than their odd-priced counterparts.

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 purchased the names of the buyers from the Toronto Land Registry Office. Of these, 1,816 addresses were deemed invalid for survey purposes because they pertained only to land transactions or to institutional buyers. With those deleted, 16,973 buyers were surveyed by mail and/or by telephone. Of the mail surveys, 351 were returned "household-moved" or "address unknown" by the Post Office. Ultimately, 3,193 surveys were completed, for an overall response rate of 19.2%. Table III compares the houses in the Toronto survey sample with the houses in the Toronto MLS sample (for the 2007–2009 period). Compared to the MLS sample, the survey sample shows slightly higher list and sales prices, and about a 10% lower days on the market. The distribution of house attributes in the two samples is remarkably similar.

[TABLE III HERE]

[TABLE IV HERE]

The Toronto survey of buyers provides unique information on the nature of the search and buying process for homes in a large North American city. Three particularly relevant questions are: "Were there other people actively bidding on the home when you submitted your first offer?"; "If yes, about how many other bidders were there?"; and "How much were you thinking about spending for the house?" As Table IV shows, just over two-thirds of buyers report only one bidder, while about one-sixth report two bidders, and slightly less than half as many report three bidders. Notably, more than three bidders are reported by about nine percent of buyers. The average budget is 412,302 Canadian dollars.

III. THE EFFECTS OF ODD PRICING ON SALES OUTCOMES

We start with a simple comparison of sales outcomes and property and agent characteristics between properties listed at odd prices and properties listed at the corresponding round prices. Odd prices are defined as list prices up to \$1K below a multiple of \$100K; round prices are defined as list prices that are multiples of \$100K and up to \$1K above.[12] The first four columns of Table V display the mean and standard deviation of these quantities by list-price type, and the last two columns present the difference between these means and the associated t-statistic.

[TABLE V HERE]

Panel A shows statistically significant differences in transaction outcomes, with odd-priced houses being associated with a lower sales ratio, more days on the market, and a lower probability of a quick sale than houses listed at the adjacent round number or just-above, previewing our regression results to follow. Since these homes are all priced within \$1,000 of the same \$100K multiple, we might expect them to be fairly similar in housing attributes, and Panel B bears this out—for the most part. On some house characteristics there are statistically significant differences; when there are such differences, it is notable that, in general, they favor odd-priced houses. For example, odd-priced houses have more bedrooms, more washrooms, and larger square footage. 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 average days on the market of properties sold before current listing.

The Toronto market shows strikingly similar comparisons; see Table A.III in the Online Appendix.

III.A. Empirical Analysis

Our objective is to measure the effect of listing a house at an odd price versus an adjacent round price on sales outcomes. To do so, we will estimate a local linear regression in a \$15K neighborhood of round listing prices, defined as multiples of \$100K between \$200K and \$1,000K.[13] Denote round prices by $\tau \in \mathcal{T} \coloneqq \{200K, \ldots, 1000K\}$ and the 15K neighborhood corresponding

[12] This is obviously a slight abuse of terminology since houses listed just-above \$100K multiples are not strictly speaking round-priced. However, as noted in Table I, there are hardly any houses listed just-above round numbers. So the differences we are reporting here are effectively the differences between odd-priced houses and round-priced houses. See footnote 14 for further discussion.

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

to a τ by $N_\tau \coloneqq [\tau - 15K, \tau + 15K)$. The collection of all such neighborhoods is $\mathcal{N} \coloneqq \bigcup_\tau N_\tau$. If P_i^L denotes the list price of property i, our universe of observations is $\mathcal{I} \coloneqq \{i : P_i^L \in \mathcal{N}\}$.

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

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

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

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

Note that for every observation, either $\texttt{Odd Price}_i$ is equal to 1, or (exactly) one of the $\texttt{Bin}_i^z$ is equal to one, or both $\texttt{Odd Price}_i$ and all $\texttt{Bin}_i^z$ are equal to zero, in which case the list price is a round price. In short, round prices serve as the reference category.

We specify the regression as follows:

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

where Y_i denotes an outcome of a sale: either sale price, $\texttt{P}_i^S$, sales ratio, $\texttt{P}_i^S/\texttt{P}_i^L$, days to sell, or whether the house sold within a week of listing. The coefficient of primary interest is β, showing the effect on outcomes of list prices in the odd-price bin $\mathcal{O}_{\tau_i}$ vis-a-vis houses in the round-price bin $\mathcal{R}_{\tau_i}$; the corresponding coefficients for list prices in the other neighboring bins

[14] We call $[\tau, \tau + 1K)$ a round-priced bin even though it may contain list prices just-above a round number. This is because we are trying to maintain a constant bin size throughout the \$15K neighborhoods while at the same time distinguishing between odd-priced and round-priced houses. As noted in Table I, there are very few houses priced just-above a round number; effectively, $[\tau, \tau + 1K)$ functions as the singleton set $\{\tau\}$. Later, in Section IV.A., we will examine \$1 bins; then the round-number bins will contain nothing but round numbers.

$\texttt{Bin}_i^z$ ($z \in \{-15K, \ldots, -2K, 1K, \ldots, 14K\}$) are collected in the 28×1 vector $\boldsymbol{\beta}_{\mathcal{B}}$.[15]

To account for the possibility that odd-priced houses differ systematically from round-priced houses in ways that affect sales outcomes, we control for a variety of covariates. These include $\mathbf{X}_i$, a vector of house characteristics (e.g., square footage, number of bedrooms, number of bathrooms, etc.), and $\mathbf{Z}_i$, a vector of agent characteristics that speak to agent experience (e.g., number of houses previously sold by the agent) and agent quality (e.g., previous average sales ratio and days on the market achieved by the agent); see Online Appendix A for the full list of house and agent characteristics. Finally, to control for other unobserved variables that might vary by house location, year of sale, agent, and listing threshold (e.g., a house priced around \$300K versus around \$400K), we include a variety of fixed effects: threshold-year-county fixed effects, denoted by $\boldsymbol{\gamma}_{\tau,y,c}$, postal code-year fixed effects, denoted by $G_{pc,y}$, and agent fixed effects, denoted by $\boldsymbol{A}$. Our most comprehensive specification, then, 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 sold by the same agent, while controlling for house and agent characteristics.[16]

[TABLE VI HERE]

Table VI presents the results of various regressions based on (1) for the U.S. cities in our database. Panels A–D in this table correspond to our four outcome measures: sale price, sales ratio, days on the market, and probability of a quick sale. Columns (1)–(5) represent specifications with progressively more controls.

In column (1) we have threshold-year-county fixed effects only. This specification simply compares average transaction outcomes for odd-priced houses versus round-priced houses within each threshold-year-county, and then averages those comparisons over all threshold-year-counties. Given our definition of odd price, the comparisons in question involve houses with list prices that differ at most by \$1,000. What column (1) is telling us is that houses listed at odd prices *underperform* relative to their round-priced counterparts on all four of our performance measures.

Of course, homes with very similar listing prices within a listing threshold-year-county may still differ in observable and/or unobservable ways that have a bearing on sales outcomes. To address the first of these 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

[15] In Section IV.A., we compare β and $\beta_{\mathcal{B}}$ to illustrate how the odd-priced bin differs from other neighboring bins.

[16] In Section III.B., we examine heterogeneity by round-price threshold (\$100K multiples), threshold type (\$100K versus \$50K versus \$10K multiples), year, and city.

characteristics, and finally, in column (5), agent fixed effects as well. Including these additional controls slightly attenuates $\hat{\beta}$, with the largest such reduction happening to days on the market with the addition of Zip Code-year fixed effects. However, even with these expanded sets of controls, the basic result from column (1) remains: odd-priced houses underperform relative to their round-numbered counterparts on both price and time to sell. Specifically, in our most comprehensive specification, odd-priced houses sell for a .65% discount relative to their round-priced counterparts and take about a week longer to sell.

III.B. Heterogeneity Analysis

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, a $50K multiple, or a $10K multiple, (iii) year of sale, and (iv) city of sale.

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

[TABLE VII HERE]

Threshold Type. Table VIII assesses whether the odd-pricing effect exists at round-number thresholds that are "less round" than $100K multiples. In particular, we expand our regression to allow for separate threshold effects at $50K and $10K multiples (that are not $100K multiples), in addition to the $100K multiples discussed above. Overall, there is a reduction in the magnitude of the odd-pricing effect, across all four response variables, as we go from $100K multiples to less-round pricing thresholds. Figure IIa presents a visualization of this effect for the sales ratio outcome variable, broken down by price level. The relative paucity of observations near $50K and $10K multiples makes those estimates relatively less precise.

[TABLE VIII HERE]

[FIGURE II HERE]

Years. Table IX examines the heterogeneity of the odd pricing effect across year-bands. On sale price, sales ratio and probability of a quick sale, odd pricing's performance worsens from 2008–2010 to 2011–2014, while for days on the market it improves; from 2011–2014 to 2015–2018, odd pricing's performance doesn't change much. except in probability of a quick sale, where it worsens. Overall, these results suggest a heightening of the odd-pricing effect in more recent times. Figure IIb illustrates the sales ratio effect by year.

[TABLE IX HERE]

Cities. In Table X, we report odd pricing effects by U.S. city. While there is some heterogeneity in the effect size, in each city odd-priced houses underperform their round-priced counterparts on each of our four performance measures. Table A.IV in Appendix D.1 shows that we see similar results in Toronto.

[TABLE X HERE]

IV. EXPLAINING THE UNDERPERFORMANCE OF ODD-PRICED HOUSES: CAN OMITTED VARIABLES DO IT?

The regressions above show that odd-priced houses underperform relative to their round-priced counterparts, on both sale price and time to sell, and this result persists over time, cities, listing threshold, and threshold type, even after controlling for house and agent characteristics, and fixed effects for threshold-year-county, postal code-year, and agent. Since a list price doesn't commit the seller to sell at that price (Han and Strange 2016), nor obliges the buyer to buy at that price (Pope et al. 2015), it is puzzling that such a small difference in list prices—as small as $1,000 on houses selling for an average price of $300,000—makes a noticeable difference in market outcomes.

There are two possible routes toward an explanation, direct and indirect, the direct posing the bigger challenge. The direct route would argue that odd pricing itself has an adverse causal effect on demand or supply conditions which manifests in the observed adverse outcomes. Left-digit bias on the part of buyers would be such an explanation, except it goes in the opposite direction: it predicts a boost in demand from odd pricing, while what we seem to be observing is a dimunition in demand. Another direct explanation, but this one focusing on the supply side, would be

Backus et al.'s (2018) cheap-talk signaling story. They argue that odd pricing signals a seller's willingness to trade time on the market for a good price. This, too, doesn't fit our data: round pricing beats odd pricing on both time on the market and sale price. In the next section we propose a direct demand-based explanation that actually explains our data.

Meanwhile, in this section, we rule out indirect explanations based on omitted variables possibly correlated with odd pricing. First we will examine three supply-side omitted variables—unobserved quality, advertising strategy, and seller desperation/urgency to sell—and argue either that they are not correlated with odd pricing or that they can't possibly be driving the observed odd-pricing effect. Second, to account for omitted-variable bias from confounders that we don't have any data on, we will bound the potential magnitude of such bias by performing a sensitivity analysis of the kind suggested by Cinelli and Hazlett (2019) and Chernozhukov et al. (2023). This analysis suggests that the potential magnitude of omitted-variable bias would be too small to overturn our results.

IV.A. Unobserved Quality

Is odd pricing picking out houses with lower unobserved quality? Unobserved quality is things that a buyer sees (and values) but which we analysts don't, e.g., curb appeal, ambiance, how "bright" the house is, amount of traffic in the neighborhood, etc. Could it be that odd-priced houses are systematically worse than round-priced houses on these attributes, and that is what is driving their relative underperformance? Right off the bat, however, this doesn't sound very plausible: why would houses that are different enough in unobserved quality to make a meaningful difference to sale price be listed so close in price? Nevertheless, we perform a series of analyses to rule out unobserved quality as a possible driver of our results.

Narrowing the Width of the List-Price Bins Doesn't Seem to Matter. The first indication that the sub-optimal performance of odd-priced houses is not being driven by unobserved quality, is that narrowing the bandwidth of the list-price bins doesn't seem to matter. To establish this, we re-estimate (1), but instead of placing list prices into \$1K bins, we treat each list price as its own bin. That is, we partition list prices in $[\tau - 15K, \tau + 15K]$ into \$1 bins. Now, with round price as the baseline, the β coefficients show how selling outcomes vary with list price in a \$15K neighborhood of a round price, while controlling for observables.

[FIGURE III HERE]

Figure III shows the results for sales ratio, days on the market, and probability of quick sale in the U.S. data. (Similar plots for the Toronto data are in the Online Appendix.) 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 corresponds to the number of transactions at each list price. Vertical bars show the 95% confidence intervals for each β coefficient. To avoid clutter, we only show estimates for the most popular list prices—list prices with at least 2,500 houses.

Note first that the yellow dot sits apart from all other points, consistently across the three 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, even though these houses are listed 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). Third, the β estimates to the right of the yellow dot are more or less similar to the β estimates to the left. Finally, further analysis (not reported here) shows that the $1 odd-pricing effects observed here aren't observed for less salient round numbers, such as $10K multiples.

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 $1 apart be the same as houses $1,000-$5,000 apart? And why does this relationship between list price and unobserved quality change discontinuously when crossing a round number? Finally, based on the last observation in the preceding paragraph, why would a house priced at, say, $479,999 have the same unobserved quality as a house priced at $480,000, but a house priced at $499,999 have lower unobserved quality than a house priced at $500,000?

In short, odd-priced houses seem to perform significantly worse than adjacent round-numbered houses beyond what we should expect based on an underlying unobserved quality-list price correlation.

Controlling for Proxies for Unobserved Quality in the Verbal Descriptions Doesn't Seem to Matter. In the U.S. MLS database (but not in the Toronto MLS database) we have a variable called "public remarks" which records the verbal descriptions of the listed properties. Section B.1 in the Online Appendix provides two examples of such descriptions. As these examples suggest, a verbal description is typically a combination of puffery—subjective claims such as "gorgeous" and "rare beauty"—and verifiable claims such as "Thermador magnetic induction cooktop" and

"Hunter Douglas shades." The latter are potentially indicative of unobserved quality. We want to see whether extracting this information and using it as additional observables in the regressions changes the odd-pricing effect.

To do this, we parse the text of the verbal property descriptions to extract several measures that reflect aspects of the property, which can be broadly categorized as "unobserved house quality," "advertising puffery," and "seller urgency or desperation to sell."

For unobserved house quality, we construct several indicators. First, we create indicator variables for verifiable features that can be confirmed upon inspection, such as "hardwood floors," "crown molding," "vaulted ceilings," and "floor-to-ceiling windows," which we refer to as "verifiable controls." Additionally, we include a variable that counts mentions of high-end kitchen elements, such as "Wolf appliances," "induction cooktop," "wine fridge," and "walk-in pantry," which we label as "high-end kitchen features." We also include indicators for premium building materials like "granite," "Calacatta marble," and "mahogany." Furthermore, we account for phrases suggesting the property's condition or potential, such as "as is," "potential," and "fixer," which we collectively refer to as "quality signals." Table A.I lists all the high-end features and quality signals.

[TABLE XI HERE]

As can be seen from Table XI, including these indices as additional controls in the regressions does not eliminate the odd-pricing effect. In fact, the odd-pricing coefficients in Table XI are substantially the same as in Table VI. This indicates that unobserved house quality, as reflected in the verbal descriptions, does not account for the observed odd-pricing effects.

IV.B. Advertising Strategy

Advertising strategy is a mix of lengthy verbal descriptions (large numbers of words), use of all-caps words and exclamation points, and subjective in-the-eye-of-the-beholder descriptors like "charming," "fabulous," and "perfection" (puffery).

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 words that do not contain sentiment. We then take the most frequently-used words from among those that remain after these filters and manually remove words that convey verifiable quality, such as the high-end features in Table A.I. The 200 words that survive are shown in Table A.II of the Online 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 word dummies form the basis for our "index of unverifiable quality."

Table XI shows that this index is positively associated with sales outcomes even in our main sample. However, crucially, it doesn't move the odd-pricing coefficient substantially—those coefficients remain more or less the same as in Table VI. In short, controlling for advertising strategy doesn't eliminate the odd-pricing effect.

IV.C. Seller Desperation and Urgency to Sell

Of course, we can't observe seller desperation or urgency to sell directly, but again, we can look for clues in the verbal descriptions. From those descriptions we extract a count of words that might indicate desperation on the part of the seller or seller urgency—words such as "motivated seller," "reduced," "asap," "seller relocating," etc. This index of seller desperation/urgency has a significant effect only on the time-to-sell outcome measures (Table XI, columns 4 and 6), but it doesn't change the odd-pricing effect for any of the four outcome measures.

IV.D. Bounding the Potential Bias from Confounders

While we believe that the above analyses support the assumption that the incidence of odd pricing versus round pricing can be taken as random conditional on our controls, in this subsection, we examine the sensitivity of our estimates to potential confounding. We utilize the methods of Cinelli and Hazlett (2019) and Chernozhukov et al. (2023) to set bounds on the potential bias from omitted variables, employing Cinelli and Hazlett (2019)'s characterization of the size of squared omitted variables bias as a function of partial-R^2s. This allows us to compare the potential magnitude of bias from unobserved confounders vis-à-vis the observed strength of association of observed covariates.

We begin by partialling out the threshold-year-county and Zip Code-year fixed effects, from the dependent variable (sales ratio) and the regressors used in our full specification, namely column (6) in Table XI (without the agent fixed effects). Working with these adjusted variables, all of our control variables account for about six percent of the variation in the sales ratio (net of the fixed effects) beyond what is explained by the "treatment," namely odd pricing versus round

pricing. Additionally, the controls explain less than one percent of the variation in the treatment. This analysis allows us to gauge the potential bias of a latent confounder whose associations with the dependent variable and treatment are as strong as *all* of our observed controls.

[TABLE XII HERE]

[FIGURE IV HERE]

As Table XII shows, the maximal absolute bias of such an omitted variable is 0.0031. In other words, for an omitted variable to overturn our results, this variable would have to have more than 1.5 times the explanatory power on the outcome and treatment as *all* of our observed controls put together. The other rows of the table show a similar analysis for subsets of controls related to the agent, housing characteristics, and public remarks. Finally, Figure IV shows the theoretical combination of partial R^2s of a latent confounder that would generate a magnitude of absolute bias that would drive our odd-pricing effect to zero (the dashed line). This analysis demonstrates the robustness of our estimates to confounders with explanatory power, either with the outcome or with the treatment, that is as strong as our extensive set of observed controls.

V. HOW ODD PRICING CAN REDUCE DEMAND FOR A HOUSE

Search is costly, especially for real estate. There are hundreds, if not thousands, of houses available for sale at any given moment in a decent-sized city, and houses are highly differentiated products. They differ in "search" attributes—price, location, number of bedrooms and bathrooms, etc.—and "experience" attributes: what the buyer sees (only) upon visiting the house—things like curb-appeal, layout, state of repair, view, etc.[17] Both screening for search attributes and inspection for experience attributes are costly, but the latter is costlier: while the former can be done at scale, the latter cannot be. For example, at most MLS websites, a buyer can simply enter parameters for price, neighborhood, number of bedrooms, number of bathrooms, etc., and filter listings by those criteria. However, personal visits will still be required to figure out which

[17]These definitions differ from the traditional definitions of these terms, due to Nelson (1970). He defines search attributes as things that can be seen before purchase and experience attributes as things that can be seen only after purchase. Instead, we are distinguishing between objective attributes that can be seen, and believed in, from a listing, and subjective attributes that will require a personal inspection to ascertain (these are usually the subject of puffery in listings and ads). There are, of course, in addition, "credence" attributes—things that an ordinary buyer will not be able to verify even on a home visit, for example, the condition of the roof or of the plumbing—and that is why professional house inspectors exist (Darby and Karni 1973).

properties meet the buyer's expectations on experience attributes. It is clear that a buyer will need to screen effectively in order to reduce the inspection burden.

To do so, prospective buyers (and/or their agents) are likely to use upper and lower bounds on price (among other things). This is because (a) buyers already has an upper bound on price in the form of a budget, and (b) price is a summary indicator of "quality" (Scitovszky 1944; Leavitt 1954; Gabor and Granger 1966; McConnell 1968).[18] By setting an upper bound on price, buyers can screen efficiently for houses that they can afford; by setting a lower bound on price, they can screen efficiently for houses that are likely to meet their "quality" expectations. The latter screen requires, of course, knowledge of the price-quality correlation, which, presumably, a buyer's agent provides. Perhaps realizing the critical role of lower and upper price bounds, all major MLS websites in the U.S. and Canada make it possible to screen easily by price, by making available separate drop-down menus for lower and upper price bounds.[19] For example, on arriving at the Chicago realtor.com website recently, one of the authors saw the default listing of all houses available for sale in Chicago—a total of 9,418 homes—corresponding to a lower bound of "No min" and an upper bound of "No max." However, by selecting a lower bound of $600,000 and an upper bound of $800,000 from the drop-down menus—with no other screens—he was able to reduce the number of listings by 92%.

When screening houses by upper and lower price bounds, buyers are likely to use round numbers. This is because: (a) people naturally think in terms of round numbers, and (b) the MLS websites' suggested lower and upper bounds feature round prices. With respect to the former, there is a large literature documenting the human tendency to use round numbers in a variety of contexts:

- Visual estimation of number of dots on a screen (Kaufman et al. 1949)
- Reporting age to the U.S. Census Survey (Turner 1958)
- Self-reported income (Zinn and Würbach 2016)

[18] As Gabor and Granger (1966) note, upper and lower bounds on price can arise simply from a perceived price-quality correlation (even without a budget constraint): "A consumer intent on a purchase has two price limits in mind: an upper limit above which the article would be judged too expensive, and a lower limit below which the quality of the item would be suspect." Their survey of housewives purchasing household goods finds support for both lower and upper price bounds and concave demand functions that are initially upward-sloping. In the real estate context, with time-to-sale as a measure of demand, Cubbin (1974) and Guren (2018) also find evidence for a concave demand function—in the San Francisco Bay Area and Coventry (United Kingdom) markets, respectively—with the former reporting an upward-sloping part at lower price levels. See also Andersen et al. (2022).

[19] In the early days of the internet, these websites featured "price sliders" instead of drop-down menus.

– Setting achievement goals (Pope and Simonsohn 2011)

– Willingness to pay for a computer game offered on a pay-what-you-want basis (Lynn et al. 2013)

– Tipping behavior in a restaurant (Lynn et al. 2013)

– Pumping gasoline at a self-service pump (Lynn et al. 2013)

– Budgeting for a car loan (Argyle et al. 2020)

In addition, as Figure A.I in the Online Appendix shows, buyers of homes in our Toronto survey also report budgets that are overwhelmingly round numbers: over 70% are $50K multiples.

As far as the MLS websites are concerned, all of them use round numbers in their suggested lower and upper price bounds. For example, the Chicago and Minneapolis realtor.com websites currently offer $90K, $180K, $250K, $350K, $450K, $500K, and $600K as possible lower bounds and $150K, $300K, $450K, $600K, $800K, $900K, and $1M as possible upper bounds.

What happens to odd-priced houses vis-à-vis their round-priced counterparts when prospective buyers screen using round-number lower and upper price bounds? Nothing, if neither bound is binding, nor if only the upper bound is binding.[20] For example, compare two houses, one listed at $299,900 and the other listed at $300,000, with respect to a prospective buyer with a lower bound below $300,000 and an upper bound of $300,000. Both properties will be in this buyer's consideration set. Now compare the same two properties with respect to a prospective buyer whose lower bound is $300,000. This buyer will *not* consider the house listed at $299,900, but will consider the house listed at $300,000. In other words, whenever an odd-priced house is considered, so will its round-numbered counterpart, but the reverse is not true: when a lower-bound is binding, the odd-priced house will not be considered, but its round-numbered counterpart will be. Thus, a round-priced house will attract a larger pool of prospective buyers than an adjacent odd-priced house. Furthermore, the additional buyers it attracts are likely to have a larger budget, and thus be willing to pay more, than the buyers considering the odd-priced house. Together, these two effects will raise the demand curve for round-priced houses over their odd-priced counterparts, explaining the latter's underperformance.[21]

[20] A round-priced bound is binding with respect to a property if the property's rounded-up list price matches the bound.

[21] We noted earlier (footnote 6) that Repetto and Solís (2020) report a positive effect of odd pricing on sales price in the Swedish real estate market. Why might their results be different from ours? There are several institutional differences between Swedish and North American real estate markets, including the one that Repetto and Solís

The results in Table IX and Figure IIb are already consistent with this story. Both show a strengthening of the odd-pricing effect from 2008 to 2018. Perhaps it is not a coincidence that broadband internet penetration in the U.S. was also increasing during this time. As Figure V shows, 50% of U.S. households had broadband access in 2008, while 70% had broadband access in 2018.

[FIGURE V HERE]

To provide a more direct test of whether screening by round-numbered lower bounds on MLS websites is leading to the underperformance of odd-priced properties, we take advantage of the fact that these websites suggest *specific* round-numbered lower bounds. Those specific numbers vary across metros and over time. For example, the suggested lower and upper price bounds at realtor.com San Diego differ from the ones at realtor.com Chicago and Minneapolis (shown above). To capture the time variation, we use The Wayback Machine to examine our U.S. metro MLS websites as they looked at various past dates.[22] From these visits 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 versus round numbers that are not suggested at a MLS website.[23] 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:

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

(2020) emphasize, namely the use of ascending-price auctions in the former iinstead of private negotiations. 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 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 this point, odd-priced houses have an advantage, either due to left-digit bias or simply because their price is lower—resulting in a larger number of bidders showing up at odd-priced auctions. In short, both in North American markets as well as in Sweden, screening by list price explains the number of bidders on a property. The only difference is that in North American markets, odd-priced houses are hurt in the screening process (because buyers use round-numbered price lower-bounds), whereas in Sweden they are not.

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

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

Now we estimate the following regression:

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

The regression includes the same set of fixed effects as (1). Note that by including fixed effects for each combination of round price, year, and county, and for each combination of postal code and year, we are effectively controlling for time- and location-specific variations in price salience. 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. Our interest is in β_2.

[TABLE XIII HERE]

Table XIII contains the result of estimating (2) for each of our key transaction outcomes. All estimates include our complete set of controls. Consistent with our previous findings, the β_1 estimate shows odd-priced houses underperforming their round-priced counterparts on all of our outcome measures. The new finding is the estimate of β_2. It is negative and statistically significant: odd-priced houses whose list prices are adjacent to round prices that appear on MLS websites' menus seem to *suffer even more* than other odd-priced houses. This is further evidence for our story that odd-priced houses have a higher probability of being excluded from prospective buyers' consideration sets and attract 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 to test directly whether buyers of odd-priced properties report fewer "bidders" than buyers of adjacent round-priced properties. Two questions from the survey are relevant to this inquiry: "Were there other people actively bidding on the home when you submitted your first offer?" and "If yes, about how many other bidders were there?" Using the answers to these questions, we repeat the same empirical design as the main analysis, but now with the goal of trying to predict the probability of multiple bidders. The results are shown in columns (1)-(2) of Table XIV. All else equal, properties that are odd-priced at \$50K multiples are 14% less likely to attract more than one bidder and 31% less likely to attract more than two bidders than their round-priced counterparts.

[TABLE XIV HERE]

Buyers of Odd-Priced Listings Have Lower Budgets. If buyers indeed use the round-numbered lower 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 XIV shows that, all else equal, buyers of round-priced properties around \$50K multiples have a 17% higher initial budget than their odd-priced counterparts.

Together, these results suggest that odd-priced houses face a lower demand curve than adjacent round-priced houses.

VI. CONCLUSION

Using housing transactions data from Chicago, Minneapolis, San Diego, Seattle, and Toronto, we document a pervasive trend of listing houses at odd prices—prices "just below" round numbers. However, this popular pricing strategy is counter-productive: On average, properties listed at odd prices sell at a nearly 0.7 per cent discount and stay on the market seven days longer than their round-priced counterparts. These effects are seen across years, geographies, and price thresholds, and they are robust to a rich set of controls: house attributes, agent characteristics, advertising verbiage (including indicators of unobserved quality and seller urgency to sell), as well as a variety of fixed effects: threshold-year-county, postal code-year, and agent.

We explore two leading explanations for why odd pricing may underperform round pricing: (i) lower unobserved quality, and (ii) fewer, and lower willingness-to-pay, buyers. We reject the first hypothesis and find support for the second. In the process, we uncover a fundamental weakness of odd pricing. Prospective buyers searching for homes are likely to screen them using round-numbered upper *and* lower price bounds: the upper bound reflecting the buyer's budget, the lower bound reflecting the "lowest acceptable quality" of house. Odd-priced houses run the risk of not making the cut on the lower bound, and attracting lower willingness-to-pay buyers.

Traditionally, the odd pricing literature has attributed the popularity of odd pricing to its success in exploiting the left-digit bias of buyers. While that may well be true for low-ticket consumer goods in posted-price settings such as a grocery store, in the high-stakes markets for real estate, where a typical home sells for several hundreds of thousands of dollars, and where the

purchase process involves formal written negotiations, it is hard to imagine buyers succumbing to left-digit bias. Indeed, the underperformance of odd-priced houses shows that they don't. It suggests, instead, the opposite: rational buyers negating the behavioral strategems of naive sellers.

ONLINE APPENDIX

A. HOUSE AND AGENT CONTROLS

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

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

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

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

B. TEXT ANALYSIS OF THE LISTING DESCRIPTIONS

In the U.S. MLS data, we use the variable "public remarks" that provides a verbal description of each listing. From these descriptions, we construct several control variables for use in the

regressions reported in Table XI: "high-end features," "urgency," "word controls," "materials controls," and "verifiable controls." See Table A.I.

[TABLE A.I HERE]

In addition, we develop the Unverifiable Index as a measure of advertising puffery, also used in Table XI, through the following steps:

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

[TABLE A.II HERE]

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

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

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

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

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

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

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

Public remark ranked highest by the unverifiable quality index

> Views! Views!! Views!!! Welcome to this gorgeous 4 bedroom, 3 bathroom property located in the highly sought-after community of Bonita Ridge Estates. With panoramic city, mountain, and valley views throughout, this rare beauty offers complete privacy. With warm - yet refined - elegance, this incredible home has been upgraded to perfection. Spanning roughly 2600 sqft of comfortable living space, its single-story (top floor) layout boasts luxurious upgrades at every turn. Interior features include Brazilian cherry wood flooring, high living room ceiling with new drywall, custom recessed lighting, new AC/Furnace and ducting, new toilets, vinyl wood-like flooring in bedrooms, new light fixtures and ceiling fans, gorgeous fire place, new paint throughout, huge updated kitchen with quartz countertops, custom cabinets, Thermador magnetic induction cooktop, custom storage areas, new windows, new blinds/window treatments, upgraded guest bathroom, 3-car attached garage, outdoor balcony with automatic awning, modern cable railing, and breathtaking views from every angle. Its beautiful master bedroom offers two spacious closets with

> custom organizers, sliding glass door to balcony with views, and automatic Hunter Douglas shades. The private master bath offers a rustic barn door, upgraded vanity with his and hers sinks, and a remodeled walk-in shower. Make your way downstairs to discover an entirely new living space with incredible possibilities. This area features a huge bonus room/living room/gym area, wet bar, fireplace, laundry room, and one spacious guest bedroom and bathroom. Step outside into a resort-like backyard on a spacious 12,197 sqft lot. Low-maintenance pebble paving, sparkling pool and spa, multiple lounge areas, fruit trees, beautiful landscaping, views throughout, and complete privacy make this dazzling outdoor space a true entertainer s delight. With both home solar and thermal pool solar, this completely move-in ready home is simply a masterpiece. Absolutely a must-see!!!

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

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

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

Public remark ranked lowest by the unverifiable quality index

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

And the words after extraction:

> rough beautiful well great good

C. HISTOGRAM OF BUYERS' REPORTED BUDGETS IN THE TORONTO SURVEY

[FIGURE A.I HERE]

D. TORONTO EMPIRICAL ANALYSIS

Table A.III compares key transaction outcomes and property/agent characteristics for homes listed just above and just below $100K 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.

[TABLE A.III HERE]

The results indicate that homes listed just above thresholds have higher sales ratios, shorter days on market, and higher probabilities of a quick sale (sold within one week). These differences preview our empirical findings. Despite being similarly priced, house characteristics do show small, statistically significant differences between groups.

D.1 Empirical Results

In this section, we estimate equation (1) and several extensions using the Toronto data, replicating our analysis of U.S. data presented in the main text. The results are remarkably consistent across all dimensions we study. Specifically:

1. **Baseline Regression Results:** Table A.IV presents estimates of equation (1), structured similarly to Table VI in the main text. The table includes four panels, each corresponding to one of our outcome measures:

    - Panel A: Sale price
    - Panel B: Sales ratio
    - Panel C: Days on the market
    - Panel D: Probability of a quick sale

[TABLE A.IV HERE]

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

2. **Threshold-Specific Effects:** Table A.V estimates separate effects for each $100K threshold ($\{200K, 300K, \ldots, 1,000K\}$). The table reports the coefficient for Odd Pricing relative to Round Pricing at each threshold.

[TABLE A.V HERE]

3. **Other Threshold Types:** Table A.VI examines whether the above-threshold pricing effect extends to other thresholds. Specifically, we expand the regression model to include effects at $50K and $10K intervals, in addition to the primary $100K thresholds. Each column of Table A.VI corresponds to a different transaction outcome, and all specifications control for house and agent characteristics, including agent fixed effects.

[TABLE A.VI HERE]

4. **Yearly Variation:** Table A.VII investigates how the above-threshold pricing effect varies across years, providing little evidence of temporal heterogeneity in the Toronto data.

[TABLE A.VII HERE]

5. **Narrowing the bin widths:** Figure A.II replicates Figure III by treating each individual 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.

[FIGURE A.II HERE]

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

[TABLE A.VIII HERE]

[FIGURE A.III HERE]

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TABLE I

SUMMARY STATISTICS, U.S. MLS DATA

Transaction year:	2008-2009 (N=94429)		2010-2012 (N=217032)		2013-2015 (N=348383)		2016-2018 (N=421494)	
Characteristic	Mean	SD	Mean	SD	Mean	SD	Mean	SD
A: Transaction outcomes								
Sales price/1000	271.33	0.469	297.13	0.353	319.18	0.297	339.13	0.27
Sales ratio	0.97	0.000	0.97	0.000	0.98	0.000	0.99	0.00
Days on market	102.52	0.306	107.63	0.208	79.31	0.121	59.31	0.11
Quick sale probability	0.03	0.001	0.03	0.000	0.05	0.000	0.14	0.00
B: Listing characteristics								
List price/1000	281.62	0.496	307.54	0.368	326.70	0.304	344.82	0.28
Just-above (%)	0.03	0.005	0.04	0.004	0.03	0.003	0.03	0.00
Exactly round (%)	1.27	0.036	1.40	0.025	1.33	0.019	1.82	0.02
Just-below (%)	8.38	0.090	8.20	0.059	7.79	0.045	7.77	0.04
C: House characteristics								
Number of bedrooms	3.29	0.003	3.37	0.002	3.31	0.002	3.28	0.00
Number of washrooms	2.48	0.003	2.59	0.002	2.56	0.002	2.53	0.00
Living area square footage	2043.82	2.692	2075.63	1.836	2020.46	1.388	1981.97	1.27
Lotsize	31219.40	2069.776	38638.14	1736.975	34995.86	500.711	30834.82	312.09
Number of fireplaces	0.71	0.003	0.73	0.002	0.68	0.001	0.64	0.00
Number of parking space	0.15	0.002	0.50	0.003	0.59	0.002	0.66	0.00
Gas heat source	0.90	0.001	0.85	0.001	0.87	0.001	0.88	0.00
Forced air	0.05	0.001	0.12	0.001	0.06	0.000	0.07	0.00
D: Agent characteristics								
Average sales ratio	0.98	0.000	0.98	0.000	0.98	0.000	0.98	0.00
Average days on market	80.83	0.145	86.49	0.094	79.43	0.066	73.64	0.06
Number of homes sold	199.45	1.117	158.72	0.597	147.70	0.462	129.54	0.41

Round prices are defined as \$100K multiples, and "just-below"/"just-above" as prices in \$1K intervals, below/above adjacent round prices. Some extreme values of sales ratio, days on the market, and lotsize have been Winsorized at the 1 and 99 percentiles. None of our analyses is sensitive to this adjustment.

TABLE II

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 price/1000	418.18	0.429	488.77	0.481	576.73	0.528	726.71	0.62
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 probability	0.18	0.001	0.25	0.001	0.29	0.001	0.39	0.00
B: Listing characteristics								
List Price/1000	425.95	0.434	494.13	0.482	577.25	0.517	705.70	0.57
Just-above (%)	0.00	0.001	0.00	0.001	0.01	0.002	0.01	0.00
Exactly round (%)	0.36	0.015	0.59	0.019	0.92	0.023	1.74	0.03
Just-below (%)	11.43	0.078	13.26	0.082	15.51	0.085	23.04	0.11
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	281.56	0.304	277.06	0.294	278.68	0.313	266.13	0.33

Round prices are defined as $100K multiples, and "just-below"/"just-above" as prices in $1K intervals, below/above adjacent round prices. Some extreme values of sales ratio, days on the market, and 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.

TABLE III

Characteristics of homes purchased by Toronto survey buyers vis-à-vis MLS sample

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 IV

SUMMARY STATISTICS: TORONTO SURVEY OF BUYERS

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

TABLE V

CHARACTERISTICS OF HOUSES LISTED NEAR $100K MULTIPLES (U.S. DATA)

	Odd-priced (N=202,231)		Round-priced (N=86,700)		Difference	
Characteristic	Mean	SD	Mean	SD	Mean	t-statistic
A: Transaction outcomes						
Sales ratio	0.976	0.000	0.981	0.000	0.004	25.262
Days on market	81.557	0.190	77.394	0.278	-4.163	-12.379
Quick sale probability	0.077	0.001	0.089	0.001	0.012	10.342
B: House characteristics						
Number of bedrooms	3.393	0.002	3.348	0.003	-0.046	-12.215
Number of washrooms	2.673	0.002	2.582	0.003	-0.091	-24.753
Living area square footage	2147.389	1.981	2046.096	2.710	-101.293	-30.173
Lotsize	39842.139	1361.052	34353.951	2078.962	-5488.188	-2.209
Number of fireplaces	0.763	0.002	0.682	0.003	-0.081	-22.372
Number of parking space	0.645	0.003	0.478	0.004	-0.168	-31.983
Gas heat source	0.862	0.001	0.882	0.001	0.020	14.726
Forced air	0.086	0.001	0.067	0.001	-0.019	-18.317
C: Agent characteristics						
Average sales ratio	0.979	0.000	0.980	0.000	0.002	23.871
Average days on market	79.155	0.091	78.012	0.137	-1.143	-6.954
Number of homes sold	139.339	0.610	149.514	0.940	10.175	9.081

Sample includes all properties listed within $1K of a 100K$ multiple. "Odd-priced" refers to homes listed in an interval $[z - 1K, z)$ and "round-priced" refers to homes listed in an interval $[z, z + 1K)$, where $z \in \{100K, 200K, \ldots, 1,000K\}$.

TABLE VI

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	-0.0075***	-0.0076***	-0.0072***	-0.0069***	-0.0065***
	(0.0005)	(0.0005)	(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	-0.0057***	-0.0058***	-0.0055***	-0.0053***	-0.0046***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
R^2	0.157	0.198	0.246	0.259	0.421
C: Dependent variable: ***Days on the market***					
Odd price	7.908***	7.339***	6.622***	6.950***	6.953***
	(0.6628)	(0.6509)	(0.6474)	(0.6551)	(0.7605)
R^2	0.197	0.230	0.271	0.287	0.439
D: Dependent variable: ***Quick sale probability***					
Odd price	-0.0377***	-0.0368***	-0.0347***	-0.0349***	-0.0347***
	(0.0028)	(0.0028)	(0.0029)	(0.0029)	(0.0034)
R^2	0.079	0.103	0.126	0.132	0.294
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
Observations	257,829	257,829	257,829	239,924	239,924

All columns report 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. The sample includes transactions within $15,000 of a $100K threshold, pooling over all thresholds and years. House and agent controls are described in Online Appendix A.

TABLE VII

SALES OUTCOMES BY LIST PRICE THRESHOLDS (U.S. CITIES)

	(log) Sale price (1)	Sales ratio (2)	Days on market (3)	Quick sale probability (4)
Odd price at $200K	-0.0062***	-0.0049***	4.247***	-0.0282***
	(0.0010)	(0.0008)	(1.323)	(0.0069)
Odd price at $300K	-0.0042***	-0.0034***	5.516***	-0.0365***
	(0.0010)	(0.0008)	(1.262)	(0.0062)
Odd price at $400K	-0.0053***	-0.0036***	8.377***	-0.0294***
	(0.0010)	(0.0009)	(1.690)	(0.0072)
Odd price at $500K	-0.0046***	-0.0031***	6.927***	-0.0360***
	(0.0013)	(0.0011)	(2.202)	(0.0088)
Odd price at $600K	-0.0075***	-0.0060***	12.45***	-0.0305***
	(0.0016)	(0.0014)	(2.589)	(0.0109)
Odd price at $700K	-0.0079***	-0.0075***	10.43***	-0.0417***
	(0.0018)	(0.0016)	(4.032)	(0.0154)
Odd price at $800K	-0.0114***	-0.0084***	13.37***	-0.0633***
	(0.0033)	(0.0025)	(4.606)	(0.0180)
Odd price at $900K	-0.0111***	-0.0097***	9.203	-0.0881***
	(0.0033)	(0.0029)	(6.320)	(0.0273)
Odd price at $1,000K	-0.0118*	-0.0073*	9.501	-0.0512*
	(0.0069)	(0.0041)	(11.75)	(0.0274)
Agent controls	Yes	Yes	Yes	Yes
House controls	Yes	Yes	Yes	Yes
Fixed-effects				
Threshold-Year-County	Yes	Yes	Yes	Yes
ZIP Code-Year	Yes	Yes	Yes	Yes
Agent	Yes	Yes	Yes	Yes
Fit statistics				
Observations	239,924	239,924	239,924	239,924
R^2	0.99414	0.42309	0.43985	0.29567
Within R^2	0.36304	0.01296	0.01665	0.00576
p-value for equality of coefficients	0.1746	0.0738	0.0507	0.2498

All columns report OLS regressions of equation (1) while allowing the β coefficients to vary by threshold. Standard errors, in parentheses, are clusterd at the zipcode level. Stars denote significance at the 1% (***), 5% (**), and 10% (*) levels. House and agent controls are described in Online Appendix A.

TABLE VIII

SALES OUTCOMES BY THRESHOLD TYPE (U.S. CITIES)

	(log) Sale price (1)	Sales ratio (2)	Days on market (3)	Quick sale probability (4)
Odd price at $100K multiple	-0.0059***	-0.0044***	6.598***	-0.0342***
	(0.0005)	(0.0004)	(0.6797)	(0.0030)
Odd price at $50K multiple	-0.0034***	-0.0024***	2.439***	-0.0266***
	(0.0004)	(0.0003)	(0.6473)	(0.0024)
Odd price at $10K multiple	-0.0046***	-0.0029***	1.342***	-0.0301***
	(0.0002)	(0.0002)	(0.3904)	(0.0020)
Agent controls	Yes	Yes	Yes	Yes
House controls	Yes	Yes	Yes	Yes
Fixed-effects				
Threshold-Year-County	Yes	Yes	Yes	Yes
ZIP Code-Year	Yes	Yes	Yes	Yes
Agent	Yes	Yes	Yes	Yes
Fit statistics				
Observations	879,319	879,319	879,319	879,319
R^2	0.99403	0.32191	0.35218	0.21115
Within R^2	0.07657	0.01133	0.01277	0.00298

All columns report OLS regressions of equation (1) while allowing the β coefficients to vary by threshold type. Standard errors, in parentheses, are clusterd at the ZIP Code level. Stars denote significance at the 1% (***), 5% (**), and 10% (*) levels. The sample includes transactions within $5,000 of a $100K, $50K, or $10K multiple, pooling over all thresholds and years. House and agent controls are described in Online Appendix A.

TABLE IX

SALES OUTCOMES BY YEAR (U.S. DATA)

	(log) Sale price (1)	Sales ratio (2)	Days on market (3)	Quick sale probability (4)
Odd price in 2008-2010	-0.0038*	-0.0031**	10.54***	-0.0298***
	(0.0021)	(0.0014)	(2.625)	(0.0075)
Odd price in 2011-2014	-0.0069***	-0.0046***	6.396***	-0.0205***
	(0.0009)	(0.0008)	(1.329)	(0.0049)
Odd price in 2015-2018	-0.0067***	-0.0046***	6.334***	-0.0414***
	(0.0006)	(0.0005)	(0.9911)	(0.0049)
Agent controls	Yes	Yes	Yes	Yes
House controls	Yes	Yes	Yes	Yes
Fixed-effects				
Threshold-Year-County	Yes	Yes	Yes	Yes
ZIP Code-Year	Yes	Yes	Yes	Yes
Agent	Yes	Yes	Yes	Yes
Fit statistics				
Observations	239,924	239,924	239,924	239,924
R^2	0.99383	0.42220	0.43932	0.29473
Within R^2	0.32873	0.01144	0.01573	0.00444
p-value for equality of coefficients	0.3640	0.5803	0.3122	0.0112

All columns report OLS regressions of equation (1) while allowing the β coefficients to vary by year. Standard errors, in parentheses, are clustered at the ZIP Code level. Stars denote significance at the 1% (***), 5% (**), and 10% (*) levels. The sample includes transactions listed within $15K of $100K multiples, pooling over all thresholds and years. House and agent controls are described in Online Appendix A.

TABLE X

THE EFFECT OF ODD PRICING ON SALES OUTCOMES, BY U.S. CITY

	(log) Sale price (1)	Sales ratio (2)	Days on market (3)	Quick sale probability (4)
Odd price in Chicago	-0.0059***	-0.0043***	8.129***	-0.0202***
	(0.0009)	(0.0007)	(1.507)	(0.0046)
Odd price in Minneapolis	-0.0061***	-0.0046***	7.525***	-0.0471***
	(0.0006)	(0.0006)	(0.8564)	(0.0053)
Odd price in San Diego	-0.0075***	-0.0052***	3.295**	-0.0420***
	(0.0015)	(0.0012)	(1.555)	(0.0097)
Agent controls	Yes	Yes	Yes	Yes
House controls	Yes	Yes	Yes	Yes
Fixed-effects				
Threshold-Year-county	Yes	Yes	Yes	Yes
ZIP Code-Year	Yes	Yes	Yes	Yes
Agent	Yes	Yes	Yes	Yes
Fit statistics				
Observations	239,922	239,922	239,922	239,922
R^2	0.99388	0.42207	0.43924	0.29507
Within R^2	0.33401	0.01123	0.01560	0.00495
p-value for equality of coefficients	0.6399	0.8055	0.0380	0.0004

All columns report OLS regressions of equation (1) while allowing the β coefficients to vary by year. Standard errors, in parentheses, are clustered at the ZIP Code level. Stars denote significance at the 1% (***), 5% (**), and 10% (*) levels. The sample includes transactions within $15K of $100K multiples, pooling over all thresholds and years. House and agent controls are described in Online Appendix A.

TABLE XI

SALES OUTCOMES 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	-0.0065***	-0.0066***	-0.0065***	-0.0065***	-0.0067***	-0.0068***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
High-end kitchen features			0.0009***			0.0007**
			(0.0003)			(0.0003)
Urgency				-0.0002		-0.0002
				(0.0004)		(0.0004)
Unverifiable index					0.0020***	0.0018***
					(0.0001)	(0.0001)
R^2	0.994	0.994	0.994	0.994	0.994	0.994
B: Dependent Variable: ***Sales ratio***						
Odd price	-0.0045***	-0.0046***	-0.0045***	-0.0045***	-0.0045***	-0.0045***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0005)
High-end kitchen features			0.0008***			0.0007***
			(0.0002)			(0.0002)
Urgency				-0.0003		-0.0003
				(0.0003)		(0.0003)
Unverifiable index					0.0017***	0.0015***
					(0.0001)	(0.0001)
R^2	0.423	0.424	0.423	0.423	0.429	0.431
C: Dependent Variable: ***Days on the market***						
Odd price	6.366***	6.334***	6.373***	6.363***	6.274***	6.238***
	(0.7577)	(0.7585)	(0.7578)	(0.7573)	(0.7653)	(0.7640)
High-end kitchen features			-0.9859**			-0.8620*
			(0.4965)			(0.5020)
Urgency				1.916***		1.794***
				(0.6416)		(0.6489)
Unverifiable index					-1.327***	-1.154***
					(0.2062)	(0.2060)
R^2	0.441	0.442	0.441	0.441	0.446	0.447
D: Dependent Variable: ***Quick sale probability***						
Odd price	-0.0273***	-0.0271***	-0.0273***	-0.0273***	-0.0251***	-0.0249***
	(0.0033)	(0.0033)	(0.0033)	(0.0033)	(0.0034)	(0.0034)
High-end kitchen features			-0.0011			0.0006
			(0.0014)			(0.0014)
Urgency				-0.0086***		-0.0080***
				(0.0026)		(0.0026)
Unverifiable index					0.0025***	0.0024***
					(0.0008)	(0.0008)
R^2	0.301	0.302	0.302	0.302	0.299	0.299
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

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 includes transactions within $15K of a $100K threshold, pooling over all thresholds and years. House and agent controls are described in Online Appendix A.

TABLE XII

Bounding the potential bias from confounders for the odd-pricing effect on sales ratio in the U.S. cities

	Estimate: −0.0054 (0.00037)				
	|Bias|	Bias bounds	95% CI	R_Y^2	R_D^2
All	0.0031 (0.000013)	[−0.0085 – −0.0023]	[−0.0093 – −0.0015]	0.0610	0.00630
Agent controls	0.00028 (0.0000011)	[−0.0057 – −0.0051]	[−0.0064 – −0.0044]	0.0120	0.00025
House characteristics	0.0019 (0.000008)	[−0.0074 – −0.0035]	[−0.0081 – −0.0027]	0.0340	0.00430
Public remarks	0.00054 (0.0000022)	[−0.0059 – −0.0049]	[−0.0067 – −0.0041]	0.0071	0.00160

The top-line estimate of −0.0054 (0.00037) is the estimated odd pricing effect on sales ratio from column (6) of Table XI (without agent fixed effects). |Bias| denotes the estimated absolute bias (with standard errors in parentheses) from omitting an unobserved confounder that explains R_Y^2 and R_D^2 proportions of the variances in the outcome and "treatment," respectively. "Bias bounds" indicate the range of adjusted estimates while accounting for potential confounding. 95% CI provides the confidence interval for the adjusted estimate. The rows correspond to different sets of covariates: all controls, agent controls, house characteristics, and public remarks (see Online Appendix B).

TABLE XIII

THE ODD PRICING EFFECT INTERACTED WITH SUGGESTED ROUND-PRICED BOUNDS ON REALTOR.COM

Model	(log) Sale price (1)	Sales ratio (2)	Days on market (3)	Quick sale probability (4)
Variables				
Odd price	-0.0034***	-0.0017***	1.384***	-0.0239***
	(0.0002)	(0.0002)	(0.4303)	(0.0021)
Odd price × Suggested round	-0.0009***	-0.0012***	1.434***	-0.0066**
	(0.0003)	(0.0003)	(0.4836)	(0.0028)
Agent controls	Yes	Yes	Yes	Yes
House controls	Yes	Yes	Yes	Yes
Fixed-effects				
Round-Year-County	Yes	Yes	Yes	Yes
Zip Code-Year	Yes	Yes	Yes	Yes
Agent	Yes	Yes	Yes	Yes
Fit statistics				
Observations	564,908	564,908	564,908	564,908
R^2	0.99409	0.32265	0.35583	0.22248
Within R^2	0.02791	0.00959	0.01669	0.00283

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 Zip Code level. Stars denote significance at the 1% (***), 5% (**), and 10% (*) levels. House and agent controls are described in Online Appendix A.

TABLE XIV

THE EFFECT OF ODD PRICING ON NUMBER OF BIDDERS AND BUYERS' BUDGETS

	Bidders > 1	Bidders > 2	(log) Budget
	(1)	(2)	(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. Stars denote significance at the 1% (***), 5% (**), and 10% (*) levels. House and agent controls are described in Appendix A.

TABLE A.I

VERIFIABLE FEATURES, QUALITY SIGNAL, AND URGENCY PHRASES

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

TABLE A.II

SUBJECTIVE, UNVERIFIABLE DESCRIPTORS

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

TABLE A.III

PROPERTY CHARACTERISTICS NEAR $\$100K$ THRESHOLDS (TORONTO DATA)

	Odd-priced (N=105793)		Round-priced (N=6036)		Difference	
Characteristic	Mean	SD	Mean	SD	Mean	t-statistic
A: Transaction outcomes						
Sales ratio	1.015	0.000	1.024	0.001	0.008	7.61
Days on market	22.56	0.083	20.45	0.346	-2.117	-5.95
Quick sale	0.33	0.001	0.39	0.006	0.060	9.37
B: House characteristics						
Number of bedrooms	3.37	0.002	3.45	0.011	0.074	6.65
Number of rooms	7.53	0.006	7.75	0.026	0.219	8.10
Number of washrooms	2.90	0.003	2.99	0.014	0.095	6.52
Lotsize	9068.92	64.255	12224.28	354.611	3155.360	8.76
Fireplace	0.64	0.002	0.67	0.006	0.026	4.01
Detached	0.18	0.001	0.13	0.004	-0.044	-9.65
Finished Basement	0.60	0.002	0.61	0.006	0.010	1.62
Family room	0.53	0.002	0.58	0.007	0.042	6.05
Driveway	0.65	0.001	0.70	0.006	0.051	8.47
Gas heat source	0.90	0.001	0.87	0.005	-0.030	-6.26
Forced air	0.90	0.001	0.88	0.004	-0.019	-4.16
C: Agent characteristics						
Average sales ratio	1.26	0.085	0.99	0.000	-0.272	-1.60
Average days on market	28.83	0.035	27.90	0.140	-0.929	-2.73
Number of homes sold	276.50	0.395	304.70	1.868	28.203	2.59

Sample consists of all properties listed within \$1K of a $\$100K$ threshold; "odd-priced" refers to homes listed in $[z-1K, z)$ and "round-priced" refers to homes listed $[z, z+1K)$, where $z \in \{100K, 200K, \ldots, 1000K\}$. See Section II.B. for additional data details.

TABLE A.IV

THE EFFECT OF ODD PRICING ON SALES OUTCOMES, POOLING ALL $100K THRESHOLDS (TORONTO)

	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. House and agent controls are described in Online Appendix A.

TABLE A.V

THE EFFECT OF ODD PRICING ON SALES OUTCOMES FOR EACH THRESHOLD (TORONTO)

	(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 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. House and agent controls are described in Online Appendix A.

TABLE A.VI

THE EFFECT OF ODD PRICING ON SALES OUTCOMES BY THRESHOLD TYPE (TORONTO)

	(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 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 includes transactions within \$5,000 of a \$100K, \$50K, or \$10K threshold types, pooling over all thresholds and years. House and agent controls are described in Online Appendix A.

TABLE A.VII

THE EFFECT OF ODD PRICING ON SALES OUTCOMES BY YEAR (TORONTO)

	(log) Sale price	Sales ratio	Days on market	Quick sale probability
	(1)	(2)	(3)	(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 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 includes transactions within \$15K of \$100K thresholds, pooling over all thresholds and years. House and agent controls are described in Online Appendix A.

TABLE A.VIII

BOUNDING THE POTENTIAL BIAS FROM CONFOUNDERS ON THE ODD-PRICING EFFECT ON SALES RATIO IN TORONTO

	Estimate: -0.0071 (0.0012)				
Benchmark	|Bias|	Bias Bounds	95% CI	R_Y^2	R_D^2
All	0.0034 (0.000021)	[−0.011 – −0.0037]	[−0.012 – −0.0019]	0.024	0.0040
Agent Controls	0.0019 (0.000012)	[−0.009 – −0.0052]	[−0.011 – −0.0034]	0.012	0.0025
House Characteristics	0.0015 (0.000009)	[−0.0086 – −0.0057]	[−0.01 – −0.0038]	0.012	0.0015

The top-line estimate of -0.0071 (0.0012) is the estimated odd pricing effect on sales ratio from column (4) of Table A.IV. |Bias| denotes the estimated absolute bias (with standard errors in parentheses) from omitting an unobserved confounder that explains R_Y^2 and R_D^2 proportions of the variances in the outcome and "treatment," respectively. "Bias bounds" indicate the range of adjusted estimates after accounting for potential confounding; 95% CI provides the confidence interval for the adjusted estimate. The rows correspond to different sets of observed covariates in column (4) of Table A.IV: all controls, agent controls, and house characteristics.

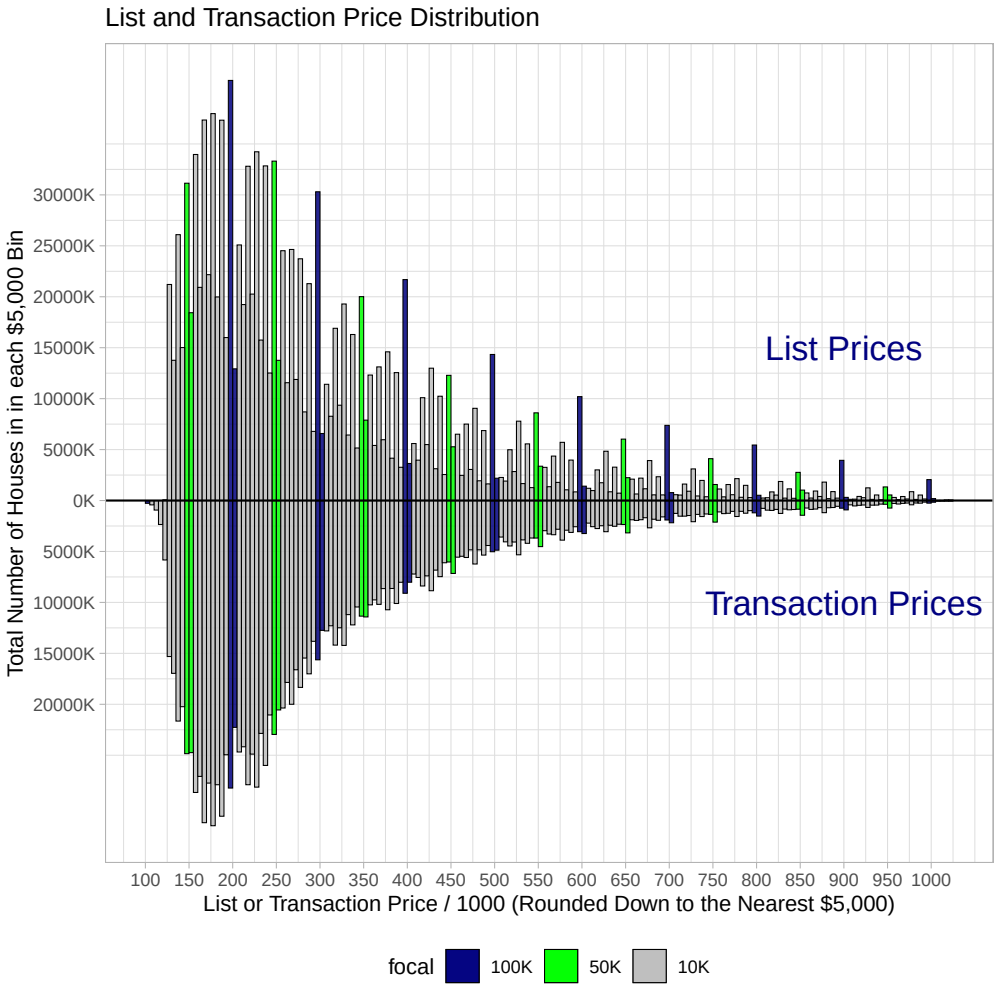
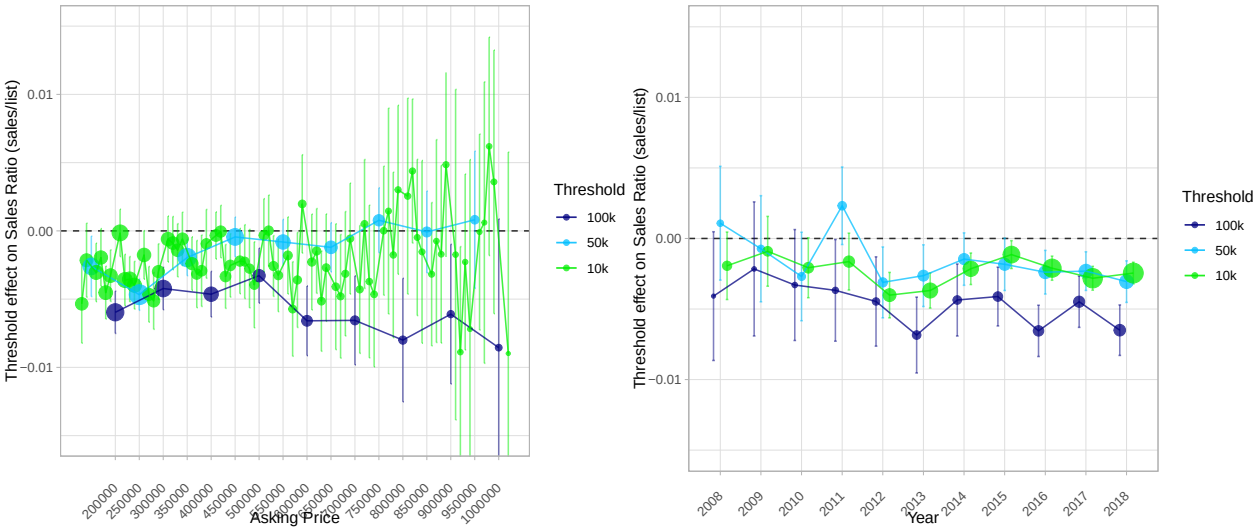


FIGURE I
Histograms of List and Sale Prices for the U.S. Metros in our Data

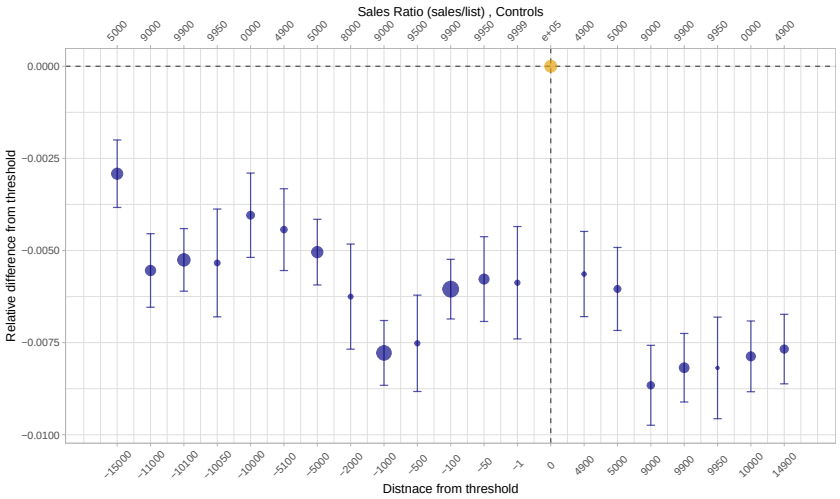
Histograms of list and sale prices for the U.S. metros in our data. Each pair of identically-colored bars is centered on a round number (a multiple of $10,000, $50,000, or $100,000). If x is a round number, the left-hand bar represents the interval $[x - 5000, x)$ and the right-hand bar represents the interval $[x, x + 5000)$.



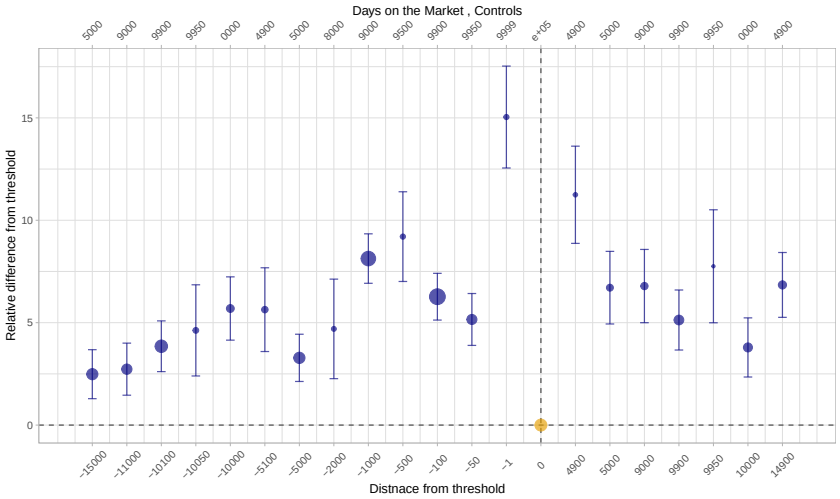
(A) (B)

FIGURE II
Sales Ratio Effect by Asking Price and Year (U.S. Data)

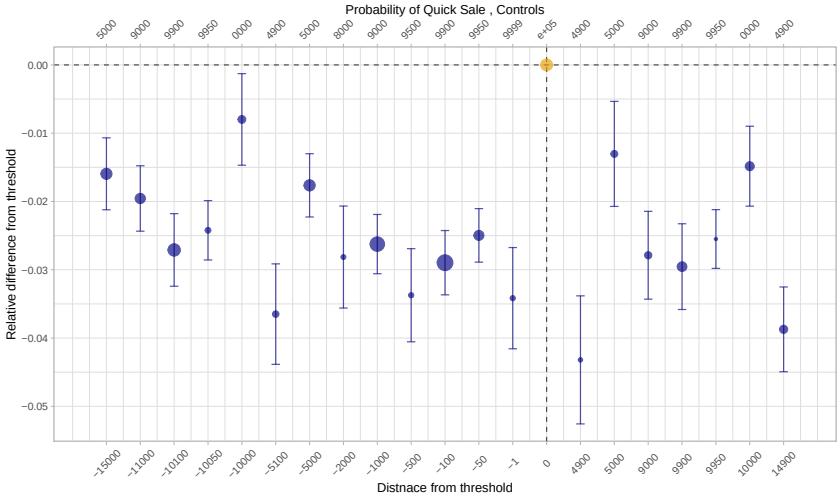
This figure displays estimates of the coefficient β from column 5 of Table VI estimated separately by threshold type and (a) listing price or (b) year



(A) Sales ratio



(B) Days on market



(C) Quick sale probability

FIGURE III
Estimates of the Odd-Pricing Effect for $1 Bins (U.S. Data)

This figure displays estimates of the odd-pricing effect for $1 bins on: (a) sales ratio, (b) days on the market, and (c) probability of a quick sale. Houses listed exactly at a $100K multiple are shown by a yellow dot at 0. In each figure, the bottom x-axis shows the list-price difference in dollars between each bin and the adjacent round number, and the top x-axis shows the last four digits of the price ending. For example, houses at -1 on the bottom x-axis and 9999 on the top x-axis, are priced $1 below a round price, such as $500,000.

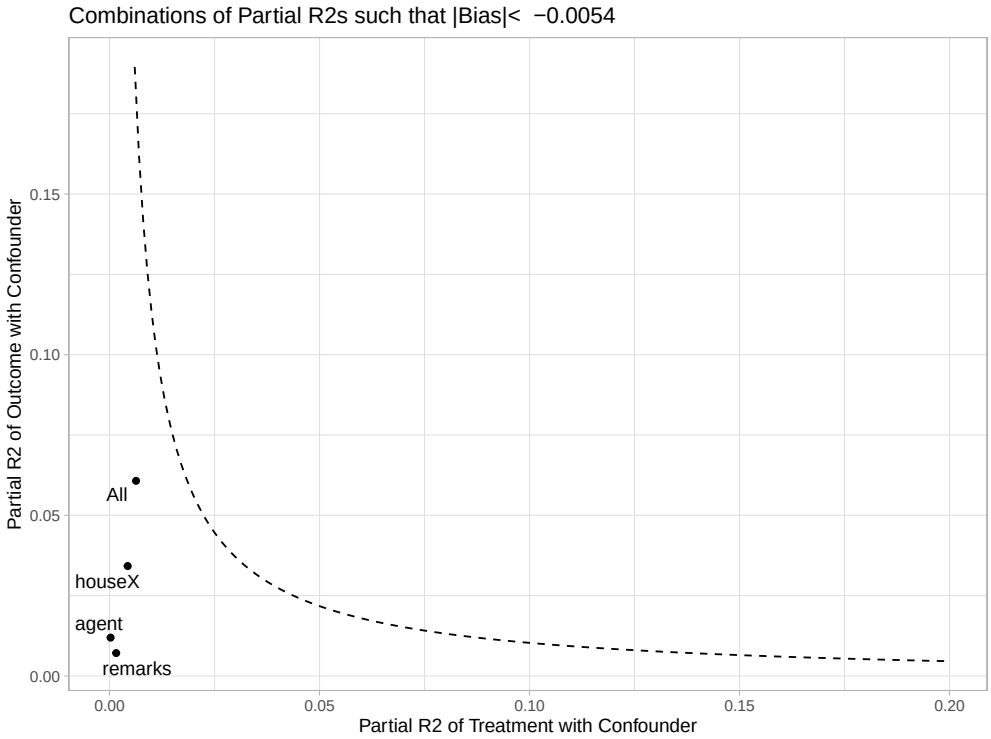


FIGURE IV
Sensitivity Analysis of Omitted Variable Bias in the Estimated Odd-Pricing Effect on Sales Ratio in the U.S. (based on Table XII)

The horizontal axis shows the fraction of residual variation in the "treatment" explained by a potential unobserved confounder (partial-R^2), while the vertical axis shows its influence on the outcome. The dashed contour represents confounder values that would yield an adjusted estimate within the bias threshold ($|\text{Bias}| < -0.0054$), assuming the worst-case direction. The labeled points indicate the explanatory power of specific sets of observed covariates—proxies for quality in the listing description ("remarks"), house controls ("houseX"), agent controls ("agent"), and all covariates ("All") from column (6) of Table XI (except agent fixed effects)—relative to potential unobserved confounders.

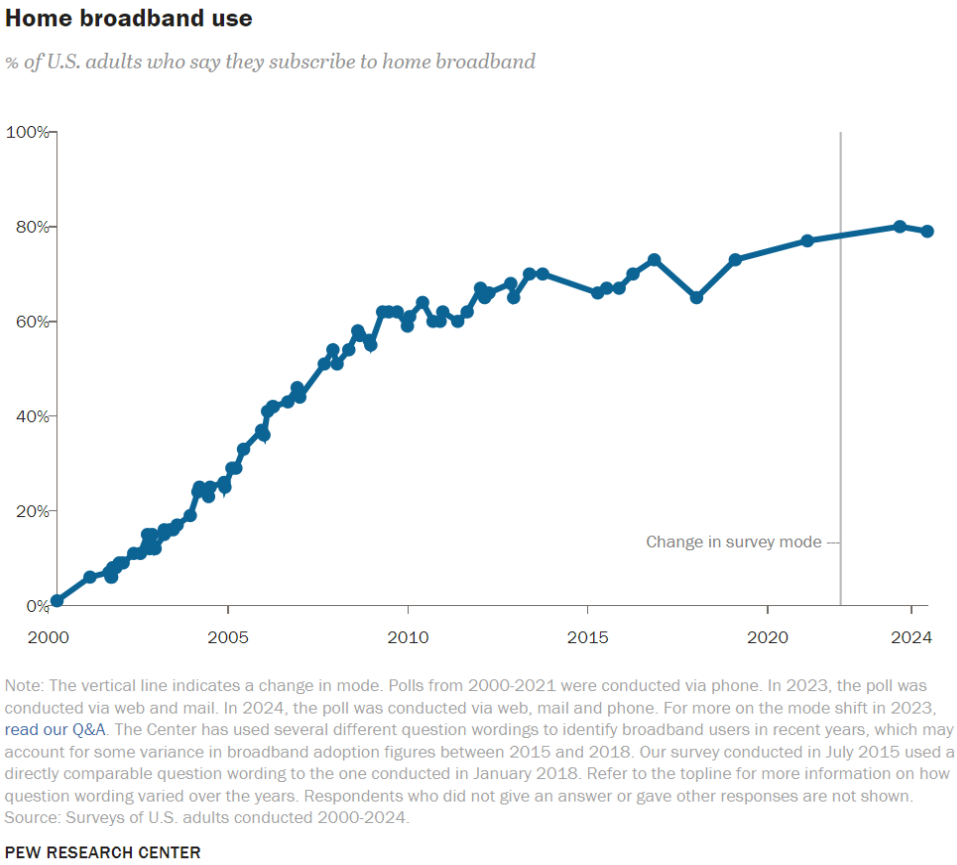


FIGURE V
Broadband Internet Penetration

Source: https://www.pewresearch.org/internet/fact-sheet/internet-broadband

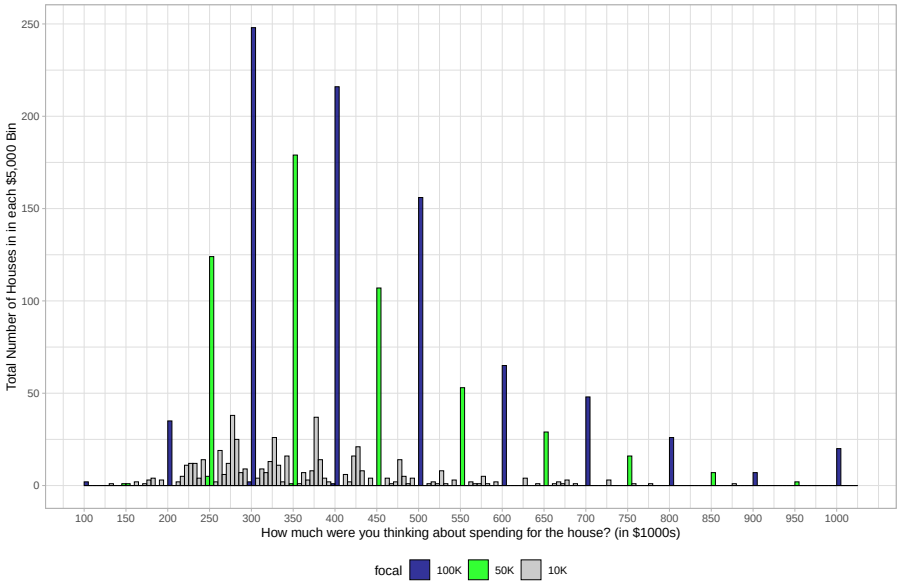
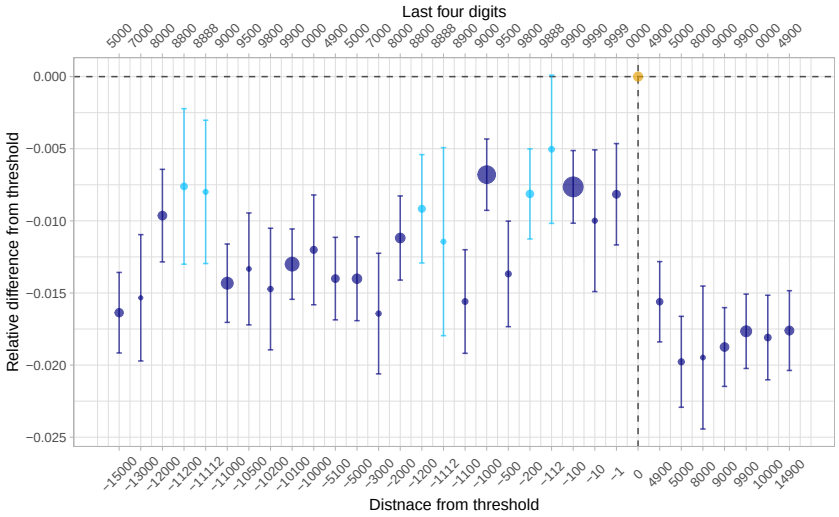
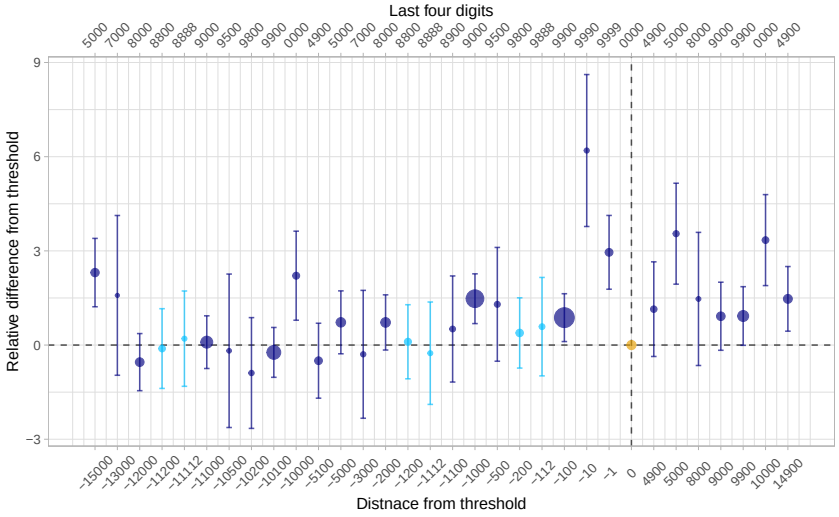


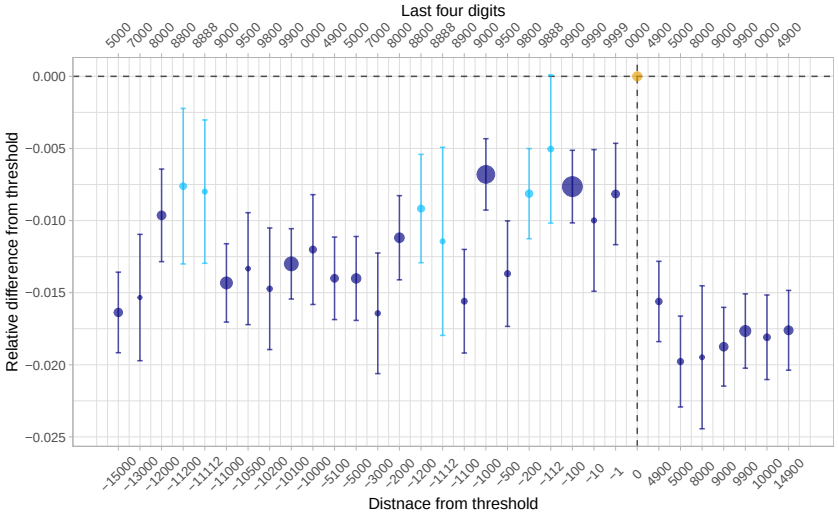
FIGURE A.I
Histogram of Buyers' Reported Budgets in the Toronto Survey



(A) Sales ratio



(B) Days on market



(C) Quick sale probability

FIGURE A.II
Estimates of the Odd-Pricing Effect in Toronto for $1 Bins

This figure displays estimates of the odd-pricing effect in Toronto for $1 bins on: (a) sales ratio, (b) days on the market, and (c) probability of a quick sale. Houses listed exactly at a $100K multiple are shown by a yellow dot at 0. In each figure, the bottom x-axis shows the list-price difference in dollars between each bin and the adjacent round number, and the top x-axis shows the last four digits of the price ending. All prices in Canadian dollars.

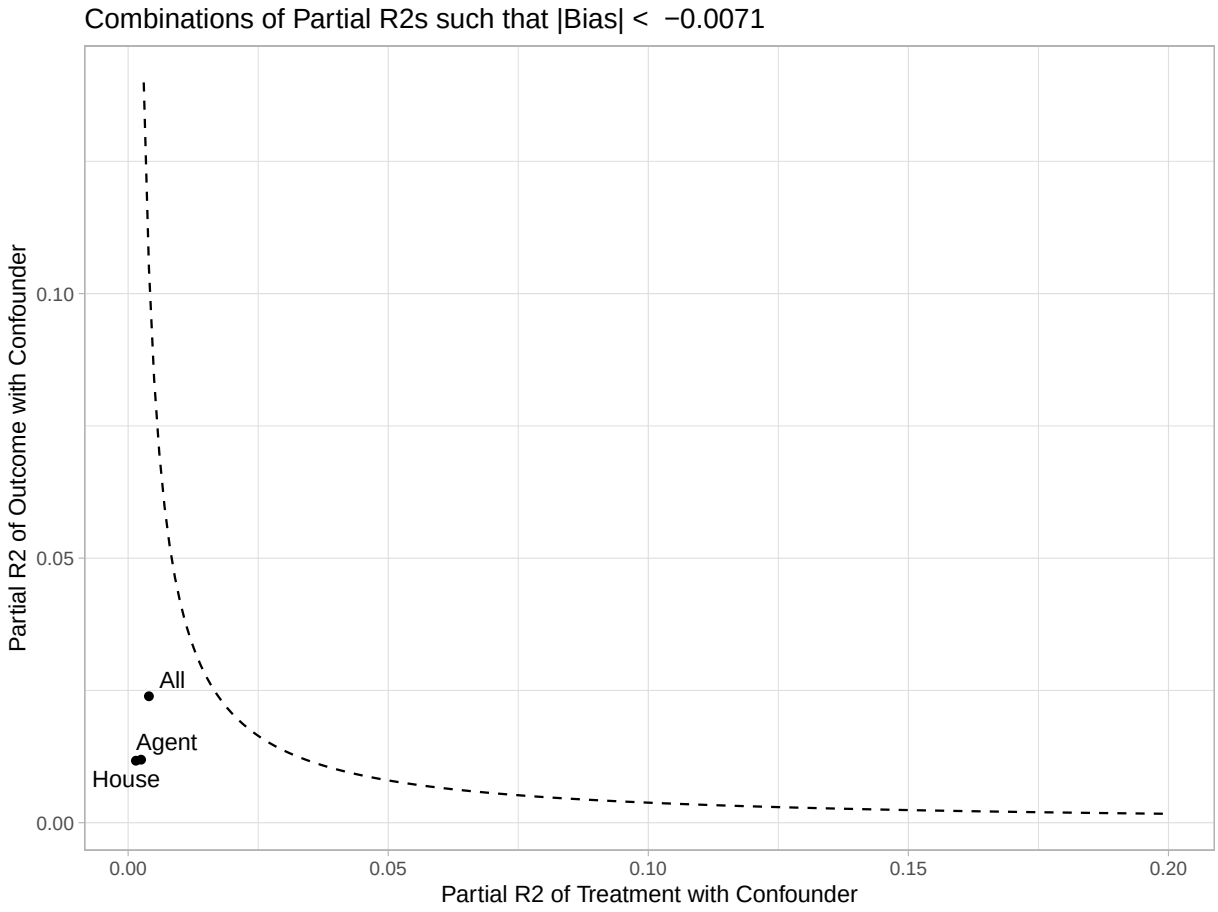


FIGURE A.III
Sensitivity Analysis of Omitted Variable Bias in the Estimated Odd-Pricing Effect on Sales Ratio in Toronto (based on Table A.VIII)

The horizontal axis shows the fraction of residual variation in the "treatment" explained by a potential unobserved confounder (partial-R^2), while the vertical axis shows its influence on the outcome. The dashed contour represents confounder values that would yield an adjusted estimate within the bias threshold ($|\text{Bias}| < -0.0071$), assuming the worst-case direction. The labeled points indicate the explanatory power of specific sets of observed covariates—house controls ("House"), agent controls ("Agent"), and all covariates ("All") from Table A.IV, column (4)—relative to potential unobserved confounders.