

Do Rounding-Off Heuristics Matter?

Evidence from Bilateral Bargaining in the U.S. Housing Market*

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Abstract

Using confidential offer-level data on the US housing market, this paper examines rounding-off heuristics in the housing bilateral bargaining process. We find that home sellers and home buyers follow different rounding-off heuristics. Sellers' list prices cluster more frequently on "charm" numbers (e.g. 349,999), compared to buyers' offer prices and negotiated final sales prices; the latter two cluster more frequently on round numbers. The choice of heuristics has important consequences for housing transaction outcomes. Round list prices yield lower sales prices compared to non-round prices without generating a shorter time on the market. Excluding trivial adjustments, buyer counteroffers are more aggressive with round list prices — there is a greater price adjustment, positive or negative, in the offer submitted compared to the list price. Round list prices also attract a greater number of buyers participating in the buying process. Our empirical findings best support a mechanism where round prices are weak anchors for buyers' valuation compared to non-round list prices, thereby allowing the possibility of some sellers strategically choosing round prices to induce bidding wars.

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1 Introduction

Bilateral bargaining plays a significant role in the allocation of resources and responsibilities in economics (Backus et al., 2020). Empirical researchers increasingly recognize the existence of various behavioral heuristics that could significantly impact bargaining outcomes, beyond the predictions made by classic models in game theory. The heterogeneity in behavioral heuristics among participants of bargaining could have important welfare implications in different markets. However, limited evidence exists on the bargaining process in high-stakes real-world settings. This paper focuses on rounding off heuristics in the U.S. housing market bargaining process.

We choose to analyze the housing market for three reasons. First, since housing constitutes a large part of the typical household’s balance sheet (Davis and Van Nieuwerburgh, 2015)¹, any irrational behavior can be costly. Second, considering that the transaction of houses often happens infrequently at the individual level, most home buyers and sellers might have limited experience and are more likely to suffer from behavioral heuristics. Third, as shown by Levitt and Syverson (2008), significant information asymmetry exists in the housing market, and real estate properties are generally heterogeneous and incomparable. This lack of information might also leave room for using heuristics in the housing bargaining process.

Despite the importance of this question, previous research mainly focuses on analysis using data from regional housing markets due to various data limitations. This paper instead contributes to a more granular analysis using two databases. The first database provides novel data from Redfin, one of the largest US online residential real estate brokerages. Compared to standard databases, one unique advantage of Redfin data is detailed records of home buyers’ actions at the offer level. This allows us to observe the history of offers made by home buyers represented by Redfin and the interaction between home buyers and home sellers across 44 states in the US from 2012–2022. The second database is the *nationwide* multiple listing service (MLS) data, which documents comprehensive information on the seller side in all the US states. The combination of these two databases enables us to track the detailed bargaining process between buyers and sellers when a property is listed on the US market.

We document a set of facts about buyers’ and sellers’ tendencies to use rounding-off heuristics. By examining the distribution of the initial list prices and final sales prices using our nationwide

¹According to FRED series ID RHORUSQ156N, the homeownership rate in the U.S. has consistently remained above 60% for several decades. Davis and Van Nieuwerburgh (2015) document that housing assets account for as much as 90% early in the life cycle to 50% in old age, using data from the Survey of Consumer Finances.

MLS sample, we observe that prices are not smoothly distributed. Instead, both the initial list prices and final sales prices tend to bunch around “special numbers”, most evidently around multiples of \$50k. There is also significant bunching around other multiples of \$5k. Interestingly, there are important differences between the distribution of the initial list price and that of the final sales price. First, initial list prices exhibit more bunching in the vicinity of round numbers that are multiples of \$5k, \$10k, and \$50k, compared to final sales prices. Second, a closer examination reveals that most of the bunching in final sales prices occurs at *exact* round numbers, while initial list prices are much more likely to bunch at numbers slightly below exact round numbers (so-called “charm numbers” for buyers).²

We find that round list prices lead to *lower* sales prices compared to charm list prices or non-special number list prices. Both round and charm prices take a shorter time on the market. However, round number list prices do not take less time on the market compared to charm list prices. Therefore, round list prices seem to be dominated by charm list prices as a pricing strategy, because they yield a lower sales price while offering no benefits on time on market. This raises questions if round list prices are the result of an implicit lack of sophistication or lack of information. To shed light on this, we further investigate the performance of round number list prices with respect to number of buyer offers and during bidding wars. We find that the number of buyer offers is larger for round list prices. In addition, we find that round-number list prices provide higher sales prices if the sales process involves a bidding war (where the sales price non-trivially exceeds the initial list price). While the relative performance of round list prices versus charm list prices recalls results in [Repetto and Solís \(2020\)](#) in the different institutional setting of the Swedish ascending price auction, it differs because round prices provide higher returns in our US housing market setting if the house undergoes a bidding war. Our results suggest that round list prices *can* be beneficial if they induce a bidding war.

The role of rounding-off heuristics and the mechanism they induce in the bargaining process can be further investigated by looking at buyer offers in response to the choice of list prices. We use offer-level data from Redfin to do this. In other words, we study patterns in the buyer offer price after the seller posts a list price but *before* the house is sold at the final sales price. Do buyer counteroffers show any adjustment from the seller list price? Excluding trivial price adjustments of less than \$100, both round list prices and charm list prices see buyer counteroffers that lead to price adjustments. However, round list prices see much greater price adjustments

²Henceforth, we use the term “special price” to refer to a price that is either exactly rounded or is a charm price.

through buyer counteroffers. This adjustment is larger for round list prices for positive (if buyer counteroffer is more than list price) and for negative (if buyer counteroffer is less than list price) price adjustments. This result holds whether we look at level change or percentage change of the adjustment. Quantitatively, when list prices are exact multiples of \$100k, the positive adjustment in offer prices is by \$7,914 dollars, compared to similar non-round and non-charm list prices. When list prices are exact multiples of \$100k, the negative adjustment in offer prices is by \$7,521 dollars, compared to similar non-round and non-charm list prices. The magnitude of this extra adjustment is sizable, and a similar phenomenon exists when list prices are multiples of \$50k, \$10k and \$5k.

Our evidence is most consistent with a mechanism where round prices are “weak anchors.” The presence of a round price on average leads to a lower sales price. Buyer counteroffers are more aggressive, leading to greater adjustment in the offers they make with respect to the initial list price. However, round prices also lead to a greater number of buyers participating in the buying process. In a bidding war, round list price houses sell for a higher value than comparable houses with non-round prices. Thus, the weak anchor can lead to price swings in either direction, and allows the possibility of some sellers *strategically* choosing round prices to induce bidding wars. The possibility of a strategic reason to choose round prices differentiates our paper from results in the psychology literature, where round prices are signals of lack of knowledge or sophistication, such as in [Mason et al. \(2013\)](#).

Our evidence also rules out mechanisms that have been suggested with respect to rounding-off heuristics in the literature. First, we can rule out that round prices are cheap talk signals, where a round list price would signal a seller’s impatience and relatively weak bargaining power ([Backus et al., 2019](#)). Since our results robustly show that round list prices yield a lower sales price, compared to non-round list prices, without providing a faster sale, they violate the incentive-compatibility constraint for a cheap talk strategy in a separating equilibrium. In other words, round list prices do not provide a trade-off between a lower sales price with a shorter time on the market. Second, we rule out an “over-shooting” mechanism, where sellers may have the motivation to use round number heuristics to round up list prices ([Lin and Puriainen, 2021](#)). Under this mechanism, it is then rational for buyers to use more aggressive negotiation tactics in response to the potentially “artificially high” prices. However, we show that buyer offer adjustments can be positive under bidding wars, and the size of the adjustment is larger for round list prices than that for non-round list prices. Finally, a long tradition has thought of round number prices as chosen by individuals with cognitive limitations ([Rosch, 1975](#); [Lacetera et al., 2012](#); [Kuo et al., 2015](#); [D’Acunto et al.,](#)

2019). However, this explanation may not be sufficient to explain the widely prevalent use of round list prices in the high-stakes housing market.

Our paper provides novel descriptive findings using real-world data. To be able to causally tease out the mechanism driving our findings and to understand the welfare implications of these heuristics, we are also running a complementary experiment with real US home buyers and sellers, closely mimicking the setting described in our real-world bargaining data. This follows related work in the housing literature (Wiltermuth et al., 2022; Thomas et al., 2010).

Our paper contributes to the following strands of literature. First, this paper is closely related to the literature on “rounding-off” behaviors. Economists have long realized the existence of rounding-off heuristics in various markets where people tend to have a special taste towards round numbers.³ Specifically, several empirical studies have examined the rounding-off behaviors in the housing market with its characteristics of infrequent transactions and high stakes involved. For example, Pope et al. (2015) document sharp spikes in the distribution of final sales prices at round numbers in the US housing market. Meng (2020) and Wiltermuth et al. (2022) examine the effect of “rounding number” prior sales price on subsequent valuations using a sample of repeat sales data in the UK and US housing market. These papers mainly focus on rounding-off behaviors related to the final negotiated sales prices. Our paper contributes to the literature by exploring both home buyers and home sellers’ rounding-off behaviors using a nationwide sample of property listings and unique *offer-level* bargaining data in the US housing market.

Second, this paper contributes to the empirical literature on negotiation and sequential bargaining. As mentioned by Backus et al. (2020), previous studies mainly examine various aspects of bargaining in theory and in laboratory experiments.⁴ However, there are few empirical studies about people’s bargaining behaviors in real-world negotiations. To fill the gap, Backus et al. (2020) study patterns of people’s bilateral bargaining behaviors on eBay’s Best Offer platform and compare observed behavior to predictions from theoretical bargaining models. Liu et al. (2023) exploit manually collected data on high-stake merger and acquisition (M&A) negotiations and discover several empirical patterns that challenge classical auction and negotiation theories. This paper

³These markets include the used car market (Lacetera et al., 2012), crowdfunding market (Lin and Pursiainen, 2021), retail market (Schindler and Kirby, 1997), stock market (Bhattacharya et al., 2012), future market (Kuo et al., 2015), etc. Potential explanations include individual cognitive limitation (Rosch, 1975; Lacetera et al., 2012; Kuo et al., 2015; Lin and Pursiainen, 2021; D’Acunto et al., 2019), cognitive shortcut, overcutting (Bhattacharya et al., 2012), lack of information (Herrmann and Thomas, 2005; Ormerod et al., 2007; Whynes et al., 2007; Kleven and Waseem, 2013), etc.

⁴Thomas et al. (2010) use a set of experiments to study how the precision and roundness of prices affect buyer behavior. Using the MLS data from South Florida and New York, they show that precise listing prices are significantly correlated with higher sales prices in the housing market.

complements the nascent literature by examining patterns of people’s bilateral bargaining behaviors in another high-stake real-world setting (i.e., the US housing market). Unlike papers that focus on final sales prices in the housing market, our paper complements the existing housing literature by using bargaining offer-level data and utilizing the whole path of revised listing prices and offer prices.⁵

Third, there is a literature on the mechanisms behind round number heuristics. [Mason et al. \(2013\)](#) establish that first-offer recipients make greater counteroffer adjustments to round versus precise offers in a lab experimental setting where participants sell cheap jewelry. Taking advantage of the relatively large sample size and real-world offer-level data, this paper discovers that an “anchor effect” exists in the high-stake housing transaction setting. In addition, and crucially, our counteroffer adjustments are not only downward adjustments, as in their paper, but can be upward adjustments too. They may provide benefits in bidding wars. Additionally, [Backus et al. \(2019\)](#) develop a cheap talk model, predicting that round number listings are associated with lower sales price, a faster arrival of offers, and a higher probability of sale. However, in our setting, round list prices are inferior strategies compared to non-round list prices, on average. Round list prices take more time on the market with a lower sale price compared to charm list prices.

This paper is organized as follows. Section 2 introduces the institutional background and describes the data. Section 3 establishes a set of novel facts about the existence of rounding-off heuristics in home buyers’ offer prices and sellers’ revised listing prices. Section 4 documents the role of using round numbers in the interactive bilateral bargaining process. Section 5 concludes.

2 Background and Data

2.1 Bargaining Process in the Housing Market

In the housing market bargaining process, sellers often engage with multiple potential buyers, with the term *buyer* referring to individuals interested in purchasing the property, regardless of the outcome. This interaction can be illustrated by a few examples of real transactions from Redfin, as depicted in Figure 1. Initially, the seller puts up her property for sale on the MLS, thereby

⁵The bulk of the studies in house search and bargaining has concentrated on variables such as sales duration ([Haurin, 1988](#); [Genesove and Han, 2012](#)), volume ([Novy-Marx, 2009](#); [Glaeser and Nathanson, 2015](#); [Ngai and Tenreyro, 2014](#)), financing ([Genesove and Mayer, 1997](#)), and their relationship with the final sales price. In comparison, because of data limitations, there have been very few empirical studies ([Merlo and Ortalo-Magné, 2004](#)) investigating the individual behavioral patterns of the bargaining process in the housing market that takes place between the seller and the buyer.

broadcasting the house listing to several potential buyers searching for a property that meets their preferences. Potential buyers can send their offers to the seller via a buyer agency such as Redfin. The seller may then choose to accept the offer or revise the price based on new information or market interest. Eventually, the seller may take the property off-market on a recorded off-market date and proceed with private negotiations with one or more buyers. Appendix C.1 gives a detailed explanation through example transactions.

We define an *event* as the combination of the property listing process and the sequence of all offers from potential buyers of the property. Each event can involve multiple rounds of bargaining, starting with the initial listing of the property and concluding with the final sales or private negotiation failure. An *action* within an event is defined as either an offer proposed by a potential buyer or a list initialization/revision made by the seller.

Regarding prices, the initial price at which the property is listed is termed the *initial list price*. The price at which the transaction is closed is called the *sales price*. The price which a potential buyer proposes when making an offer is referred to as the buyer’s *offer price*. The list price when the buyer makes the offer is referred to as the *current list price*.

This paper utilizes data from two sources: event-level data from the Multiple Listing Service (MLS), and action-level data from Redfin. The event-level data allows us to concentrate on the outcomes of each listing event, while the action-level data provides detailed insights into the bargaining process. Therefore, integrating these two types of data provides a comprehensive understanding of the bargaining process in the housing market.

2.2 Institutional Background of Multiple Listing Services (MLS) Data

Our study utilizes event-level data sources from the Multiple Listing Services (MLS), a real estate database managed by local real estate boards and leveraged by real estate agents to advertise properties for sale. The MLS system is commonly adopted throughout the United States, serving as a primary listing and marketing platform for residential and commercial properties. Each local MLS is specific to a geographic region and administered by a board of real estate brokers and agents who pay to access the database. The MLS database is routinely updated in real-time, providing agents and brokers with the latest information on available properties. The MLS presents a diverse array of listing information, including location, price, list dates, agent information, and housing characteristics. Furthermore, the MLS serves as a centralized platform for agents to collaborate, sharing information regarding properties, clients, and coordinating showings and negotiations. Given the

widespread adoption of MLS, it is a comprehensive source of data on the U.S. housing market.

There are multiple benefits of using MLS data. First, MLS data provides almost complete coverage of housing transactions in the United States. As a result, we use MLS data whenever feasible to perform event-level analyses. Second, MLS data spans from 2000 to 2022, covering both periods of economic expansion and contraction. This allows us to examine heterogeneity effects in both hot and cold market conditions. The extended time frame of the MLS data provides a unique perspective on market dynamics.

To ensure the relevance and quality of our study, we have implemented a set of standard filters on the property listings. First, we restrict our analysis to single-family homes, multi-family homes (2-4 units), condos, coops, and townhouses. Second, we exclude foreclosures and short sales from our sample, as they may have different market dynamics than regular sales. Since our research primarily centers around housing prices, we have only retained observations with the non-missing initial list prices. Other cleaning of the data is described in [C.2](#). After applying these filters, our final dataset comprises 33,247,837 unique properties and 64,820,263 events across 50 states and Washington D.C. in the U.S. for the period between 2000 and 2022. [Figure B1](#) illustrates the geographic distribution of transactions in our final dataset at the county level. The majority of events in our sample are concentrated on the West and East Coasts, as well as in important population centers.

2.3 Institutional Background of Redfin Data

To complement the event-level data with information on buyer-seller interactions, we use confidential offer-level housing market data from Redfin. Redfin is a ‘full-service’ brokerage that combines the traditional brokerage system of providing in-person agents with a sophisticated online interface. It generates revenue by assisting users in buying or selling homes through its platform and hiring agents to aid with the process. It was one of the first online real estate brokerages to employ map-based search in 2004, before the introduction of Google Maps. Since going public in 2017, it has become one of the major real estate web portals in the United States. Redfin hires agents for both the buyer and seller sides.

The typical procedure for a buyer to make an offer through Redfin is as follows. If a Redfin customer is interested in buying a house, Redfin provides an agent to the buyer at no expense. This is the typical market structure where the buyer agent is often a sub-agent of the seller agent.⁶

⁶There is extensive literature on the role of agents and the MLS in the U.S. housing market. See [Han and Strange](#)

Redfin suggests buyers apply for a pre-approval of a mortgage first. Once the lender approves, the buyer is encouraged to book home tours. The tour can be in-person or through video chat. Then the buyer can reach out to an agent to start an offer. The buyer can adjust their existing offer directly, or, if the offer is rejected, the buyer may submit a second offer to the same property. Figure B2 depicts the panel seen by a prospective buyer when starting an offer on Redfin. The buyer does not pay agent commissions, and the seller pays the agent commissions for both sides.⁷

We use Redfin data in our study to examine the bargaining process in the housing market. However, it should be noted that our data only captures a portion of this process. Specifically, our data is buy-side, meaning that we are only able to observe events that involve at least one Redfin-represented buyer. Within these events, we can observe every price initialization/revision made by the seller on the MLS, as well as the offer price(s) submitted by Redfin on behalf of the buyer(s). Nonetheless, offers submitted by other buyer agencies are not observable. Despite this limitation, Redfin records a proxy for the number of offers submitted by other potential buyers. Furthermore, while we cannot observe private negotiations, we can ascertain whether the buyer represented by Redfin is successful in purchasing the property or not. In the case of rejection, we are able to see the recorded reason for rejection. Even if the offer is rejected, Redfin records sales price data. In fact, we have sales price data for approximately 90.9% of all property listings in our dataset.

Our Redfin data spans across 45 states from January 1, 2012, to December 31, 2022. We conduct a similar data cleaning process as we do for MLS, which is described in detail in Appendix C.3. The dataset encompasses 296,640 bargaining events and 293,793 unique properties listed on Redfin. As depicted in Figure B3, our dataset covers a wide area of major cities, with a notable emphasis on the West Coast, where Redfin was initially founded and expanded into. Our sample also includes significant population centers like Texas and Florida. However, our analysis excludes New York due to the Real Estate Board of New York’s (REBNY) aggregation of listing data, which precludes the collection of the requisite listing data.

(2015), Benjamin et al. (2007), Miceli et al. (2007), Zietz and Sirmans (2011) for more details. A related paper that looks at the role of mediation in bargaining outcomes in the used-car market is Larsen et al. (2020). We do not focus on this aspect of the market in this paper, but we control for buyer agent fixed effects throughout our analysis.

⁷The seller pays the listing and buyer agents’ commissions. Redfin charges 1.5% of the sales price as the listing commission. This listing commission can be as low as 1% if the seller continues buying her next home with Redfin within 365 days of selling her property. Meanwhile, the buyer pays for the closing costs of this transaction, which covers expenses like taxes, lender fees, and title insurance. See Appendix D for more details about the fee structure.

2.4 Data Description

Table 1 provides the summary statistics for the MLS dataset. The sample consists of 64,820,263 housing bargaining events in the U.S. from 2000 to 2022. On average, properties were initially listed at \$345,203. The ensuing average sales price stands at \$334,799, which is 96.12% of the initial list price. The average days-on-market (DOM) is 58.63. We define a *bidding war* as a scenario where the sales price surpasses the initial list price by over \$100.⁸ Conversely, a *negotiation* is characterized by a sales price that falls more than \$100 below the initial list price. Within our MLS sample, bidding wars constitute 22% of the listings, whereas negotiations account for approximately 63%. The remaining listings are those with minimal price deviations. The dataset predominantly comprises single-family homes and townhouses, representing 93% of all listings. The typical property in the sample is characterized by an average age of 35.19 years, with three bedrooms and two bathrooms, encompassing an average living area of 1,886 square feet.

Table 2 provides summary statistics for the Redfin dataset. Panel A presents the summary statistics at the event level. The list price revision history from the Redfin data allows us to have a more detailed look at the list price dynamics during the bargaining. The average initial list price of a property is \$555,149. We can also observe the final list price of the house before it was taken off the market. The average final list price is \$548,631. This suggests that, on average, property sellers tend to reduce their initial asking price by around \$6,518 throughout the listing period. Of these bargaining events, 27% have the listing prices revised at some point by the sellers during the listing duration. The average number of price revisions is 0.51, with more than half of the events having no list price revision. Note that the list price in the Redfin sample is much higher than that in the MLS sample primarily because the Redfin data mainly covers large cities and comes from a period of housing market boom (post 2012).

The average sales price is \$573,579, which is higher than the initial list price. This indicates that unlike in the MLS data, bidding wars dominate the Redfin sample. It is worth noting that 7.53% of the events in our sample have a missing sales price, which corresponds to the events without a successful final sale. Looking at other variables in Panel A, we observe that the average time a property spends on the market is 37.26 days, shorter than that in the MLS data.

Panel B of Table 2 shows the summary statistics at the buyer-offer level. The total number of buyer offers recorded in our dataset is 314,829. The average buyer offer price is \$552,284, which is \$1,011 higher than the average list price at the time of making the offer (called ‘current list price’).

⁸A detailed rationale behind this definition is discussed subsequently.

In particular, among all offers, 41% of the offer are upward adjustments over the list price, while 39% of the offers are downwards adjustments to the list price. The remaining share corresponds to the offers which deviate from the list price by no more than \$100. When a Redfin buyer makes an offer during a bargaining event, the buyer-side agent records the number of additional offers made at the time, including offers made by buyers not represented by Redfin. 60% of all offers have at least one competing offer at the same time. On average, there are 3.71 additional offers competing with the offer made by Redfin. Redfin also documents the final status of each offer submitted by Redfin-represented buyers, including whether the offer is closed successfully and the reason why an offer fails. The top reason for rejection is “competing offer”, accounting for 45% of all offers. The second most common reason is an “unsatisfactory price” being submitted, that accounts for 10% of all offers.

3 Descriptive Patterns of Rounding-Off Heuristics

We start by examining rounding-off behavior at the event level.⁹ We use the more comprehensive nationwide MLS data and, wherever relevant, relate it to findings documented in the existing literature.

Our examination of the MLS data reveals persistent bunching around “special” prices. One “natural” way to define the special prices is by looking at the number of *ending zeros* at the end of prices. Figure 2 shows the number of ending zeros for each initial list price bin of \$100,000, for prices in the range \$100,000 - \$999,999.¹⁰ We see a significant fraction of list prices in each range having 3 or more ending zeroes. As the initial list price increases, the number of ending zeroes also increases. This makes it important to control for the list price in regressions when tracking the effect of these rounding-off heuristics.

However, there are several drawbacks of using the number of ending zeroes to characterize the rounding-off heuristics in the housing market. First, in high-stakes market having some ending zeroes is common. For example, it would not be considered abnormal to have a house listed at \$432,000. We need to determine whether there are systematic patterns in the density of price choices in the data, with respect to “special price” heuristics. Second, as we will see, it is not only with ending zeroes that we can correctly classify the choice of special price heuristics. A significant

⁹Recall that an event is the full sequence of actions starting from initial listing to final sales.

¹⁰We restrict the range from \$100,00 to \$999,999 because all prices have 6 digits within this range. Therefore there are no mechanical effects of fewer/more digits in the price leading to fewer/more zeroes.

fraction of sellers also use charm prices (e.g. 449,900), which we will formally define below.

To address the drawbacks of using the number of ending zeroes, we carefully examine the distribution of prices, of the initial list price and the final sales price of properties in the MLS sample, as shown in Figure 3.¹¹ Each bar here represents a \$1k price range.¹² Panels (a) and (c) plot the distribution of the initial list price and final sales price in the price range of \$100k-\$1m. Panels (b) and (d) are the zoomed-in versions of Panels (a) and (c), restricted to the price range of \$300k-\$500k.¹³

Based on Figure 3, it is evident that prices are not smoothly distributed. Instead, both the initial list prices and final sales prices tend to cluster around specific “special” values, particularly around multiples of \$50k. For example, Panel (b) shows that roughly 1.2% of the initial list prices cluster around \$400k, whereas less than 0.1% of the observations cluster around \$402k to \$404k. Similarly, there is significant bunching around other multiples of \$5k, although not as pronounced as that around multiples of \$50k. A similar phenomenon can also be observed in the final sales price.

While clustering exists in the distributions of both initial list prices and final sales prices, an important difference between the two is that most of the bunching in final sales prices occurs *at* exactly round numbers. In contrast, initial list prices bunch at numbers slightly below exactly round numbers (so-called “charm numbers”). This suggests that during the bargaining process, there are mass shifts from charm prices to round prices.

To explain this difference, we further analyze the dynamics between the initial list price and the final sales price. Specifically, for a given level of initial list price, we are interested in the resulting final sales price. Figure 4 shows this connection between the initial list price and the final sales price through heatmaps. We first calculate the “discount” of each observed listing, defined as the difference between the initial list price and the final sales price. Then, for each level of initial list price, we provide the share of observations at each discount level, normalized within each initial list price column. Therefore, the observation shares from each column sum up to 1, where each column corresponds to \$1k price range. We remove observations with discounts close to zero, in the range [-\$500,\$500), to provide a clearer illustration.

The results reveal that at any given initial list price level, most final sales prices tend to round down to a special number. This pattern is robust across all price ranges. In Figure 4, this is depicted

¹¹For robustness check, Figure B6 shows the same set of plots using Redfin data.

¹²In this paper, “k” is used to represent thousands and “m” is used to denote millions.

¹³In the appendix, Figures B7 and B8 show the zoomed-in plots over other price ranges.

as the salient 45-degree lines that strikingly end on a round number. For example, the 45-degree line passing through \$400k corresponds to observations that round towards \$400k in the final sales price. The heatmap cannot be used to conclude that there is more clustering on specific special prices — a fact we already learned from Figure 3 — because we normalize observations *within* each column. However, the heatmap helps us understand the dynamic movement of prices from the initial list price stage to the final sales price. Another finding from the heatmaps is that, as the initial list price increases, as we go from panels (a) to (h) of Figure 4, the 45-degree lines crossing the horizontal axis at multiples of \$50k become more salient. This implies that the rounding levels increase with the initial list price, a finding we verify later.

However, the event-level prices cannot provide further insights into the dynamics of the bargaining process. We must dig into the action-level interactions between buyers and sellers to understand why we observe the mass shifting from charm prices to round prices. Taking advantage of the offer-level data from Redfin, we document the rounding-off behavior among buyers and sellers at the action level. Figure 5 plots the price distributions from buyers and sellers at the action level. Each bin spans \$1k. Panels (a) and (c) show the distribution of the buyer’s offer price and the seller’s list price, respectively. Panels (b) and (d) are the zoomed-in versions of panels (a) and (c) in the price range of [\$300k,\$500k] dollars. Similar to the distribution of prices at the event level, panels (a) and (c) show that the highest densities for both offer and list prices are around the multiples of \$50k. The second highest set of densities is around multiples of \$5k.

Comparing Figure 3 with Figure 5, we find that the clustering patterns of buyer offer prices are more similar to final sales prices at the event level. In particular, buyer offer prices cluster at exactly round numbers, instead of charm numbers. Therefore, the shifts from charm prices in initial list prices to round numbers in sales price are driven by the strong preference for buyers to choose round numbers.¹⁴

Although the distribution reveals insights into the “special values” where the prices cluster, we need a systematic way to group the special values observed in the data. To do this, we determine the natural rounding levels in the housing market by analyzing the distribution of the rightmost digits of prices. Figures 6 and 7 plot the distribution of the three and four rightmost digits of prices.¹⁵ Figure 6 shows the distribution of the rightmost digits of the initial list price and the final sales price using the MLS sample. Panels (a) and (b) use three rightmost digits of the price on the

¹⁴ Additionally, the relatively smoother distribution seen in final sales prices comes from buyer offer price choices.

¹⁵ No additional patterns are revealed when looking at the 5 rightmost digits.

x-axis. For example, 000 refers to the prices with at least three ending zeros. 901-999 refers to the prices where the three rightmost digits are in the range 901-999, both boundaries included (e.g., \$350,901 to \$350,999). Panel (a) shows that half of the initial list prices in the MLS have at least three ending zeros. Separately, more than 30% of all observations end with 900. This contributes to the “charm” prices, which are the prices slightly below exact round prices, in Figure 3. For the final sales price, Panel (b) shows that approximately three quarters of final sales price have at least three ending zeros. However, it should be clear that while the large number of observations of prices ending with digits in the range of 901-999 is insightful (telling us about the existence of “charm prices”), having a large number of observations with 3 ending zeroes is not. This is because multiples of \$1k are the common standard in the housing market data, with only a few remaining combinations (e.g., “000”, “500”, “900”) with non-trivial mass. We need to investigate further.

To expand the granularity of our analysis, we examine the distribution of the four rightmost digits of the listed prices, as shown in Panels (c) and (d). This enables a more nuanced understanding of pricing strategies. Notably, there is pronounced concentration at multiples of \$5k and \$10k. The initial list prices predominantly end in the range of 9001-9999, with about 25% of observations falling within this bracket, a trend absent in final sale prices. Intriguingly, within the 9001-9999 bracket, a significant 76.36% of listings are priced at 9900. A similar concentration is observed in the 4001-4999 range, where 75.48% end in 4900. This observation informs our definition of “charm” prices as those slightly below a round figure by up to \$100. Apart from round and charm prices, initial listings show a distinct aggregation at the 9000 mark. This pattern, however, is not mirrored at the 4000 level. Therefore, we categorize these as “special 9k” prices, representing a significant clustering distinct from both round and charm prices. Finally, note that the final sales price distribution of rightmost 4 digits is different from the initial list price distribution of rightmost 4 digits. Figure 7, which shows the distribution of rightmost digits of offer prices at the action level using Redfin data, also exhibits a similar trend as the final sales price.

Given the above observations, we will focus on round, charm, and special 9k prices at the rounding level of \$5k. To allow for heterogeneous effects at different rounding levels, we define the prices at rounding levels of \$5k, \$10k, \$50k, and \$100k, so that they are mutually exclusive. Formally, define the set of rounding levels as $\mathcal{X} := \{5k, 10k, 50k, 100k\}$. For notational convenience, we use $x|p$ to denote “ p is a multiple of x ”.

Definition 1. (Round Price) We define a price p to be a **round price at rounding level** $x \in \mathcal{X}$ if p is a multiple of x but not a multiple of a higher rounding level. We use $R_x(p)$ to denote whether

price p is a round number at x . Formally, for all $x \in \mathcal{X}$,

$$R_x(p) := \mathbb{1} \left\{ \begin{array}{l} x|p, \text{ and} \\ R_{\tilde{x}}(p) = 0, \forall \tilde{x} \in \mathcal{X} \text{ with } \tilde{x} > x \end{array} \right\}$$

For example, \$450k is a round number at \$50k level, but not a round number at \$100k, \$10k, or \$5k level.

Definition 2. (Charm Price) We define a price p to be a **charm price at rounding level** $x \in \mathcal{X}$ if p is at most \$100 away from a multiple of x , and if p is not a charm price at higher rounding level. We use $C_x(p)$ to denote whether price p is a charm number at x . Formally, for all $x \in \mathcal{X}$,

$$C_x(p) := \mathbb{1} \left\{ \begin{array}{l} \exists a \in (0, 100] \text{ s.t. } x|(p+a), \text{ and} \\ C_{\tilde{x}}(p) = 0, \forall \tilde{x} \in \mathcal{X} \text{ with } \tilde{x} > x \end{array} \right\}$$

Definition 3. (Special 9k Price) We define a price p to be a **special 9k price at rounding level** $x \in \mathcal{X}$ if p is exactly \$1,000 away from a multiple of x , and if p is not a special 9k price at higher rounding level. We use $S_x(p)$ to denote whether price p is a special 9k number at x . Formally, for all $x \in \mathcal{X}$,

$$S_x(p) := \begin{cases} 0 & \text{if } x = 5k \\ \mathbb{1} \left\{ \begin{array}{l} x|(p+1k), \text{ and} \\ S_{\tilde{x}}(p) = 0, \forall \tilde{x} \in \mathcal{X} \text{ with } \tilde{x} > x \end{array} \right\} & \text{if } x \in \mathcal{X} \setminus \{5k\} \end{cases}$$

Note that as special 9k price does not exist at \$5k level, when $x = 5k$, the indicator is always zero.

To make the definition more concrete, Table A2 shows the example classification of prices around \$450k into the format group we defined above. We term all other prices as **precise price**.

With the “special” prices defined, Table A3 presents the groupwise summary statistics based on the price format group and the associated rounding level. The data is divided into four panels based on the pricing strategy used: round prices, special 9k prices, charm prices, and precise prices. In Panel A, we see that there are more observations for finer rounding levels, conditional on the initial list price being a round number. The finest (\$5k) rounding level accounts for approximately 58% of all observations with a round initial list price. However in Panel B and C, conditional on

the initial list price being a charm number or special 9k, there is no such pattern.

The subsequent columns in each panel offer further insights into successful events. The first of these columns presents the initial list price for different groups, which enables us to examine the relationship of the initial list price with the chosen listing strategy, which is the first step in the bargaining process. We use deflated prices to control for the effect of inflation over time. In general, listings with round initial prices or special 9k have higher initial list prices compared to charm prices. This relationship is true at every rounding level. Within each panel, the groups with the highest average initial list price are at the \$100k level for all three special price groups. Comparing the average initial list price within each panel, the average initial list price increases with the rounding level, consistent with our observation in Figure 2. This pattern persists using sales price, as well as the unit sales price.

Other variables also exhibit distinct patterns. Round initial list prices are associated with fewer days on the market compared to special 9k, charm, and precise prices. However, there is very little difference within each panel. In terms of the probability of getting into a bidding war or negotiation, round initial list price is associated lower chance of negotiation. These patterns have been described in terms of pricing strategy (charm, round etc) and the rounding level (100k, 50k etc). However, arguably the most interesting question is whether the pricing strategy and rounding level of two similar houses produces any effect on various outcomes. In the regressions in the next section, we control for list prices so that the comparison will be between similar houses with similar prices but different price strategies, say round versus charm.

4 Empirical Findings

4.1 Sellers' Rounding-off Behavior and Consequences

In this subsection, we examine how sellers' use of rounding-off heuristics affects outcomes of interest in the housing bargaining process. Furthermore, we use our buyer offer level data from Redfin to understand how buyers react to different list price formats used by the sellers and shed light on underlying mechanisms.

To study the welfare implications for different list price formats used by sellers, we utilize the comprehensive MLS dataset of listing events by the sellers. We run the following specifications at

the event level:

$$Y_{i,t} = \sum_{x \in \mathcal{X}} [\theta_x R_x(p_{i,t}) + \psi_x S_x(p_{i,t}) + \beta_x C_x(p_{i,t})] + g(p_{i,t}) + X_{i,t}\gamma + \tau_{l(i),t} + \alpha_i + \varepsilon_{i,t} \quad (1)$$

where $Y_{i,t}$ is the event-level outcome of property i initially listed at time t . $p_{i,t}$ is the initial list price of property i initially listed at time t . $R_x(p_{i,t})$, $S_x(p_{i,t})$, and $C_x(p_{i,t})$ are the dummies for whether $p_{i,t}$ is a special price. In our descriptive evidence, we find that sellers are more likely to round off higher list prices. We therefore have to account for the correlation between the initial list price and list price precision formats. Specifically, we use $g(p_{i,t})$, which is the restricted cubic spline of log initial list price, to provide a flexible control of this correlation. Crucially, α_i denotes the individual property fixed effects. Hence, we use repeat sales of the same properties to control for any observable and unobservable time-invariant characteristics of a property that may affect its sales price. In addition, we also control for the time-varying housing characteristics of property age, denoted by $X_{i,t}$. $\tau_{l(i),t}$ denotes the location-time fixed effects that account for time-varying heterogeneity across different geographic areas. These effects allow us to control for fluctuations and seasonality in the housing market at a granular geographic level. In our main specification, we adopt calendar year-month by Zip Code fixed effects. Robust standard errors are clustered at the property level.

Our coefficients of interest are θ_x , ψ_x , and β_x . Under a repeat sales design, we estimate the effects of using different list price formats on the outcomes of bargaining, by comparing identical properties sold at different listing events at nearly identical list prices, with the only difference being whether the sellers use round, charm, special 9k, or precise list prices. Because we are always comparing identical products listed at nearly identical prices, we rule out an important confounding factor that sellers who systematically misprice their homes tend to use a certain list price format. For example, it is possible that sellers who use round list prices tend to overshoot their list prices if we were to compare *different* homes with similar list prices but with different list price formats. For greater legibility, the regression specification is always Equation (1) but result plots and figures that we present in the coming sections focus on coefficients on charm and round prices. The appendix has the full set of coefficients, including for special 9k prices.

Figure 8 estimates Eq. (1) at the event level using all repeat-sales transactions in the MLS during 2000–2022. We first examine the likelihood of discount for each listening event. Recall that the discount is the difference between the initial list price and the sales price. Panel (a) of Figure

8 shows the regression result using a dummy of whether the listing event ends up with a trivial discount as the dependent variable. A trivial discount is defined as a discount with an *absolute* value of no more than \$100. We find that all coefficients are significantly positive compared to the benchmark group of precise prices. In other words, special list prices lead to sales prices that are very close to the listed price. Therefore, at least part of the role special list prices play seems to be to make the seller’s valuation of the house more salient to the buyer, anchoring the final sales price close to the initial list price. In trivial adjustment cases, charm prices typically see a round-up to the nearest round number in these cases (431,900 to 432,000). Round prices typically see final sales price at the same value as the round initial list price.

While trivial price changes are an important part of the housing bargaining process, they do not constitute more than 20% in any category of price format. Conditional on the discount being non-trivial, Panel (b) of Figure 8 examines if the transaction leads to a bidding war. We see that all categories of special price formats lead to a lower chance of bidding wars. In addition, there is no significant difference between the likelihood of a bidding war in round or charm prices at the same rounding level.

To further examine other event-level outcomes, Panel (c) of Figure 8 plots the coefficients using log of sales price as the dependent variable. What is fascinating here is that there is a distinct difference between the effect of round and charm prices even while both types of price formats lead to lower sales price. Round prices lead to much lower sales price at the same rounding level. At the \$100k level, for example, round initial list prices lead to a 0.40 percentage point decrease in the final sales price. This effect represents a \$1,133 ($0.4\% \times \$283,360$, the average sales price of events with precise list prices) lower sales price, compared with the omitted group of precise list prices. The decrease in sales prices amounts to 11.4% of the typical discount-off events with precise list prices. In comparison, at the \$100k level, charm initial list prices only lead to a 0.06 percentage point decrease in the final sales price, which is \$170 or 1.7% decrease in the final sales price than the group with precise list price. This suggests that the charm-price strategy outperforms the round-price strategy in terms of influencing sales prices.

However, it may be possible that a lower sales price is traded off for a faster time on the market. Apart from the sales price, we also estimate the effect of rounding-off behavior on days-on-market (DOM) which measures the speed of transaction in Panel (d) of Figure 8. We find that round prices actually take a longer time on the market than charm prices at every rounding level. Round price listings at the \$100k level, for example, spend 2.17 days less on the market than precise price

listing. This accounts for $2.17/58.81 = 3.7\%$ faster than the average DOM for precise listings.

Combining the effects of round/charm list price on the event level outcomes, we find that in general, both round and charm list prices lead to lower DOM with the tradeoff of a lower sales price and lower chance of bidding war. However, round price listings seem to be strictly dominated by charm price listings. Specifically, the round list price leads to lower sales prices without generating faster sales or a higher chance of bidding wars in general.

[Backus et al. \(2019\)](#) document using eBay bargaining that sellers who list items at exact multiples of \$100 accept a lower price in exchange for a quicker sale. They propose the “Cheap-talk” hypothesis which argues round list price is a rational strategy by the sellers to signal their weak bargaining position to buyers. Round list prices are cheap-talk signals that the sellers are impatient and willing to accept a lower sales price in exchange for a faster sale. Compared with eBay bargaining, housing bargaining involves much higher stakes, which potentially explains why our results differ. In our setting, round list prices yield lower sales prices without a faster sale compared to charm prices, hence strictly dominated. This violates the incentive-compatibility constraint for the signaling strategy in a separating equilibrium.

However, as we observe in the data, there is still a non-trivial amount of sellers who choose exact round prices when setting the initial list price. This cannot be explained by our observations so far. Is it because these sellers are irrational or there exists some trade-off unexplored by our analysis? To answer this question, we explore the heterogeneous effect of the pricing strategy from an ex-post perspective. We split the sample based on whether the event ends up as a bidding war or negotiation. Then, we estimate Eq. 1 using the subsample.

Panels (e) and (f) of Figure 8 show the regression results using log sales price and DOM as the dependent variable, respectively. While the DOM exhibits similar results in the bidding war and negotiation case, the effect of price format on the final sales price diverges. First, the general pattern. Special prices lead to a higher sales price in a bidding war while a lower price in negotiation. More closely, we see that round prices perform more poorly than charm prices in negotiations. In bidding wars, round prices do about as well as charm prices. Combining these observations, there isn’t much advantage to using round prices even in the bidding war scenario.

To further understand why the charm list prices dominate round list prices, we go to the offer level data from Redfin to examine how the rounding-off behavior affects outcomes during the

bargaining process. We use the following regression specification at the buyer-offer level:

$$Y_{j,t} = \sum_{x \in \mathcal{X}} [\theta_x R_x(p_{j,t}) + \psi_x S_x(p_{j,t}) + \beta_x C_x(p_{j,t})] + g(p_{j,t}) + X_{j,t}\gamma + \tau_{l(j),t} + \xi_{a(j),t} + \varepsilon_{j,t} \quad (2)$$

Here, $Y_{j,t}$ is the dependent variable of offer j in response to the current list price at time t . The variables $R_x(p_{j,t})$, $S_x(p_{j,t})$, and $C_x(p_{j,t})$ are binary variables indicating whether the current list price $p_{j,t}$ is a round or a charm number, respectively, at the rounding level x . Similar to Eq. 1, we control for potential confounding variables, including the cubic spline of log current list price $p_{j,t}$, and a set of housing characteristics in $X_{j,t}$ including property type, log of square foot, number of bedrooms and bathrooms.

To account for unobserved factors, we augment our model by including a set of fixed effects. We introduce the location-by-time fixed effects $\tau_{l(j),t}$, where $l(j)$ indicates the location of offer j . These effects allow us to control for nationwide and regional housing market fluctuations and the seasonality in the housing market. Additionally, we incorporate the year-by-agent fixed effect $\xi_{a(j),t}$ to control for time-invariant characteristics of agents and the impact of their experience over time.

Figure 9 shows the estimating results of Equation (2) using offer outcomes and competition measures as dependent variables. The dependent variable in Panel (a) is a binary variable indicating whether the offer directly leads to a successful house purchase. The regression results of Panel (a) show that generally, both the round and the charm current list prices are negatively associated with a buyer's success probability. On average, a round current list price at the \$100k level is associated with a decrease in buyer's success by 3.1 percentage points. However, the reduction for charm prices is smaller, by 1.1 percentage points at the \$100k rounding level. The same difference in success rates are observed for the \$5k level as well. For other levels, the point estimates suggest a similar story but their confidence bands overlap.

While it is difficult to isolate the mechanism of how the rounding-off behavior of a seller affects the buyer's success probability, we can partly trace out the mechanism by exploring the reasons for offer failures. In principle, conditional on the sample where the offer failed, the mechanism that drives the negative correlation between the buyer's success rate and the round list price will have an opposite effect when using the corresponding reason for failure as the dependent variable. Panel (c) of 9 shows that i) both round and charm price leads to higher share of offers failed due to competition; ii) this is more so for round price than charm price. Panel (d) confirms that the failures are not due to unsatisfactory price. Finally, the hypothesis can be tested more directly

from Panel (b) of Figure 9 which uses the total number of offers as the dependent variable. It confirms the competition story. Furthermore, round prices induce more offers than charm prices.

4.2 Buyers Reciprocate with the Same Price Format and Rounding Level

So far, we have shown that both round and charm list prices lead to lower sales prices and faster sales. Round list prices induce more buyer offers and lead to a lower success probability per buyer offer.

In this subsection, we examine how buyers react to the different list price formats used by the sellers as a consequence of sellers' list price strategy. The first question is whether buyers are more likely to choose an offer at the same round level with the same price format (round vs. charm) when the seller chooses a round or charm list price than when the seller chooses a precise price.

To answer this question, Table 3 presents the regression results of Eq. (2) using the indicator of the round offer price at a specific level as the dependent variable. This implementation helps us to identify, at a given level of round/charm current list price, what is the rounding level that the buyer is more likely to use. Specifically, the dependent variable of the regression shown in Table 3 is whether the buyer offer price is a round number at the rounding level $x \in \mathcal{X}$, where x is \$100k in Column (1), \$50k in Column (2), \$10k in Column (3), and \$5k in Column (4).

The results from Table 3 show that there exists a strong correlation between the rounding levels of buyers and sellers. We call it the coordination of rounding levels between buyers and sellers. In particular, the diagonal entries of the coefficient table are significantly positive and very large in magnitude compared with off-diagonal elements. This suggests that when the current list price is a round or charm number at a certain level, the buyer is more likely to make a round-price offer at that same level. For example, the first coefficient in Column (1) implies that having a round current list price at multiples of \$100k increases the probability of the offer price being a round number at \$100k by 17.7 percentage points. Regarding the off-diagonal elements, most of the off-diagonal elements for the round current list price indicators are also significantly positive. However, this effect is not evident for charm prices. The results are consistent using the initial-list sample with small differences in the magnitude of the coefficients.

To identify the mechanisms that drive the coordination of rounding levels, we exclude certain observations to see whether the coordination persists. It is plausible that the coordination of rounding levels is driven by small adjustments relative to the list price. Formally, we define buyer

price adjustment as the difference between the buyer offer price and the current list price.¹⁶ There are two cases of particular interest.

1. Case 1: A current list price is a round number, and the buyer proposes an offer with zero price adjustment. Then, the buyer offer price will mechanically be a round number.
2. Case 2: A current list price is a charm number, and the buyer makes a trivial upward adjustment such that the offer is the nearest round number of the list price.

If small adjustments drive coordination of rounding levels, removing the observations with only small adjustments will reduce the magnitude of the diagonal coefficients significantly. Indeed, the regression results from Table 4 confirm this hypothesis. Specifically, we restrict the sample to observations with an adjustment greater than \$100 in absolute value, which rules out both Case 1 and Case 2 above.¹⁷ Comparing Table 3 with Table 4, removing the observations with trivial adjustments significantly decreases the magnitude of diagonal coefficients. These results confirm that buyers’ tendencies to make counteroffers with zero or trivial adjustments when they respond to an exact round or charm list price drive most of the coordination in rounding between buyers and sellers during bargaining that we observed before.

4.3 Anchoring Effect of Round/Charm List Price

We have seen that trivial adjustments play a key role in explaining the reciprocation between rounding precision and level between buyers and sellers. Does this mean that the offer prices are closer to the list prices in general when sellers use round/charm list prices? To answer this question, we first need to establish a better understanding of the direction and magnitude of the buyer price adjustment. In terms of direction, an upward adjustment indicates a bidding war, where the buyer’s offer price is above the current list price of the property. On the other hand, a downward adjustment signals bargaining, where the buyer is negotiating down the list price. Regarding the magnitude of the adjustment, we split the sample by whether the absolute value of the adjustment is above or below \$100, defined as “trivial adjustments”.

The results presented in Table A4 provide insight into the direction and magnitude of the buyer price adjustment, given the type of current list price. The table is divided into three panels, each representing a different type of current list price: round current list price, charm current list price,

¹⁶The current list price is the list price at the time of buyer offer.

¹⁷We use \$100 in absolute value so that the exclusion is symmetric. However, a breakdown in A4 shows that most of the non-zero trivial (i.e., adjustment is no more than \$100 in modulus) adjustments correspond to Case 2.

and the control group of precise current list price. For each panel, the table reports the percentage of observations with a downward adjustment greater than 100, upward adjustment greater than 100, downward adjustment less than or equal to 100, zero adjustments, and upward adjustment less than or equal to 100. For example, in Panel C, conditional on the seller using a precise list price, approximately 55% of the buyer offers have a downward adjustment of more than 100, while 28% have an upward adjustment of more than 100. On the other hand, around 17% of the observations have a downward adjustment of less than or equal to 100, and approximately 0.15% have an upward adjustment of less than or equal to 100. Each row sums up to \$100.

Table A4 shows that, compared with precise list prices, round list prices are less likely to induce non-trivial downward adjustments, while the charm current list prices are slightly more likely to induce non-trivial downward adjustments from buyers. Specifically, about 55% of buyer offers responding to precise list prices involve a non-trivial downward adjustment. This number is approximately 50% for the group of round list prices and 56% for the group of charm list prices. Regarding non-trivial upward adjustments, while there is no significant difference between panel A and panel C (28%), the share of buyer offers with a non-trivial upward adjustment conditional on the current list price being a charm number is much lower (about 20% depending on the rounding level). Overall, these results suggest that a round list price will reduce the chance for a buyer to make a non-trivial downward adjustment, while a charm current list price will reduce the chance for a non-trivial upward adjustment. However, we also see that more buyers tend to choose trivial adjustments conditional on round/charm list price. Therefore, the overall effects are ambiguous.

To formally test the correlation between the magnitude of adjustment and sellers' rounding-off behavior, Figure 10 presents the regression results of estimating Eq. (2) with the measures of the magnitude of buyer adjustment as dependent variables. The outcome variable is the adjustment in Panel (a), and the adjustment rate in Panel (b), i.e., the magnitude of adjustment divided by the current list price. Since both buyers' and sellers' behavior can be very different in the scenario of bidding wars (with non-trivial upward adjustments), and bargaining (with non-trivial downward adjustments), we split the sample by non-trivial downward and non-trivial upward adjustments and present coefficient results. Trivial adjustments are not part of either of these sub-samples. A clear and strong result that emerges from both panels is that round prices induce more aggressive adjustments in both upward and downward directions, as compared to charm prices. In addition, the magnitude of the coefficients generally decreases with the rounding level, i.e., a "more rounded" price, in general, leads to greater price adjustment. The anchoring effect for round prices is indeed

weaker than for other prices.

4.4 Buyer’s Rounding-off Behavior and Consequences

So far, we have examined sellers’ rounding-off behavior and their consequences in terms of bargaining outcomes and how buyer offers respond. However, the rounding-off behavior is not unique to sellers. In this subsection, we study whether buyers’ rounding-off behavior could also have some consequences on the outcomes of bargaining.

To incorporate the buyers’ rounding-off behavior, we extend Eq. (2) as

$$Y_{j,t} = \sum_{k \in \{b,s\}} \sum_{x \in \mathcal{X}} [\theta_{x,k} R_x(p_{k,j,t}) + \beta_{x,k} C_x(p_{k,j,t}) + \eta_k \log(p_{k,j,t})] + X_{j,t} \gamma + \tau_{l(j),t} + \xi_{a(j),t} + \varepsilon_{j,t} \quad (3)$$

To the specification in Eq. (2), we add the round/charm *offer price* indicators $R_x(p_{b,j,t})$ and $C_x(p_{b,j,t})$ as the regressors of interest. Because of the existence of interactive rounding behavior, we use the round/charm list price indicators as controls. In addition to the controls used for Eq. (2), we also control for the number of additional offers and the buyer’s adjustment from the list price. The former helps to condition on the property-level market tightness and the latter captures the direction and magnitude of buyers’ bargaining intention. For the latter, we control for the price adjustment, and dummies indicating whether the adjustment is upward, downward, or zero. The set of fixed effects is the same as in the baseline model.

The most direct outcome that corresponds to the offer is the success probability. Column (2) of Table A7 presents the regression results of Eq. (3) using the indicator of successful offer as the outcome variable. The regression result shows that, on average, using a round buyer offer price at multiples of 100k reduces the buyers’ chance of success by 3.1 percentage points.

One potential reason for the differential effects between round and charm prices might be the different directions and magnitudes of the offer-price adjustment between the two groups. As indicated in Table A5, the magnitudes of price adjustment related to the round offer prices and charm offer prices are quite different. Specifically, except for the rounding level of \$1k, more than 70% of all offers with charm offer prices have zero adjustments. This share is below 30% for offers with round prices. These differential structures might significantly change the mean success probability of the group. For example, an offer with a trivial adjustment is closer to the sellers’ expected sales price and therefore has a greater chance of succeeding.

To further test whether the relationship is driven by cases with trivial adjustments, Columns

(5) and (6) further split the sample into the subsamples with non-trivial and trivial adjustments, respectively. The mean success probability of precise-price offers with non-trivial adjustments is 53.1%, lower than that of precise-price offers with trivial adjustments, which is 60.5%. This is consistent with our expectations that smaller adjustment increases the success probability of the offer. Within each group of adjustments, the success probability of charm price offers is not significantly different from precise price offers. However, the success probability for round buyer offers with non-trivial adjustments is significantly lower than that of the precise offers, conditional on the level of price adjustment.

There might be several reasons for this persistent negative effect. Similar to the signaling effect of round list price, the use of round offer price could indicate that the buyer is less informed or less sophisticated. This could make the seller less willing to negotiate or more likely to reject the offer outright. Another possibility is that a round offer may be perceived as less thoughtful and serious than a precise offer by the seller. For example, an offer of \$501,234 may be considered more thoughtful and deliberate than an offer of \$500,000. These reasons could also explain why a coarser rounding level will amplify the negative effect on the success probability, as we observe in the regression results.

The success of an offer is not the end of the bargaining. Conditional on a successful offer, how does the buyer’s rounding-off behavior affect the bargaining outcomes? We consider two other outcomes: price and speed of transaction. In terms of the price, we focus on how the behavior affects the final sales price of the property. Regarding speed, we consider two measures: the acceptance time and the private negotiation time. Acceptance time is defined as the time difference between the offer acceptance date and the offer submission date. It accounts for the time for the seller to make the acceptance decision. The private negotiation time is defined as the time difference between the final sales date and the offer acceptance date. It primarily measures the time for the private negotiation process, i.e., based on the final offer price, and how fast the buyer and the seller can agree on the final sales price.

Table A12 shows the regression results of Eq. (3) using the log of the final sales price as the dependent variable. Columns (1) and (2) show that the sales price associated with round buyer offers are significantly negative, while it is positive for charm buyer offer prices. Combined with the results from Table A11, this implies that although the round buyer offers are less likely to be accepted on average, once it is accepted, the buyer can extract more surplus from the bargaining. On the other hand, the charm buyer prices are associated with higher sales prices. After controlling

for the direction of offer adjustment in Column (3) and indicator of trivial/non-trivial adjustment in Column (4), most of the coefficients become smaller in magnitude. Taking Column (4) as an example, using a round offer price at multiples of \$50k reduces the sales price by approximately 0.23%. This effect becomes smaller as the buyer uses more refined offer prices, and becomes positive when the buyer chooses a round price at multiples of \$1k. Meanwhile, the use of charm offer prices increases the final sales price by 0.15% to 0.44%, depending on the rounding level.

Price is not the only dimension people consider during the bargaining process. From sellers' behavior, we observe a tradeoff between the sales price and TOM through the choice of round/charm list price. We examine if a similar phenomenon exists in buyers' choices. Table A13 shows the regression results of Eq. (3) using the acceptance time as the dependent variable. Acceptance time is defined as the difference between the offer acceptance date and the offer submission date. It captures the time for the seller to make a decision on the offer. The results show that the effects of round/charm offer prices on acceptance time depend on the rounding level. A coarser round number is associated with a longer acceptance time. For example, Column (4) shows that using a round offer price at multiples of \$50k increases the sellers' consideration time by 0.26 days relative to the control group. On the other hand, using a round offer price at multiples of \$1k reduces the time by 0.12 days. The impact of charm prices is negative but insignificant in most of the specifications.

While the acceptance time, in general, is very short (2.6 days for the control group on average), the private negotiation process may, on average, be more than 40 days. Does the choice round/charm buyer offer price have an effect on the private negotiation time? The idea is that the buyer's offer price is the starting point of the private negotiation process and could be an important anchor. Table A14 presents the results. Columns (1) to (4) show that the round-price offers are associated with shorter negotiation time while charm-offer prices may increase the private negotiation time. These effects are primarily driven by the non-trivial adjustment cases. One possible explanation is that round-number prices are better reference points that help both parties to achieve an agreement. These results are also consistent with our previous observations that the use of round list prices reduces the TOM of the listing compared with using charm list prices.

Overall, when the buyer proposes a round-price offer, the chance of acceptance is lower. However, once it is accepted, it might reduce the final sales price and the time to achieve an agreement. The use of charm offer prices is mostly ambiguous and indifferent from the precise offers in most cases. Despite the lower chance of success, our findings explain the wide existence of round-price

usage among buyers.

4.5 Next Steps

So far, we have analyzed the interactive rounding-off behavior and the impact of both buyers' and sellers' rounding-off behavior. Another dimension we can explore further is the heterogeneous effects of the rounding-off behavior. The effect of round number heuristics on final outcomes may vary depending on market hotness. For example, in a hot seller's market, there are more buyers per house, and buyers may be more willing to pay a premium for a property given expectations of future price increases. In that case, one would expect prices to be higher for houses. However, how round numbers differentially affect the final sales price depends on which mechanism operates the market. Similarly, in a cooler market, buyers may be more sensitive to the price, and the effect of round numbers and charm numbers on sale outcomes may further explain the mechanism at play in the choice of these salient price points.

The role of the buyer and seller agent experience may also be important for price-setting strategies. Using MLS data, we can construct agent experience measures to explicitly control agent experiences instead of controlling them through agent fixed effects. There are two types of heterogeneous effects in agent experience we can exploit. First, buyer and seller agents may change their beliefs about setting prices at round/charm prices to reduce the time-on-market of the property. This would be a learning effect. Secondly, it is possible that more experienced agents better understand the signal delivered through special prices and therefore take advantage of it. This would be a signaling effect.

Despite the set of novel descriptive findings using real-world data, the current version of the draft lacks the establishment of causality. Therefore, it is difficult to fully understand and precisely quantify the mechanisms. Given this caveat, we also plan to establish a set of causal facts through complementary experiments.

5 Conclusion

This paper studies the rounding-off heuristics in the bilateral bargaining process in the US housing market. Using an offer-level Redfin database and the nationwide MLS data, we document a set of novel empirical facts of decision makers' bargaining behaviors in this high-stake, real-world setting. Round list prices seem to be weak anchors for valuation. While on average they can lead to lower

final sales price and a longer time on the market compared to charm prices, they may lead to higher price adjustments through bidding wars, thus suggesting a strategic reason for using them.

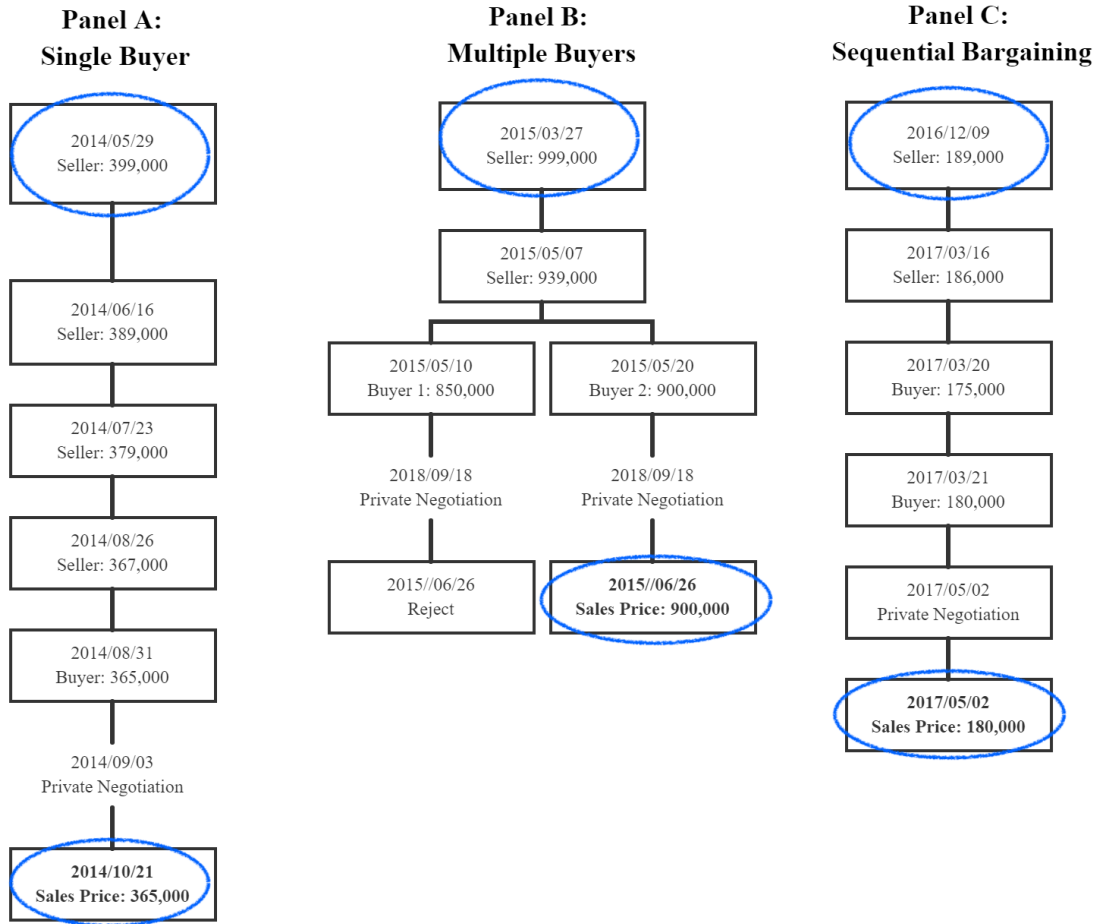
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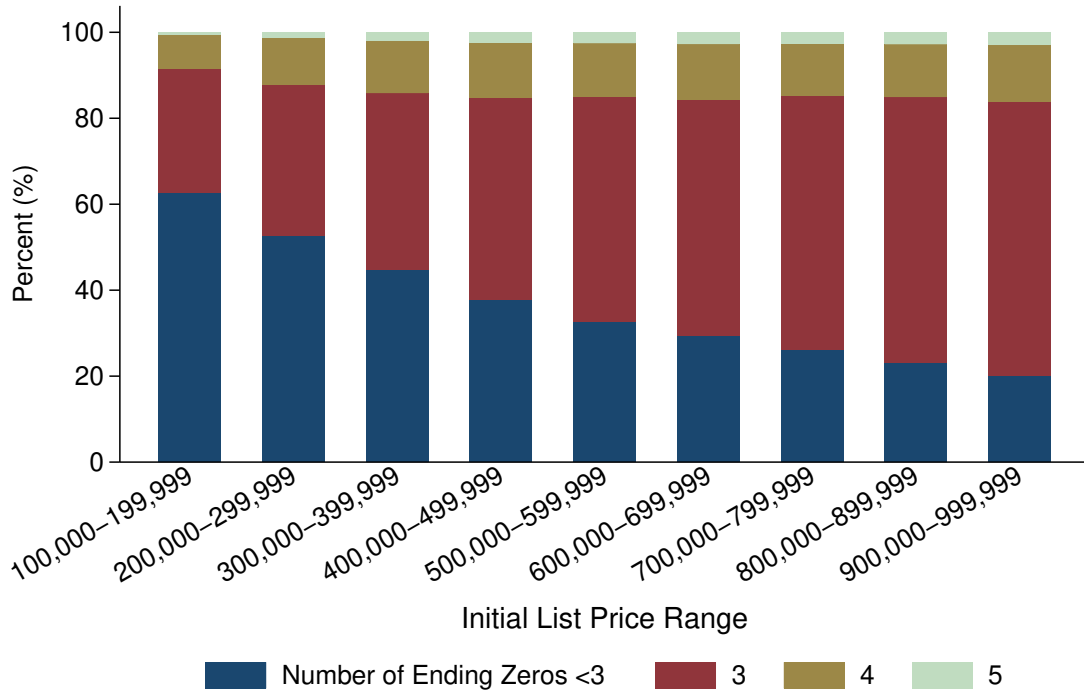
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Figure 1: Illustration of Bargaining Events



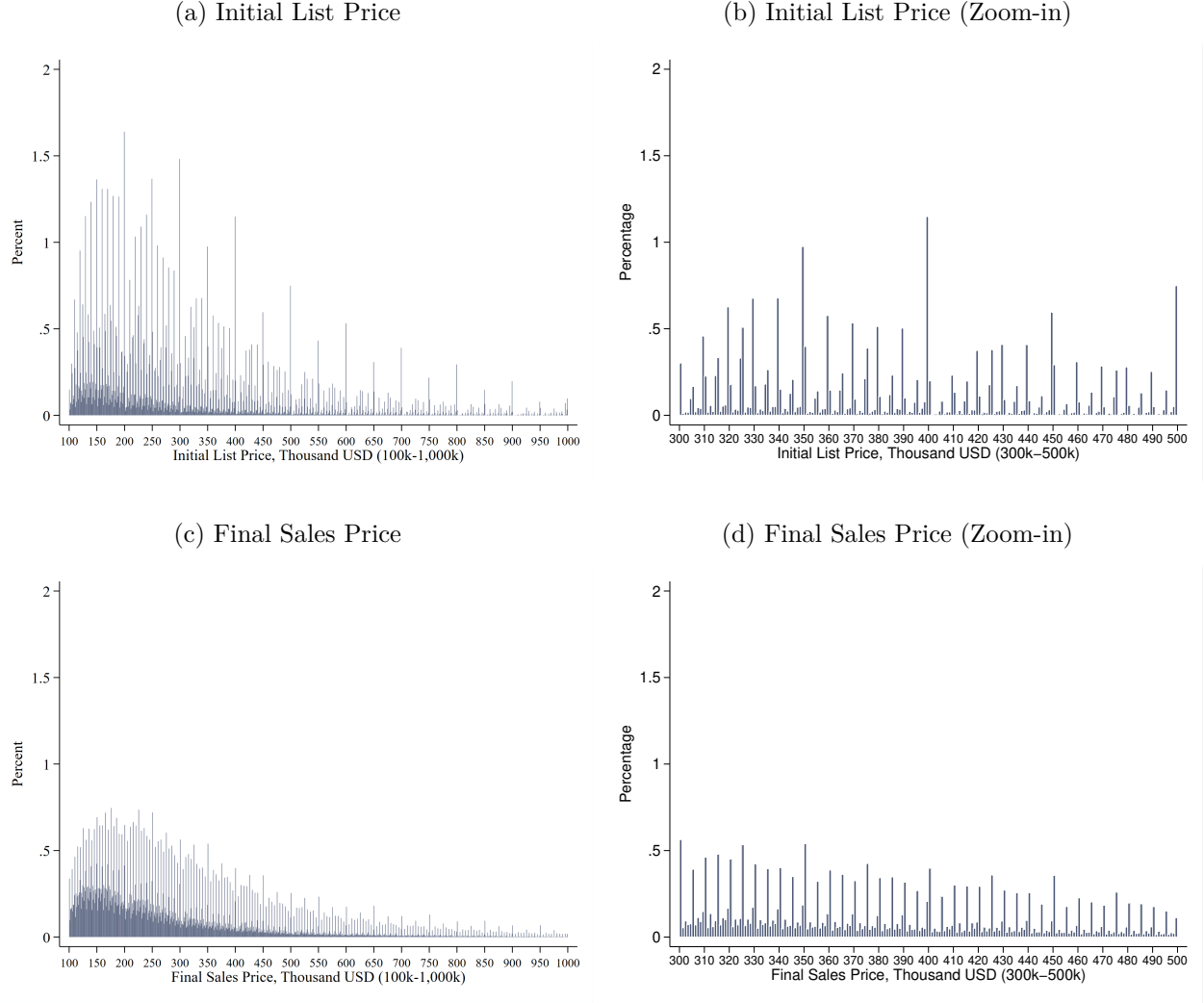
Notes: This figure shows three real bargaining events we observe in Redfin data to illustrate the bargaining events.

Figure 2: Larger Initial List Prices Have More Ending Zeros

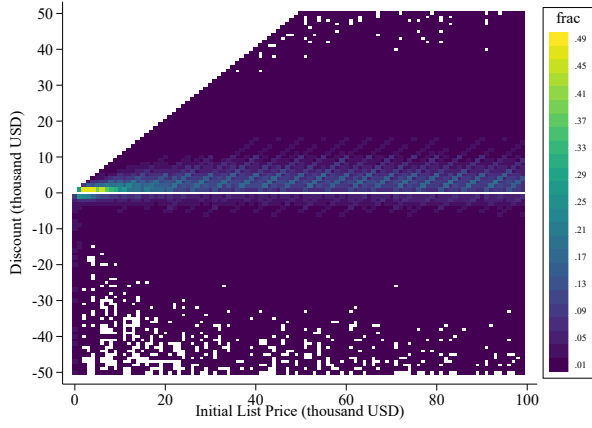


Notes: This figure illustrates the distribution of the number of ending zeros within each initial list price range. Shares are normalized within each price range. The term ‘ending zeros’ refers to the sequence of zeros that appear at the end of each initial list price. For instance, the initial list price of \$109,000 contains three ending zeros. The scope of this plot is confined to observations with an initial list price ranging from \$100,000 to \$999,999, within which the digit count consistently remains six. Figure B5 shows the share of observations across price ranges.

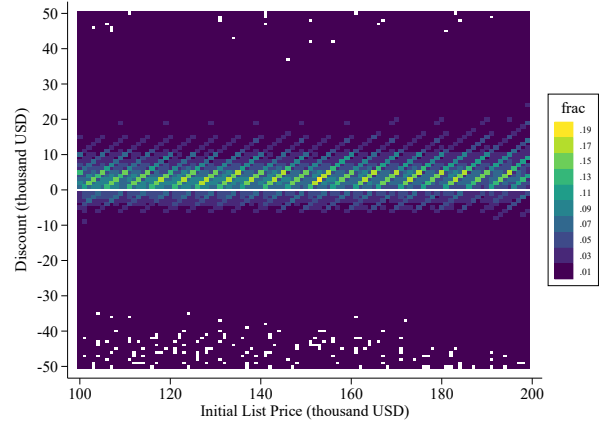
Figure 3: Distribution of Event-Level Prices (MLS)



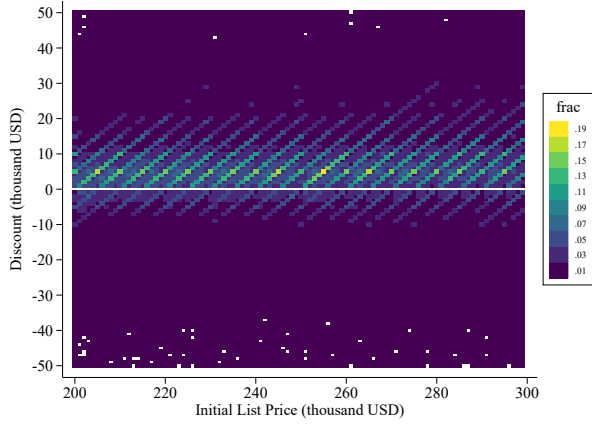
Notes: This figure shows the distribution of the initial list price and final sales price of properties using the MLS sample. This table presents summary statistics for our MLS data. The sample consists of 64,820,263 housing bargaining events on MLS data in the U.S. from 2000 to 2022. We restrict our focus to single-family, condos, and townhouses. We only keep observations with a non-missing initial list price and final sale price. We also drop foreclosures and short sales. All prices are in thousand U.S. dollars. Each bar represents a 1k price range. Panels (a) and (c) plots the distribution of the initial list price and final sales price in the price range of 100k-1,000k USD. Panels (b) and (d) are the zoom-in versions of panels (a) and (c), restricted to the price range of 300k-500k USD. Both boundaries are included. For robustness check, figure B6 shows the same set of plots using Redfin data. Figures B7 and B8 show the zoom-in plots over other price ranges.



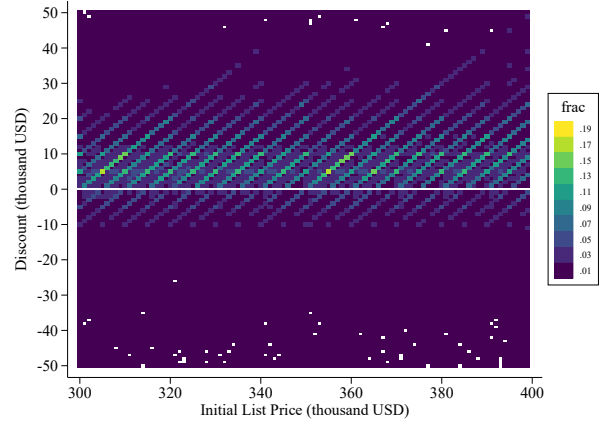
(a) [\$0k,\$100k]



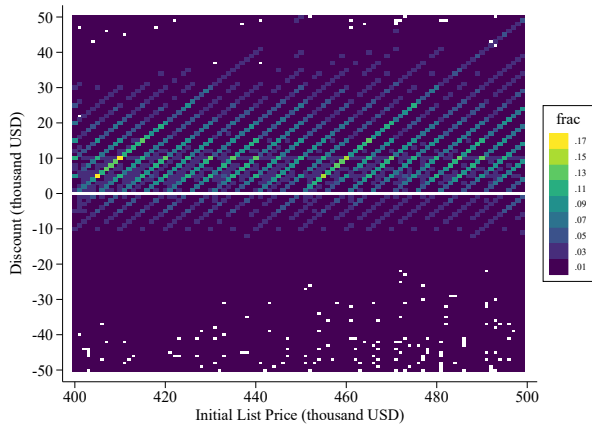
(b) [\$100k,\$200k]



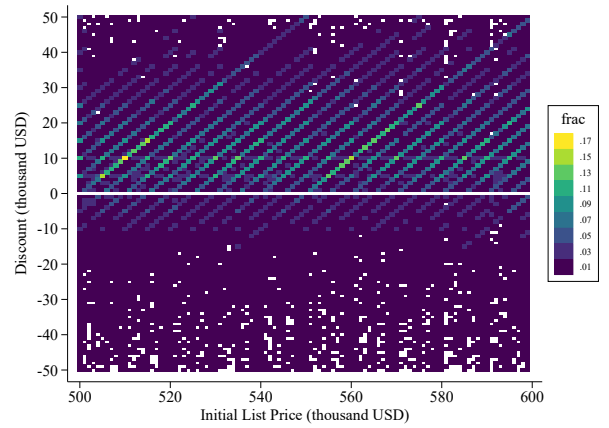
(c) [\$200k,\$300k]



(d) [\$300k,\$400k]

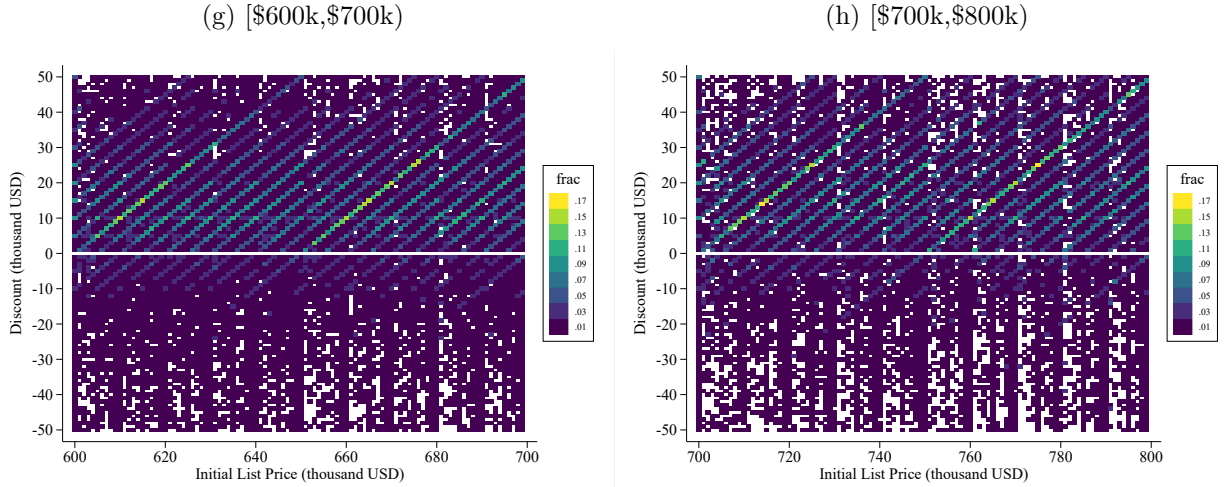


(e) [\$400k,\$500k]



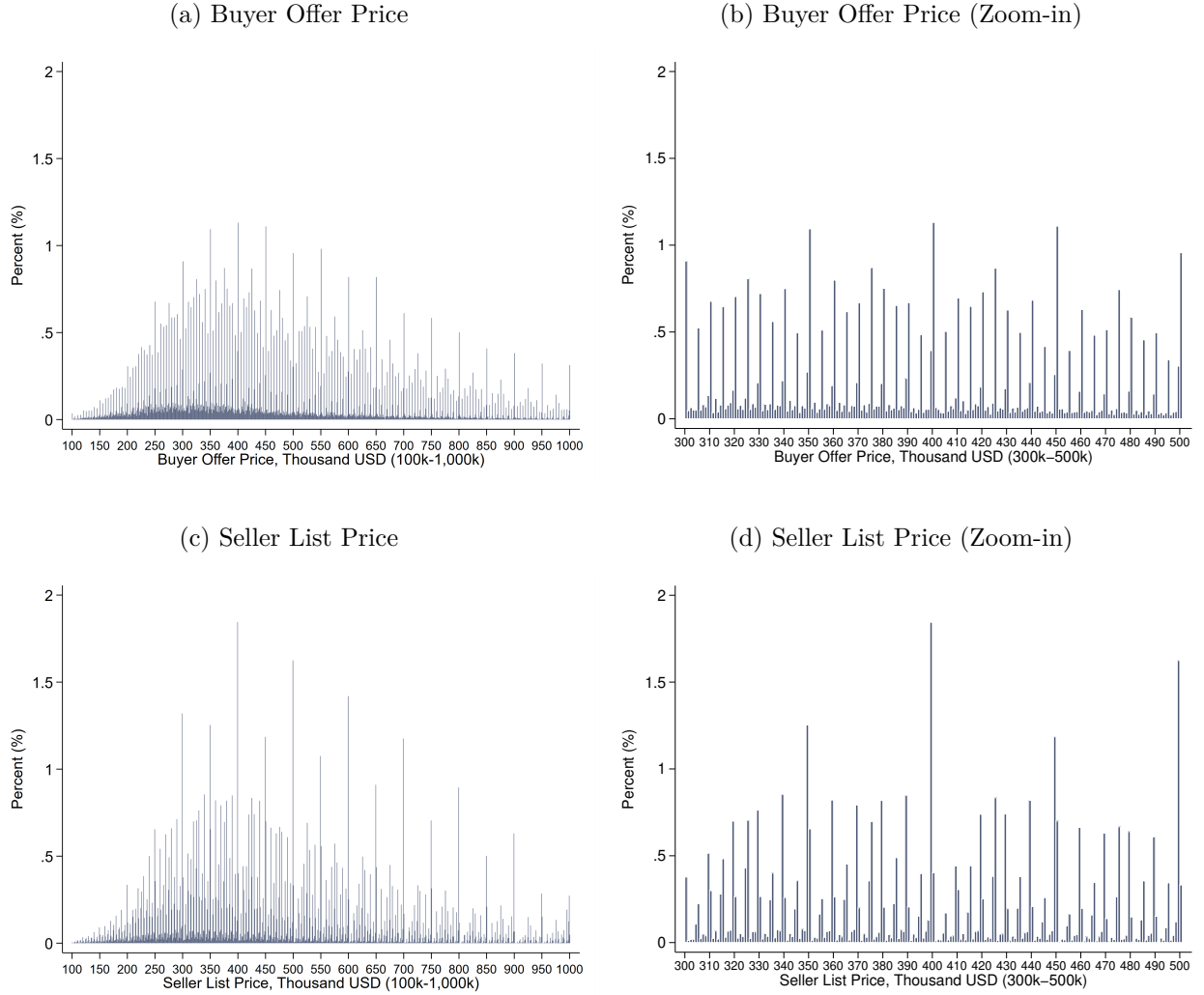
(f) [\$500k,\$600k]

Figure 4: Heatmap of Discount against Initial List Price Cont. (Column-Normalized)



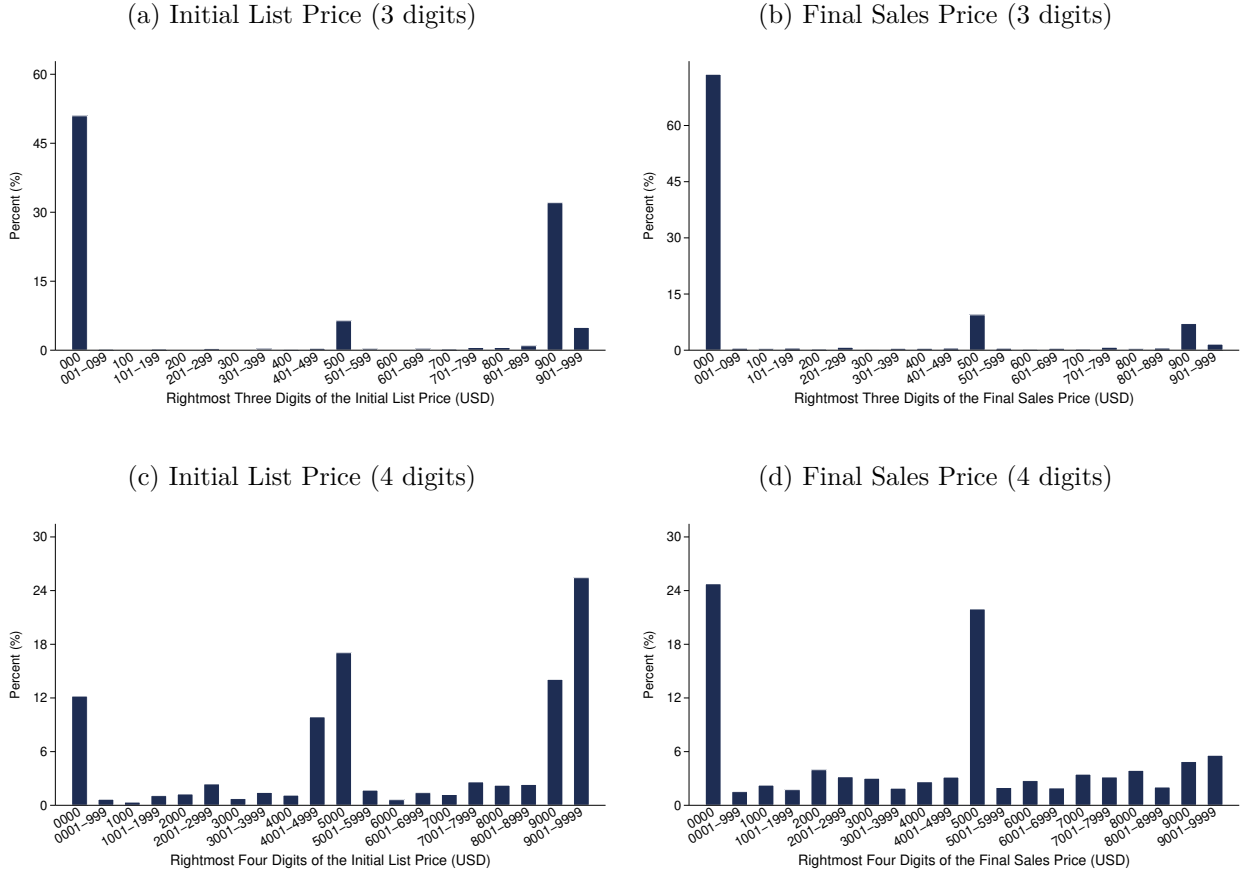
Notes: This figure shows the heatmaps of the discount against the initial list price in our selected MLS dataset. This table presents summary statistics for our MLS data. The sample consists of 64,820,263 housing bargaining events on MLS data in the U.S. from 2000 to 2022. We restrict our focus on single-family, condo, and townhouse. We only keep observations with a non-missing initial list price and final sale price. We also drop foreclosures and short sales. All prices are in thousand U.S. dollars. Each figure plots the heatmap corresponding to a 100k-wide price range. Each bin (both horizontal and vertical) corresponds to a 1k-wide price range. For example, the squares at price equals 100k refer to observations with price in $[99.5, 100.5k)$. To better focus on the range with most of the observations, we removed observations with a discount greater than 50k or less than $-\$50k$. In addition, to make our result more silent, we remove the observations with discount close to 0, that is, in the range $[-\$500, \$500)$. After removing these observations, we normalize the fraction within each column (1k-wide price range), which means that the fractions from each column sum up to 1.

Figure 5: Distribution of Action-Level Prices (Redfin)



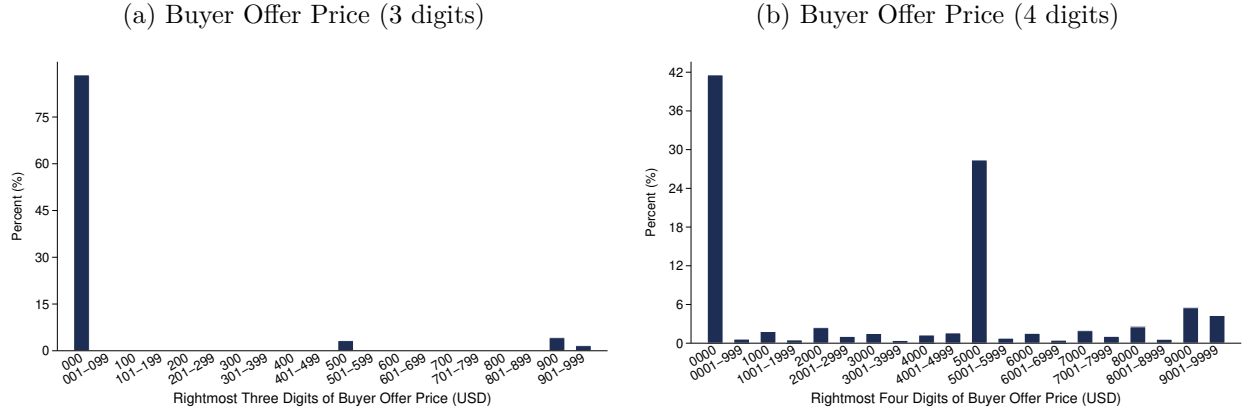
Notes: This figure shows the distribution of the buyer offer price and the seller list price of properties using the Redfin sample. The sample consists of buyer and seller interactions from 296,640 housing bargaining events on Redfin's platform across 45 states in the U.S. from January 2012 to December 2022. All prices are in thousand U.S. dollars. Each bar represents a 1k price range. Panels (a) and (c) plots the distribution of the buyer offer and seller list price in the price range of 100k-1,000k USD. Panels (b) and (d) are the zoom-in versions of panels (a) and (c), restricted to the price range of 300k-500k USD. Both boundaries are included. For robustness check, Figure B9 shows the zoom-in plots over other price ranges.

Figure 6: Event-level Distribution of the Rightmost Digits (MLS)



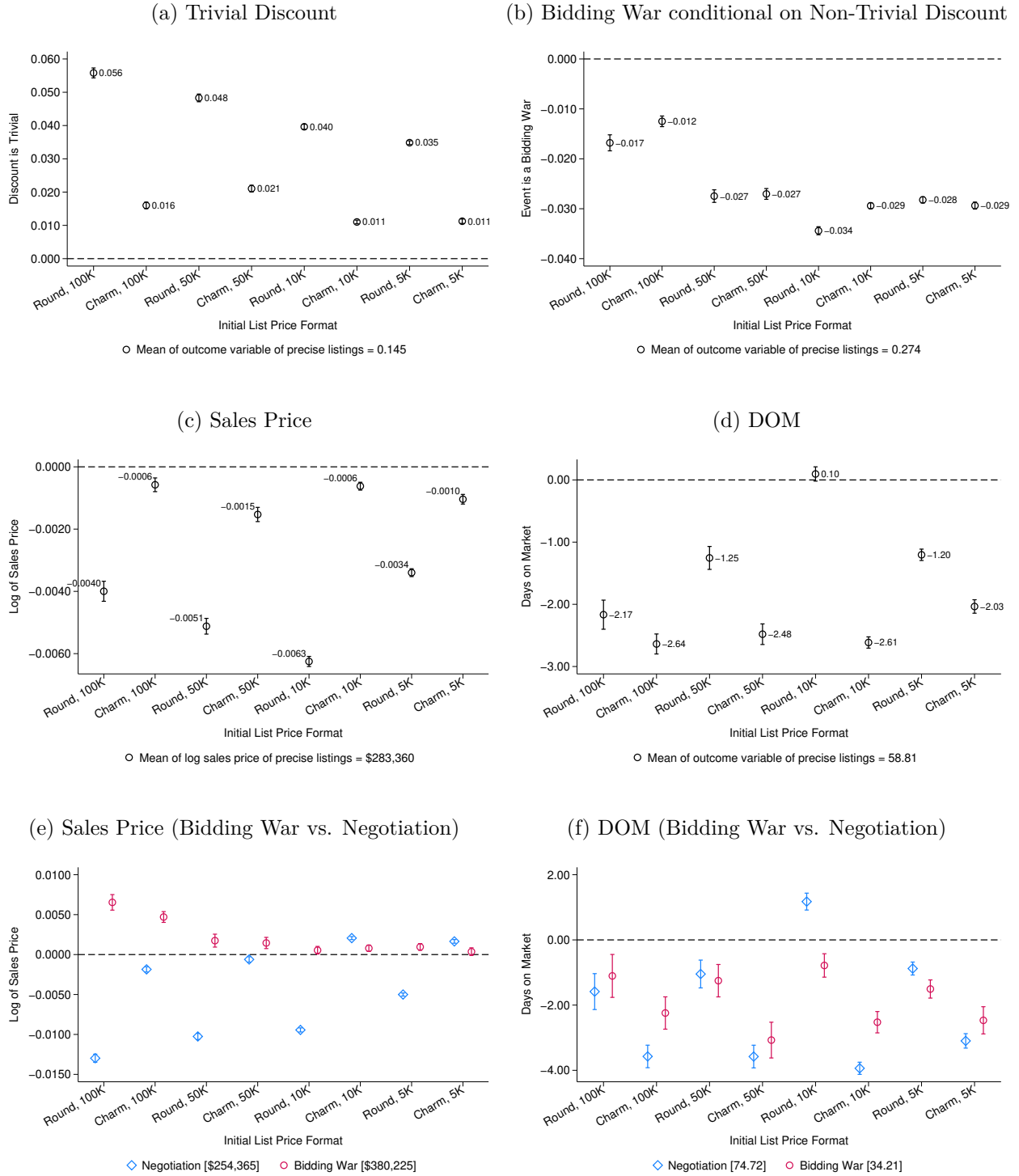
Notes: This figure shows the distribution of the rightmost digits of the initial list price and the final sales price at the event level using the MLS sample. The sample consists of 64,820,263 housing bargaining events on MLS data in the U.S. from 2000 to 2022. We restrict our focus to single-family, condos, and townhouses. We only keep observations with a non-missing initial list price and final sale price. We also drop foreclosures and short sales. Each bar represents a 1k price range. Panels (a) and (c) show the rightmost-digit distribution of the initial list price. Panels (b) and (d) show the rightmost-digit distribution of the final sales price. Panels (a) and (b) use the 3 rightmost digits while panels (c) and (d) use the 4 rightmost digits. Figure B10 shows a more refined version of the distribution. For robustness check, figure B11 shows the same set of plots using Redfin data.

Figure 7: Action-level Distribution of the Rightmost Digits (Redfin)



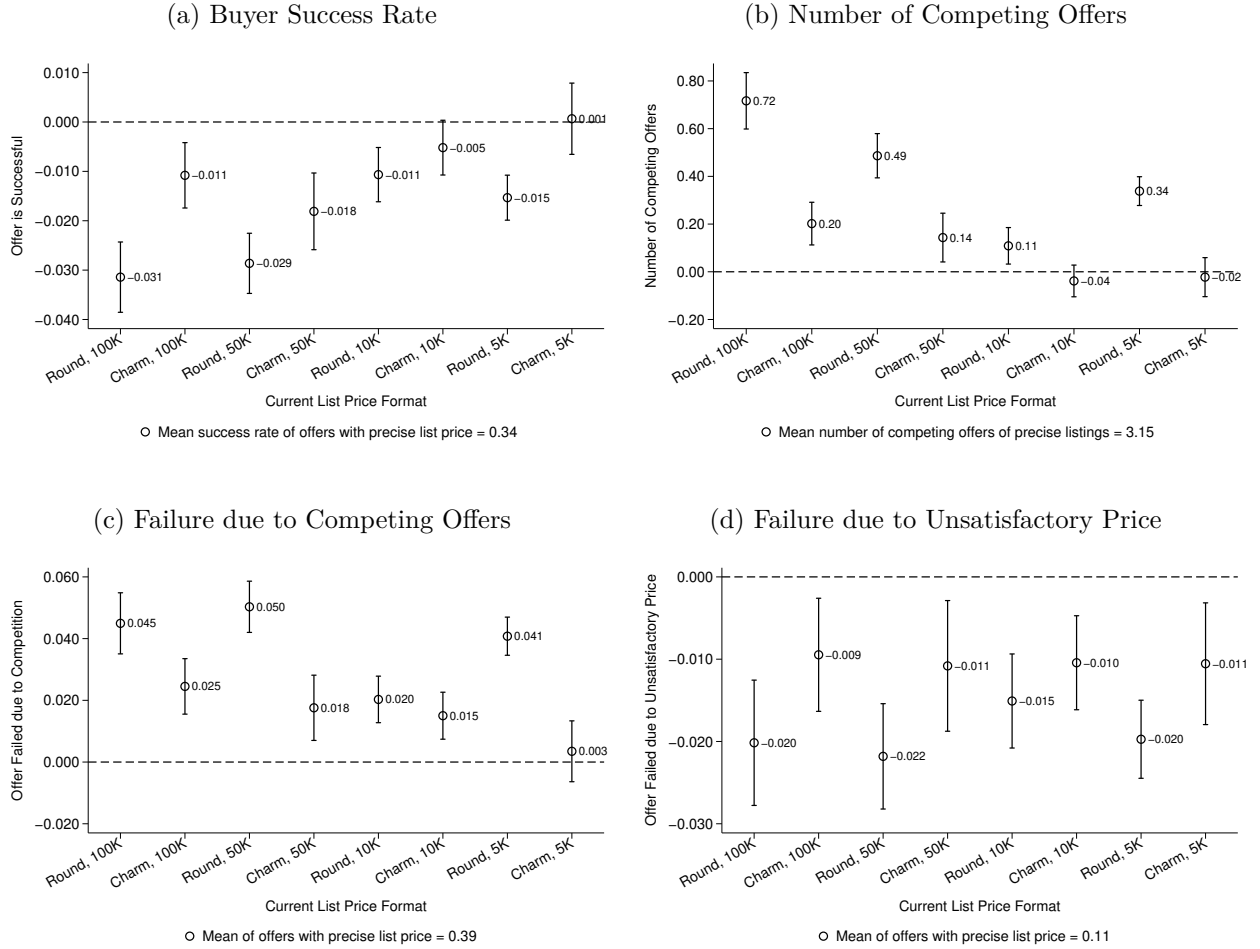
Notes: This figure shows the distribution of the rightmost digits of the buyer offer price and the seller list price at the event level using the Redfin sample. The sample consists of buyer and seller interactions from 296,640 housing bargaining events on Redfin’s platform across 45 states in the U.S. from January 2012 to December 2022. Panels (a) and (c) show the rightmost-digit distribution of the buyer offer price. Panels (b) and (d) show the rightmost-digit distribution of the seller list price. Panels (a) and (b) use the 3 rightmost digits while panels (c) and (d) use the 4 rightmost digits. Figure [B13](#) shows a more refined version of the distribution.

Figure 8: Effects of Initial List Price on Event-Level Outcomes



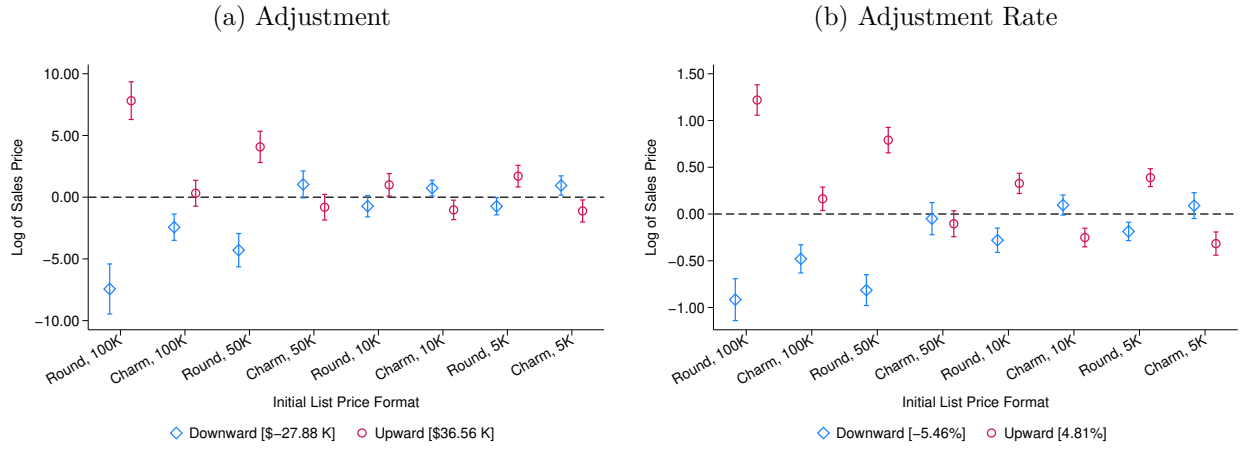
Notes: This set of figures plots the effect of the initial list price format on the event-level outcomes along with 90% CI. In particular, the sample used in Panel (b) excludes the observations with a trivial discount. Panels (e) and (f) split the sample into bidding wars and negotiations. For better illustration, we omit the results on special 9k. The full set of results on the equivalent regressions are reported in Table A6. The control means are reported in the legends.

Figure 9: Effects of Current List Price on Competition



Notes: This set of figures plots the effect of the current list price format on offer outcomes and the competition, along with 90% CI. In particular, the sample used in Panels (c) and (d) includes only failed offers. For better illustration, we omit the results on special 9k. The full set of results on the equivalent regressions are reported in Table A7. The control means are reported in the legends.

Figure 10: Anchoring Effect



Notes: This set of figures plots the anchoring effect of the special current list prices along with 90% CI. In each panel, we split the sample by upward and downward adjustment. For better illustration, we omit the results on special 9k. The full set of results on the equivalent regressions are reported in Table A10. The control means are reported in the brackets.

Table 1: Descriptive Statistics for the MLS Sample

	Mean	SD	P10	Median	P90	N
Initial List Price	345,203	291,358	96,500	259,900	689,000	64,820,263
Sales Price	334,799	286,574	90,000	251,500	670,000	64,477,176
Discount	10,747	44,381	-10,000	5,000	40,000	64,477,176
Days on Market (DOM)	58.63	74.15	3	31	151	61,636,793
Bidding War	0.22	0.41	0	0	1	64,477,176
Negotiation	0.63	0.48	0	1	1	64,477,176
Property Age (Years)	35.19	28	3	30	74	61,566,943
Number of Bedrooms	3.16	0.97	2	3	4	63,620,672
Number of Bathrooms	2.22	0.98	1	2	3	64,717,148
Living Area (Square Feet)	1,886	901.1	1,007	1,681	3,019	57,362,286
Single Family	0.82	0.38	0	1	1	64,820,263
Townhouse	0.11	0.32	0	0	1	64,820,263
Condo	0.004	0.064	0	0	0	64,820,263
Coop	0.036	0.19	0	0	0	64,820,263
Multi-Family (2-4 Units)	0.024	0.15	0	0	0	64,820,263

Notes: This table presents summary statistics for our MLS data. The sample consists of 64,820,263 housing bargaining events on MLS data in the U.S. from 2000 to 2022. The data process of MLS data is described in Appendix C.2. Table A1 provides additional details on the variable definitions.

Table 2: Descriptive Statistics For the Redfin Sample

	Mean	SD	P10	Median	P90	N
<i>Panel A: Event Level</i>						
Initial List Price	555,149	322,373	254,900	475,000	940,000	298,529
Final List Price	548,631	313,261	250,000	469,900	927,000	298,529
Sales Price	573,579	349,052	257,900	480,000	980,000	276,050
Days on Market (DOM)	37.26	51.99	3	14	101	296,660
Discount	-20,300	78,432	-84,000	-5,000	33,950	276,050
Number of Revisions	0.51	1.13	0	0	2	298,529
Bidding War	0.56	0.50	0	1	1	276,050
Negotiation	0.35	0.48	0	0	1	276,050
Property Age (Years)	41.93	30.52	9	35	88	277,919
Number of Bedrooms	3.36	1.05	2	3	5	297,902
No. Bathrooms	2.42	0.84	1.5	2.5	3.5	297,715
Approximate Square Feet	2,098	957.4	1,093	1,910	3,333	286,821
Single Family Residential	0.75	0.43	0	1	1	298,529
Condo/Co-op	0.16	0.37	0	0	1	298,529
Townhouse	0.069	0.25	0	0	0	298,529
Multi-Family (2-4 Units)	0.019	0.14	0	0	0	298,529
<i>Panel B: Buyer Offer Level</i>						
Buyer Offer Price	552,284	320,730	250,000	470,000	941,000	314,829
Current List Price	551,274	313,422	254,900	474,950	929,000	314,829
Price Adjustment	1,011	51,813	-35,000	0	35,100	314,929
Adjustment Rate	-0.001	0.068	-0.072	0	0.068	314,929
Upward Adjustment	0.41	0.49	0	0	1	314,929
Downward Adjustment	0.39	0.49	0	0	1	314,929
Number of Competing Offers	3.71	5.64	0	1	10	278,191
Successful Offer	0.29	0.46	0	0	1	314,829
Failed Offer due to Competition	0.45	0.50	0	0	1	314,829
Failed Offer due to Unsatisfactory Price	0.10	0.30	0	0	1	314,829

Notes: This table presents summary statistics for our Redfin data. The sample consists of buyer and seller interactions from 296,640 housing bargaining events on Redfin’s platform across 45 states in the U.S. from January 2012 to December 2022. Panel A describes the information at the event level. Panel B provides information at the buyer-offer level. We winsorize the initial listing price, final listing price, final sales price, buyer offer price, and current listing price at level 0.01% and 99.5%. Property age, number of revisions, number of bedrooms, number of bathrooms, and number of additional offers are winsorized at level 99.9%. The living area is winsorized at level 0.01% and 99.9%. Table A1 provides additional details on variable definitions and construction.

Table 3: Interactive Rounding by Round Level of Buyer Offer Prices

	Round Buyer Offer Price, x			
	(1)	(2)	(3)	(4)
	$x = 100K$	$x = 50K$	$x = 10K$	$x = 5K$
Round, 100K	0.177*** (0.005)	0.002 (0.004)	0.016*** (0.006)	0.028*** (0.006)
Round, 50K	-0.012*** (0.003)	0.190*** (0.004)	0.008* (0.005)	0.031*** (0.005)
Round, 10K	0.003 (0.002)	0.000 (0.002)	0.205*** (0.004)	0.016*** (0.004)
Round, 5K	-0.001 (0.002)	-0.003 (0.002)	-0.001 (0.003)	0.226*** (0.003)
Special 9K, 100K	0.010*** (0.003)	0.002 (0.003)	0.024*** (0.005)	0.039*** (0.005)
Special 9K, 50K	-0.019*** (0.004)	0.008** (0.004)	0.006 (0.006)	0.028*** (0.006)
Special 9K, 10K	-0.009*** (0.002)	-0.002 (0.002)	0.011*** (0.004)	0.007* (0.004)
Charm, 100K	0.049*** (0.003)	-0.012*** (0.003)	0.024*** (0.005)	0.026*** (0.005)
Charm, 50K	-0.026*** (0.003)	0.064*** (0.004)	0.010* (0.006)	0.020*** (0.005)
Charm, 10K	-0.006*** (0.002)	-0.002 (0.002)	0.045*** (0.004)	0.008** (0.004)
Charm, 5K	-0.010*** (0.003)	-0.002 (0.003)	0.001 (0.005)	0.062*** (0.005)
Obs.	269,129	269,129	269,129	269,129
Control Mean	0.08	0.07	0.24	0.21
R^2	0.22	0.21	0.19	0.21
Log of Current List Price	✓	✓	✓	✓
Housing Characteristics	✓	✓	✓	✓
Year $\times$ Month FE	✓	✓	✓	✓
Year $\times$ Zip-Code FE	✓	✓	✓	✓
Year $\times$ Buyer Agent FE	✓	✓	✓	✓

Notes: This table presents the effect of current list price format on the buyer offer formats. This table presents summary statistics for our Redfin data. The sample consists of buyer and seller interactions from 296,640 housing bargaining events on Redfin's platform across 45 states in the U.S. from January 2012 to December 2022. Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Mechanism Test of Interactive Rounding

	Round Buyer Offer Price, x			
	(1) $x = 100K$	(2) $x = 50K$	(3) $x = 10K$	(4) $x = 5K$
Round, 100K	-0.050*** (0.004)	0.013*** (0.005)	0.048*** (0.007)	0.058*** (0.007)
Round, 50K	0.000 (0.004)	-0.055*** (0.003)	0.041*** (0.006)	0.067*** (0.006)
Round, 10K	0.013*** (0.003)	0.006** (0.003)	0.003 (0.005)	0.039*** (0.005)
Round, 5K	0.007*** (0.002)	0.004* (0.002)	0.020*** (0.004)	0.027*** (0.004)
Special 9K, 100K	0.008** (0.004)	-0.004 (0.004)	0.020*** (0.005)	0.031*** (0.005)
Special 9K, 50K	-0.020*** (0.004)	0.009* (0.005)	0.008 (0.007)	0.028*** (0.007)
Special 9K, 10K	-0.007** (0.003)	-0.003 (0.003)	0.019*** (0.005)	0.012** (0.005)
Charm, 100K	-0.068*** (0.003)	-0.009*** (0.003)	0.053*** (0.006)	0.059*** (0.006)
Charm, 50K	-0.021*** (0.004)	-0.063*** (0.003)	0.045*** (0.007)	0.058*** (0.007)
Charm, 10K	0.001 (0.003)	0.004 (0.003)	-0.033*** (0.005)	0.030*** (0.005)
Charm, 5K	-0.002 (0.003)	0.004 (0.003)	0.020*** (0.006)	-0.012** (0.006)
Obs.	212,042	212,042	212,042	212,042
Control Mean	0.09	0.08	0.29	0.26
R^2	0.24	0.22	0.21	0.21
Log of Current List Price	✓	✓	✓	✓
Housing Characteristics	✓	✓	✓	✓
Year $\times$ Month FE	✓	✓	✓	✓
Year $\times$ Zip-Code FE	✓	✓	✓	✓
Year $\times$ Buyer Agent FE	✓	✓	✓	✓

Notes: This table presents the correlation between round buyer offer prices at different levels and charm/round seller list prices after excluding observations with zero or trivial adjustments. This table presents summary statistics for our Redfin data. The sample consists of buyer and seller interactions from 296,640 housing bargaining events on Redfin's platform across 45 states in the U.S. from January 2012 to December 2022. The dependent variable is whether the buyer offer price is a round number at a specific level. Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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A Additional Tables

Table A1: Dictionary of Variables

Variable	Definition
<i>Panel A: Event Level</i>	
Initial List Price	The initial list price of the property made by the seller
Final List Price	The list price after the final seller price revision of the property
Sales Price	Sales price of the property
Days on Market	The number of days from the initial list date to the off-market date
Discount	Initial list price minus sales price
Number of Revisions	The number of list price revisions, excluding the initial listing
Bidding War	Whether the discount is below $-\$100$
Negotiation	Whether the discount is above $\$100$
Property Age (Years)	Number of years from the time the property was built to the time it was listed
Number of Bedrooms	Number of bedrooms in the property
Number Bathrooms	Number of bathrooms in the property
Living Area	Approximate size of the property in square feet
<i>Panel B: Buyer Offer Level</i>	
Buyer Offer Price	The price buyer proposed as an offer to the seller
Current List Price	The list price when the buyer made the offer
Price Adjustment	Buyer off price minus current list price
Adjustment Rate	Price adjustment divided by current list price
Upward Adjustment	Whether the adjustment is above $\$100$
Downward Adjustment	Whether the adjustment is below $-\$100$
Number of Competing Offers	Number of additional offers competing at the same time
Successful Offer	Whether the deal status of the buyer offer is “closed (success)”
Failed Offer due to Competition	Whether the deal status of the offer is “failed due to multiple offers”
Failed Offer due to Unsatisfactory Price	Whether the deal status of the offer is “failed due to price”

Notes: This table presents the definition of key variables at the event level and the offer level.

Table A2: Examples of Price Format

	\$100k	\$50k	\$10k	\$5k
Round	400,000	450,000	440,000	455,000
Special 9k	399,000	449,000	439,000	N/A
Charm	399,900-399,999	449,900-449,999	439,900-439,999	454,900-454,999
Precise	All other prices, e.g., \$451,320			

Notes: This table provides the example classification of prices around \$450k into different format groups.

Table A3: Groupwise Statistics based on Initial List Price

	<i>N</i>	Initial List Price (\$)	Sales Price (\$)	Unit Sales Price (\$/sqft)	DOM (Days)	Bidding War (%)	Negotiation (%)
<i>Panel A: Round Initial List Prices</i>							
100k	1,080,863	629,296	603,495	280.40	51.17	27.06	54.43
50k	1,852,402	589,558	568,678	275.67	53.03	25.74	57.00
10k	4,588,708	340,447	330,861	194.46	50.21	24.47	56.36
5k	10,474,424	417,334	405,004	220.07	53.41	23.25	59.65
<i>Panel B: Special 9k Initial List Prices</i>							
100k	1,966,313	621,517	604,296	325.68	58.51	29.91	61.43
50k	1,287,568	565,885	550,035	302.46	60.23	26.24	64.28
10k	5,359,249	409,709	396,187	230.58	60.04	21.76	67.03
<i>Panel B: Charm Initial List Prices</i>							
100k	2,191,787	392,563	379,847	197.84	57.04	22.92	62.76
50k	1,983,069	332,531	321,098	173.04	58.20	19.81	65.13
10k	9,585,937	261,443	252,252	144.83	58.68	18.27	66.74
5k	5,117,052	234,696	226,260	132.20	59.04	17.86	66.76
<i>Panel C: Precise Initial List Prices</i>							
Precise Price	15,545,999	270,691	264,443	154.54	61.15	22.26	61.59

Notes: This table shows the groupwise statistics based on whether the initial list price is a charm/round number. This table presents summary statistics for our MLS data. The sample consists of 64,820,263 housing bargaining events on MLS data in the U.S. from 2000 to 2022.

Table A4: Breakdown of Buyer Price Adjustment by Sellers' Behavior

	% of Observations with				
	Adjustment > 100		Adjustment ≤ 100		
	Downward	Upward	Downward	Zero	Upward
<i>Panel A: Round Current List Price</i>					
Round Current List Price (50k)	46.55	27.96	0.02	25.44	0.03
Round Current List Price (10k)	50.40	25.22	0.03	24.27	0.09
Round Current List Price (5k)	49.37	27.19	0.01	23.40	0.03
Round Current List Price (1k)	50.61	33.59	0.01	15.76	0.03
<i>Panel B: Charm Current List Price</i>					
Charm Current List Price (50k)	52.16	23.93	0.15	13.60	10.16
Charm Current List Price (10k)	56.21	21.01	0.18	15.09	7.51
Charm Current List Price (5k)	56.69	19.17	0.19	16.01	7.94
Charm Current List Price (1k)	59.96	18.72	0.19	18.07	3.06
<i>Panel C: Control Group</i>					
Precise List Price	54.99	28.26	0.09	16.51	0.15

Notes: This table shows the breakdown of the price adjustment conditional on the list price being a round/charm number. The sample consists of buyer and seller interactions from 147,709 housing bargaining events on Redfin's platform across 45 states in the U.S. from January 2012 to December 2019.

Table A5: Breakdown of Buyer Price Adjustment by Buyers' Behavior

	% of Observations with				
	Adjustment > 100		Adjustment ≤ 100		
	Downward	Upward	Downward	Zero	Upward
<i>Panel A: Round Offer Price</i>					
Round Offer Price (50k)	53.51	28.21	0.00	12.27	6.01
Round Offer Price (10k)	62.09	27.42	0.00	6.90	3.58
Round Offer Price (5k)	55.60	25.08	0.01	17.70	1.63
Round Offer Price (1k)	44.16	32.24	0.02	23.25	0.33
<i>Panel B: Charm Offer Price</i>					
Charm Offer Price (50k)	5.79	3.94	1.09	88.27	0.90
Charm Offer Price (10k)	11.12	3.77	1.09	83.65	0.36
Charm Offer Price (5k)	13.93	7.60	0.96	77.14	0.37
Charm Offer Price (1k)	36.02	24.82	0.47	38.56	0.13
<i>Panel C: Control Group</i>					
Precise Offer Price	42.10	37.38	0.07	19.85	0.60

Notes: This table shows the breakdown of the price adjustment conditional on the offer price being a round/charm number. The sample consists of buyer and seller interactions from 147,709 housing bargaining events on Redfin's platform across 45 states in the U.S. from January 2012 to December 2019.

Table A6: Correlation between Event-Level Outcomes and Round/Charm Initial List Price

	Trivial Discount	Bidding War	Log of Sales Price			Days on Market		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Round, 100K	0.0558*** (0.0009)	-0.0168*** (0.0010)	-0.0040*** (0.0002)	-0.0130*** (0.0003)	0.0065*** (0.0006)	-2.1668*** (0.1422)	-1.5855*** (0.2809)	-1.1047*** (0.3359)
Round, 50K	0.0483*** (0.0007)	-0.0275*** (0.0008)	-0.0051*** (0.0002)	-0.0103*** (0.0002)	0.0017*** (0.0005)	-1.2541*** (0.1120)	-1.0462*** (0.2176)	-1.2508*** (0.2534)
Round, 10K	0.0396*** (0.0005)	-0.0344*** (0.0005)	-0.0063*** (0.0001)	-0.0094*** (0.0002)	0.0005* (0.0003)	0.0960 (0.0697)	1.1752*** (0.1320)	-0.7836*** (0.1832)
Round, 5K	0.0348*** (0.0004)	-0.0282*** (0.0004)	-0.0034*** (0.0001)	-0.0050*** (0.0001)	0.0010*** (0.0003)	-1.2040*** (0.0555)	-0.8783*** (0.1013)	-1.5063*** (0.1423)
Special 9K, 100K	-0.0190*** (0.0006)	0.0219*** (0.0008)	-0.0013*** (0.0002)	-0.0046*** (0.0002)	0.0031*** (0.0005)	-1.1888*** (0.1152)	-1.5224*** (0.2140)	-1.3532*** (0.2112)
Special 9K, 50K	-0.0131*** (0.0008)	0.0045*** (0.0009)	-0.0017*** (0.0002)	-0.0024*** (0.0003)	0.0004 (0.0006)	-0.8930*** (0.1367)	-1.2557*** (0.2473)	-1.4349*** (0.2547)
Special 9K, 10K	-0.0093*** (0.0004)	-0.0093*** (0.0005)	-0.0016*** (0.0001)	0.0002 (0.0001)	-0.0009*** (0.0003)	-1.5763*** (0.0720)	-2.4259*** (0.1254)	-2.2123*** (0.1755)
Charm, 100K	0.0160*** (0.0006)	-0.0125*** (0.0006)	-0.0006*** (0.0001)	-0.0019*** (0.0002)	0.0047*** (0.0004)	-2.6377*** (0.0977)	-3.5744*** (0.1763)	-2.2424*** (0.2529)
Charm, 50K	0.0210*** (0.0006)	-0.0270*** (0.0007)	-0.0015*** (0.0001)	-0.0006*** (0.0002)	0.0015*** (0.0004)	-2.4806*** (0.1008)	-3.5782*** (0.1776)	-3.0731*** (0.2797)
Charm, 10K	0.0110*** (0.0003)	-0.0294*** (0.0004)	-0.0006*** (0.0001)	0.0021*** (0.0001)	0.0008*** (0.0002)	-2.6140*** (0.0551)	-3.9380*** (0.0951)	-2.5247*** (0.1668)
Charm, 5K	0.0112*** (0.0004)	-0.0294*** (0.0004)	-0.0010*** (0.0001)	0.0017*** (0.0001)	0.0004 (0.0003)	-2.0348*** (0.0658)	-3.0976*** (0.1131)	-2.4667*** (0.2128)
Obs.	34,949,465	35,165,621	34,949,465	17,900,944	5,562,533	33,291,119	16,946,191	5,396,994
Control Mean	0.145	0.274	283,360	254,365	380,225	58.81	74.72	34.21
R^2	0.611	0.708	0.996	0.997	1.000	0.709	0.767	0.927
Sample	All	Non-Trivial Discount	All	Negotiation	Bidding War	All	Negotiation	Bidding War
g (list price)	YES	YES	YES	YES	YES	YES	YES	YES
Property Characteristics	YES	YES	YES	YES	YES	YES	YES	YES
Year-Month-Zipcode FE	YES	YES	YES	YES	YES	YES	YES	YES
Property FE	YES	YES	YES	YES	YES	YES	YES	YES

Notes: This table presents the effect of initial list price format on the event-level outcomes. Robust standard errors are clustered at the property level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A7: Correlation between Buyer Success Probability and Round/Charm Current List Price

	(1) No. of Competing Offers	(2) Success	(3) Failure Competition	(4) Failure Price
Round, 100K	0.718*** (0.084)	-0.031*** (0.004)	0.045*** (0.006)	-0.020*** (0.005)
Round, 50K	0.487*** (0.061)	-0.029*** (0.004)	0.050*** (0.005)	-0.022*** (0.004)
Round, 10K	0.109** (0.053)	-0.011*** (0.003)	0.020*** (0.005)	-0.015*** (0.003)
Round, 5K	0.338*** (0.042)	-0.015*** (0.003)	0.041*** (0.004)	-0.020*** (0.003)
Special 9K, 100K	0.457*** (0.064)	-0.026*** (0.004)	0.034*** (0.005)	-0.008* (0.004)
Special 9K, 50K	0.229*** (0.078)	-0.019*** (0.005)	0.035*** (0.007)	-0.025*** (0.005)
Special 9K, 10K	0.061 (0.047)	-0.011*** (0.004)	0.018*** (0.005)	-0.010*** (0.004)
Charm, 100K	0.202*** (0.060)	-0.011*** (0.004)	0.025*** (0.006)	-0.010** (0.004)
Charm, 50K	0.141** (0.067)	-0.018*** (0.005)	0.018*** (0.007)	-0.011** (0.005)
Charm, 10K	-0.038 (0.046)	-0.005 (0.004)	0.015*** (0.005)	-0.010*** (0.004)
Charm, 5K	-0.024 (0.054)	0.001 (0.004)	0.003 (0.006)	-0.010** (0.005)
Obs.	237,075	270,706	189,078	189,078
Control Mean	3.15	0.37	0.59	0.16
R^2	0.49	0.45	0.42	0.36
g (Current List Price)	yes	yes	yes	yes
Housing Characteristics	yes	yes	yes	yes
Year $\times$ Month FE	yes	yes	yes	yes
Year $\times$ Zip-Code FE	yes	yes	yes	yes
Year $\times$ Buyer Agent FE	yes	yes	yes	yes

Notes: This table presents the correlation between buyer's outcomes and competition and charm/round seller list prices. This table presents summary statistics for our Redfin data. The sample consists of buyer and seller interactions from 296,640 housing bargaining events on Redfin's platform across 45 states in the U.S. from January 2012 to December 2022. Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A8: Correlation between Buyer Success Probability and Round/Charm Current List Price (Bidding War)

	(1) No. of Competing Offers	(2) Success	(3) Failure Competition	(4) Failure Price
Round, 100K	0.634*** (0.135)	-0.021*** (0.004)	0.014** (0.006)	-0.003 (0.004)
Round, 50K	0.479*** (0.106)	-0.022*** (0.004)	0.025*** (0.005)	-0.010*** (0.004)
Round, 10K	-0.030 (0.097)	-0.014*** (0.004)	0.008 (0.005)	-0.003 (0.003)
Round, 5K	0.292*** (0.080)	-0.013*** (0.003)	0.020*** (0.004)	-0.005** (0.003)
Special 9K, 100K	0.388*** (0.113)	-0.019*** (0.004)	0.015*** (0.005)	-0.003 (0.004)
Special 9K, 50K	0.095 (0.136)	-0.018*** (0.006)	0.019*** (0.006)	-0.010** (0.005)
Special 9K, 10K	-0.066 (0.094)	-0.009** (0.004)	0.004 (0.005)	-0.001 (0.003)
Charm, 100K	0.236** (0.113)	-0.007 (0.005)	0.014** (0.006)	-0.006* (0.004)
Charm, 50K	0.154 (0.129)	-0.017*** (0.005)	0.007 (0.007)	-0.001 (0.005)
Charm, 10K	-0.113 (0.095)	-0.003 (0.004)	0.012** (0.005)	-0.008** (0.003)
Charm, 5K	-0.006 (0.120)	-0.014*** (0.005)	0.011 (0.006)	-0.009** (0.004)
Obs.	118,214	141,054	118,486	118,486
Control Mean	6.02	0.22	0.80	0.09
R^2	0.42	0.47	0.42	0.45
g (Current List Price)	yes	yes	yes	yes
Housing Characteristics	yes	yes	yes	yes
Year $\times$ Month FE	yes	yes	yes	yes
Year $\times$ Zip-Code FE	yes	yes	yes	yes
Year $\times$ Buyer Agent FE	yes	yes	yes	yes

Notes: This table presents the correlation between buyer's outcomes and competition and charm/round seller list prices in the case of bidding war. This table presents summary statistics for our Redfin data. The sample consists of buyer and seller interactions from 296,640 housing bargaining events on Redfin's platform across 45 states in the U.S. from January 2012 to December 2022. Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A9: Correlation between Buyer Success Probability and Round/Charm Current List Price (Negotiation)

	(1) No. of Competing Offers	(2) Success	(3) Failure Competition	(4) Failure Price
Round, 100K	0.116*** (0.043)	-0.033** (0.014)	0.031 (0.025)	-0.029 (0.025)
Round, 50K	0.106*** (0.035)	-0.035*** (0.011)	0.030 (0.020)	-0.038* (0.020)
Round, 10K	0.035 (0.026)	-0.018** (0.009)	0.001 (0.016)	-0.035** (0.015)
Round, 5K	0.058*** (0.021)	-0.020*** (0.007)	0.024* (0.013)	-0.038*** (0.013)
Special 9K, 100K	0.069** (0.030)	-0.027*** (0.010)	0.011 (0.019)	-0.019 (0.019)
Special 9K, 50K	0.068* (0.038)	-0.009 (0.013)	-0.003 (0.024)	-0.024 (0.023)
Special 9K, 10K	0.037 (0.024)	-0.010 (0.009)	0.014 (0.016)	-0.031** (0.015)
Charm, 100K	0.078*** (0.030)	-0.014 (0.010)	0.035* (0.019)	-0.022 (0.018)
Charm, 50K	0.117*** (0.035)	-0.021* (0.012)	0.012 (0.022)	-0.042** (0.021)
Charm, 10K	0.044** (0.022)	-0.016** (0.008)	0.020 (0.014)	-0.011 (0.014)
Charm, 5K	0.006 (0.027)	-0.004 (0.010)	-0.022 (0.018)	-0.014 (0.018)
Obs.	65,973	72,687	28,140	28,140
Control Mean	0.59	0.56	0.30	0.28
R^2	0.57	0.48	0.55	0.54
g (Current List Price)	yes	yes	yes	yes
Housing Characteristics	yes	yes	yes	yes
Year $\times$ Month FE	yes	yes	yes	yes
Year $\times$ Zip-Code FE	yes	yes	yes	yes
Year $\times$ Buyer Agent FE	yes	yes	yes	yes

Notes: This table presents the correlation between buyer's outcomes and competition and charm/round seller list prices in the case of negotiation. This table presents summary statistics for our Redfin data. The sample consists of buyer and seller interactions from 296,640 housing bargaining events on Redfin's platform across 45 states in the U.S. from January 2012 to December 2022. Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A10: Anchoring Effect around Round/Charm Prices

	Adjustment (\$ K)			Adjustment Rate (%)		
	(1) Full Sample	(2) Downward	(3) Upward	(4) Full Sample	(5) Downward	(6) Upward
Round, 100K	1.063 (0.875)	-7.521*** (1.233)	7.914*** (0.984)	0.628*** (0.089)	-0.935*** (0.139)	1.224*** (0.105)
Round, 50K	-0.424 (0.623)	-4.553*** (0.805)	4.180*** (0.852)	0.291*** (0.067)	-0.828*** (0.101)	0.790*** (0.092)
Round, 10K	-1.204*** (0.383)	-0.662 (0.510)	0.999* (0.565)	0.100* (0.051)	-0.279*** (0.078)	0.327*** (0.070)
Round, 5K	0.524 (0.372)	-0.612 (0.401)	1.629*** (0.591)	0.321*** (0.043)	-0.182*** (0.058)	0.384*** (0.064)
Special 9K, 100K	-0.022 (0.659)	-4.618*** (0.834)	0.116 (0.892)	0.423*** (0.069)	-0.715*** (0.096)	0.368*** (0.092)
Special 9K, 50K	0.742 (0.733)	1.398 (0.851)	-0.169 (1.017)	0.403*** (0.083)	-0.014 (0.105)	0.168 (0.112)
Special 9K, 10K	-0.539 (0.393)	0.840* (0.440)	-1.625*** (0.596)	0.102** (0.050)	0.004 (0.067)	-0.142** (0.070)
Charm, 100K	-1.170** (0.493)	-2.395*** (0.638)	0.215 (0.664)	0.086 (0.062)	-0.471*** (0.092)	0.152** (0.077)
Charm, 50K	-0.813* (0.460)	1.084* (0.656)	-0.978 (0.639)	0.104 (0.066)	-0.041 (0.105)	-0.118 (0.088)
Charm, 10K	-0.549* (0.333)	0.871** (0.368)	-1.123** (0.518)	-0.006 (0.048)	0.102 (0.065)	-0.258*** (0.065)
Charm, 5K	-0.421 (0.359)	1.024** (0.454)	-1.233** (0.556)	0.001 (0.058)	0.086 (0.082)	-0.323*** (0.078)
Obs.	270,706	90,007	114,275	270,706	90,007	114,275
Control Mean	2.34	-27.88	36.56	-.48	-5.46	4.81
R^2	0.47	0.66	0.63	0.47	0.49	0.49
g (Current List Price)	yes	yes	yes	yes	yes	yes
Housing Characteristics	yes	yes	yes	yes	yes	yes
Year $\times$ Month FE	yes	yes	yes	yes	yes	yes
Year $\times$ Zip-Code FE	yes	yes	yes	yes	yes	yes
Year $\times$ Buyer Agent FE	yes	yes	yes	yes	yes	yes

Notes: This table presents the correlation between the magnitude of adjustment and charm/round seller list prices. This table presents summary statistics for our Redfin data. The sample consists of buyer and seller interactions from 296,640 housing bargaining events on Redfin's platform across 45 states in the U.S. from January 2012 to December 2022. Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A11: Correlation between Buyer Success Probability and Round/Charm Offer Price

Dependent Variable:	Success					
	(1) All	(2) All	(3) All	(4) All	(5) Non-Trivial	(6) Trivial
Round Buyer Offer Price (50k)	−0.074*** (0.006)	−0.079*** (0.006)	−0.069*** (0.006)	−0.065*** (0.006)	−0.076*** (0.007)	0.092 (0.083)
Round Buyer Offer Price (10k)	−0.042*** (0.006)	−0.051*** (0.006)	−0.048*** (0.006)	−0.043*** (0.006)	−0.050*** (0.006)	0.026 (0.130)
Round Buyer Offer Price (5k)	−0.028*** (0.006)	−0.038*** (0.006)	−0.036*** (0.006)	−0.034*** (0.006)	−0.038*** (0.006)	−0.061 (0.143)
Round Buyer Offer Price (1k)	−0.018*** (0.006)	−0.022*** (0.006)	−0.022*** (0.006)	−0.023*** (0.006)	−0.023*** (0.006)	−0.062 (0.114)
Charm Buyer Offer Price (50k)	0.040*** (0.012)	0.019 (0.012)	0.027** (0.012)	−0.002 (0.012)	0.007 (0.033)	0.100 (0.096)
Charm Buyer Offer Price (10k)	0.038*** (0.010)	0.024** (0.010)	0.022** (0.010)	−0.006 (0.010)	0.003 (0.021)	−0.028 (0.146)
Charm Buyer Offer Price (5k)	0.040*** (0.013)	0.028** (0.012)	0.025** (0.012)	0.000 (0.013)	0.032 (0.024)	−0.079 (0.165)
Charm Buyer Offer Price (1k)	0.042*** (0.014)	0.025* (0.014)	0.023* (0.013)	0.014 (0.013)	0.020 (0.016)	−0.121 (0.138)
Obs.	152,720	152,720	152,675	152,675	120,160	30,648
Control Mean	0.546	0.546	0.546	0.546	0.531	0.605
R^2	0.19	0.27	0.27	0.27	0.27	0.38
Round/Charm Current List Price	✓	✓	✓	✓	✓	✓
Log of Current List Price	✓	✓	✓	✓	✓	✓
Housing Characteristics	✓	✓	✓	✓	✓	✓
Contract Temrs	✓	✓	✓	✓	✓	✓
Year × Month FE	✓	✓	✓	✓	✓	✓
Year × County FE	✓	✓	✓	✓	✓	✓
Year × Buyer Agent FE	✓	✓	✓	✓	✓	✓
No. Additional Offers		✓	✓	✓	✓	✓
Price Adjustment			✓	✓	✓	✓
Upward/Downward/Zero Adjustment Dummy				✓	✓	✓

Notes: This table presents the correlation between the buyer's success probability and round buyer offer prices. The sample consists of buyer and seller interactions from 147,709 housing bargaining events on Redfin's platform across 45 states in the U.S. from January 2012 to December 2019. The dependent variable is a binary variable indicating whether the offer directly leads to a successful house purchase. The independent variables of interest are whether the buyer offer price is a round/charm number. Columns (1) to (4) use all offers. To further test whether the relationship is driven by cases with trivial adjustments, Columns (5) and (6) further split the sample into the subsamples with non-trivial and trivial adjustments, respectively. All regressions control for the log of the current list price and housing characteristics. Housing characteristics include the property age, property type, log of square foot, # of bedrooms, and # of bathrooms. We also impose Year × Month, Year × Month, Year × County, and Year × Buyer Agent fixed effects. To take the interactive rounding behavior into account, we additionally control for the set of round/charm list price indicators, as well as the number of additional offers, the price adjustment, and dummies indicating whether the adjustment All round/charm indicators are defined in a mutually exclusive way for both buyer offer price and current list price. For example, if an offer price is a round number at multiples of 50k, it is not classified as a round number at multiples of 10k. Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A12: Correlations between Final Sales Price and Buyer Behavior

Dependent Variable:	Log(Sales Price)					
	(1) All	(2) All	(3) All	(4) All	(5) Non-Trivial	(6) Trivial
Round Buyer Offer Price (50k)	−0.0085*** (0.001)	−0.0073*** (0.001)	−0.0038*** (0.001)	−0.0023*** (0.001)	−0.0031*** (0.001)	0.0075 (0.008)
Round Buyer Offer Price (10k)	−0.0072*** (0.001)	−0.0057*** (0.001)	−0.0004 (0.001)	0.0004 (0.001)	0.0007 (0.001)	−0.0573*** (0.021)
Round Buyer Offer Price (5k)	−0.0061*** (0.001)	−0.0045*** (0.001)	0.0003 (0.001)	0.0008 (0.001)	0.0012* (0.001)	−0.0089 (0.011)
Round Buyer Offer Price (1k)	−0.0013* (0.001)	−0.0006 (0.001)	0.0012** (0.001)	0.0013** (0.001)	0.0018*** (0.001)	0.0095 (0.008)
Charm Buyer Offer Price (50k)	0.0024** (0.001)	0.0056*** (0.001)	0.0024** (0.001)	0.0015 (0.001)	−0.0010 (0.003)	0.0049 (0.010)
Charm Buyer Offer Price (10k)	0.0046*** (0.001)	0.0061*** (0.001)	0.0025*** (0.001)	0.0016* (0.001)	0.0055*** (0.002)	−0.0576** (0.023)
Charm Buyer Offer Price (5k)	0.0039*** (0.001)	0.0066*** (0.001)	0.0026** (0.001)	0.0016 (0.001)	0.0038 (0.002)	−0.0091 (0.014)
Charm Buyer Offer Price (1k)	0.0059*** (0.001)	0.0078*** (0.001)	0.0051*** (0.001)	0.0044*** (0.001)	0.0061*** (0.002)	0.0128 (0.010)
Obs.	66,816	66,816	66,816	66,816	50,782	14,011
Ctrl Mean of Final Sales Price	449,936	449,936	449,936	449,936	447,792	457,419
R^2	0.995	0.996	0.997	0.997	0.996	0.998
Round/Charm Current List Price	✓	✓	✓	✓	✓	✓
Log of Current List Price	✓	✓	✓	✓	✓	✓
Housing Characteristics	✓	✓	✓	✓	✓	✓
Contract Terms	✓	✓	✓	✓	✓	✓
Year × Month FE	✓	✓	✓	✓	✓	✓
Year × County FE	✓	✓	✓	✓	✓	✓
Year × Buyer Agent FE	✓	✓	✓	✓	✓	✓
No. Additional Offers		✓	✓	✓	✓	✓
Direction of Offer Adjustment			✓	✓	✓	✓
Trivial/Nontrivial Adjustment				✓		

Notes: This table presents the correlation between the round/charm offer prices and the final sales price of the property, conditional on the successful offer. The sample consists of buyer and seller interactions from 147,709 housing bargaining events on Redfin’s platform across 45 states in the U.S. from January 2012 to December 2019. The dependent variable is the log of the final sales price associated with the offer. The independent variables of interest are whether the buyer offer price is a round/charm number. Columns (1) to (4) use all successful offers. To further test whether the relationship is driven by cases with trivial adjustments, Columns (5) and (6) further split the sample into the subsamples with non-trivial and trivial adjustments, respectively. All regressions control for the log of the current list price and housing characteristics. Housing characteristics include the property age, property type, log of square foot, # of bedrooms, and # of bathrooms. We also impose Year × Month, Year × Month, Year × County, and Year × Buyer Agent fixed effects. To take the interactive rounding behavior into account, we additionally control for the set of round/charm list price indicators, as well as the number of additional offers, the price adjustment, and dummies indicating whether the adjustment is upward, downward or zero. All round/charm indicators are defined in a mutually exclusive way for both buyer offer price and current list price. For example, if an offer price is a round number at multiples of 50k, it is not classified as a round number at multiples of 10k. Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A13: Correlations between Acceptance Time and Buyer Behavior

Dependent Variable:	Acceptance Time (Days)					
	(1) All	(2) All	(3) All	(4) All	(5) Non-Trivial	(6) Trivial
Round Buyer Offer Price (50k)	0.3554*** (0.083)	0.3580*** (0.083)	0.2446*** (0.082)	0.2630*** (0.083)	0.3089*** (0.098)	0.3860 (0.921)
Round Buyer Offer Price (10k)	0.1706** (0.073)	0.1738** (0.073)	0.0047 (0.073)	0.0150 (0.073)	-0.0073 (0.084)	0.1655 (4.571)
Round Buyer Offer Price (5k)	0.0868 (0.072)	0.0901 (0.072)	-0.0280 (0.072)	-0.0218 (0.072)	-0.0518 (0.084)	1.5071 (1.943)
Round Buyer Offer Price (1k)	-0.0977 (0.074)	-0.0964 (0.074)	-0.1236* (0.074)	-0.1221* (0.074)	-0.1422* (0.086)	1.5858** (0.650)
Charm Buyer Offer Price (50k)	-0.4564*** (0.143)	-0.4513*** (0.143)	-0.0724 (0.147)	-0.0842 (0.147)	1.1102* (0.664)	-0.3409 (0.919)
Charm Buyer Offer Price (10k)	-0.3255*** (0.114)	-0.3228*** (0.114)	0.0566 (0.119)	0.0452 (0.119)	0.2093 (0.307)	-0.1721 (4.621)
Charm Buyer Offer Price (5k)	-0.4602*** (0.145)	-0.4549*** (0.145)	-0.0955 (0.148)	-0.1078 (0.148)	-0.4576 (0.303)	1.4989 (2.082)
Charm Buyer Offer Price (1k)	-0.2586* (0.153)	-0.2540* (0.153)	-0.0925 (0.152)	-0.1011 (0.152)	-0.3525** (0.173)	0.8393 (1.131)
Obs.	67,797	67,797	67,797	67,797	51,611	14,146
Ctrl Mean	2.59	2.59	2.59	2.59	2.691	2.233
R^2	0.291	0.291	0.297	0.298	0.320	0.349
Round/Charm Current List Price	✓	✓	✓	✓	✓	✓
Log of Current List Price	✓	✓	✓	✓	✓	✓
Housing Characteristics	✓	✓	✓	✓	✓	✓
Contract Terms	✓	✓	✓	✓	✓	✓
Year × Month FE	✓	✓	✓	✓	✓	✓
Year × County FE	✓	✓	✓	✓	✓	✓
Year × Buyer Agent FE	✓	✓	✓	✓	✓	✓
No. Additional Offers		✓	✓	✓	✓	✓
Direction of Offer Adjustment			✓	✓	✓	✓
Trivial/Nontrivial Adjustment				✓		

Notes: This table presents the correlation between the round/charm offer prices and the offer acceptance time conditional on the successful offer. The sample consists of buyer and seller interactions from 147,709 housing bargaining events on Redfin's platform across 45 states in the U.S. from January 2012 to December 2019. The dependent variable is the acceptance time, which is defined as the difference between the offer acceptance date and the offer submission date. Acceptance time is winsorized at 99.8%. The independent variables of interest are whether the buyer offer price is a round/charm number. Columns (1) to (4) use all successful offers. To further test whether the relationship is driven by cases with trivial adjustments, Columns (5) and (6) further split the sample into the subsamples with non-trivial and trivial adjustments, respectively. All regressions control for the log of the current list price and housing characteristics. Housing characteristics include the property age, property type, log of square foot, # of bedrooms, and # of bathrooms. We also impose Year × Month, Year × Month, Year × County, and Year × Buyer Agent fixed effects. To take the interactive rounding behavior into account, we additionally control for the set of round/charm list price indicators, as well as the number of additional offers, the price adjustment, and dummies indicating whether the adjustment is upward, downward or zero. All round/charm indicators are defined in a mutually exclusive way for both buyer offer price and current list price. For example, if an offer price is a round number at multiples of 50k, it is not classified as a round number at multiples of 10k. Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

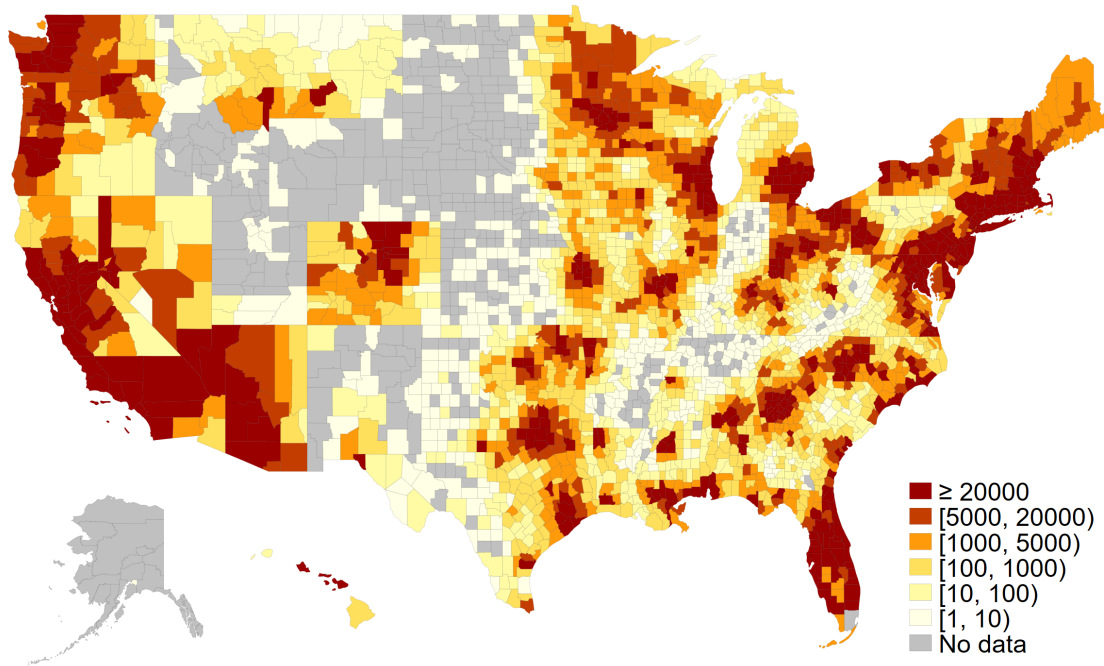
Table A14: Correlations between Private Negotiation Time and Buyer Behavior

Dependent Variable:	Private Negotiation Time (Days)					
	(1) All	(2) All	(3) All	(4) All	(5) Non-Trivial	(6) Trivial
Round Buyer Offer Price (50k)	-2.7443*** (0.443)	-2.7858*** (0.442)	-2.6157*** (0.439)	-2.6490*** (0.440)	-1.9188*** (0.482)	33.0567 (24.022)
Round Buyer Offer Price (10k)	-2.6213*** (0.415)	-2.6721*** (0.415)	-2.4200*** (0.410)	-2.4386*** (0.411)	-1.9854*** (0.445)	3.2975 (7.632)
Round Buyer Offer Price (5k)	-2.5301*** (0.412)	-2.5837*** (0.412)	-2.4590*** (0.408)	-2.4700*** (0.408)	-1.9000*** (0.443)	-10.6841 (6.712)
Round Buyer Offer Price (1k)	-2.0554*** (0.422)	-2.0784*** (0.422)	-2.0835*** (0.421)	-2.0860*** (0.421)	-1.6278*** (0.453)	25.7949 (17.194)
Charm Buyer Offer Price (50k)	2.2367** (0.953)	2.1367** (0.952)	1.1593 (0.992)	1.1809 (0.993)	8.5675* (4.731)	46.4542* (27.046)
Charm Buyer Offer Price (10k)	2.5170*** (0.787)	2.4699*** (0.786)	1.5078* (0.822)	1.5292* (0.823)	5.6616*** (2.172)	16.9771 (12.436)
Charm Buyer Offer Price (5k)	4.1649*** (1.142)	4.0750*** (1.141)	3.1851*** (1.166)	3.2078*** (1.168)	5.4082* (2.869)	5.9074 (10.777)
Charm Buyer Offer Price (1k)	6.5684*** (1.427)	6.5015*** (1.427)	6.1488*** (1.429)	6.1647*** (1.430)	5.3124*** (1.720)	47.0628** (19.240)
Obs.	66,902	66,902	66,902	66,902	50,859	14,020
Ctrl Mean	42.086	42.086	42.086	42.086	40.973	45.977
R^2	0.299	0.299	0.300	0.300	0.335	0.385
Round/Charm Current List Price	✓	✓	✓	✓	✓	✓
Log of Current List Price	✓	✓	✓	✓	✓	✓
Housing Characteristics	✓	✓	✓	✓	✓	✓
Contract Terms	✓	✓	✓	✓	✓	✓
Year $\times$ Month FE	✓	✓	✓	✓	✓	✓
Year $\times$ County FE	✓	✓	✓	✓	✓	✓
Year $\times$ Buyer Agent FE	✓	✓	✓	✓	✓	✓
No. Additional Offers		✓	✓	✓	✓	✓
Direction of Offer Adjustment			✓	✓	✓	✓
Trivial/Nontrivial Adjustment				✓		

Notes: This table presents the correlation between the round/charm offer prices and the private negotiation time, conditional on the successful offer. The sample consists of buyer and seller interactions from 147,709 housing bargaining events on Redfin's platform across 45 states in the U.S. from January 2012 to December 2019. The dependent variable is the private negotiation time is defined as the difference between the final sales date and the offer acceptance date. Private negotiation time winsorized at 99.8%. The independent variables of interest are whether the buyer offer price is a round/charm number. Columns (1) to (4) use all successful offers. To further test whether the relationship is driven by cases with trivial adjustments, Columns (5) and (6) further split the sample into the subsamples with non-trivial and trivial adjustments, respectively. All regressions control for the log of the current list price and housing characteristics. Housing characteristics include the property age, property type, log of square foot, # of bedrooms, and # of bathrooms. We also impose Year $\times$ Month, Year $\times$ Month, Year $\times$ County, and Year $\times$ Buyer Agent fixed effects. To take the interactive rounding behavior into account, we additionally control for the set of round/charm list price indicators, as well as the number of additional offers, the price adjustment, and dummies indicating whether the adjustment is upward, downward or zero. We define charm numbers using the fixed-band definition. All round/charm indicators are defined in a mutually exclusive way for both buyer offer price and current list price. For example, if an offer price is a round number at multiples of 50k, it is not classified as a round number at multiples of 10k. Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B Additional Figures

Figure B1: Geographical Distribution of Transactions in MLS (2000–2022)



Notes: This map shows the geographical distribution of 64,820,263 transactions across 50 states and Washington D.C. in the U.S. from 2000 to 2022 from our selected MLS data.

Figure B2: Start an Offer Panel

Start an Offer

Tell us about the offer you have in mind. You'll get answers to all your home-buying questions, and you're under no obligation to work with us.



REDFIN AGENT
Responds within 4 business hours.



Buy with Amber and you'll get a **\$2,429** commission refund.

Tell Us About Yourself

First Name *

Last Name *

Email *

Phone *

More Details (Optional)

How much would you like to offer?

How do you plan on buying?

☐ Loan

☐ All Cash

Have you toured this home in person?

☐ Yes

☐ No

Comments

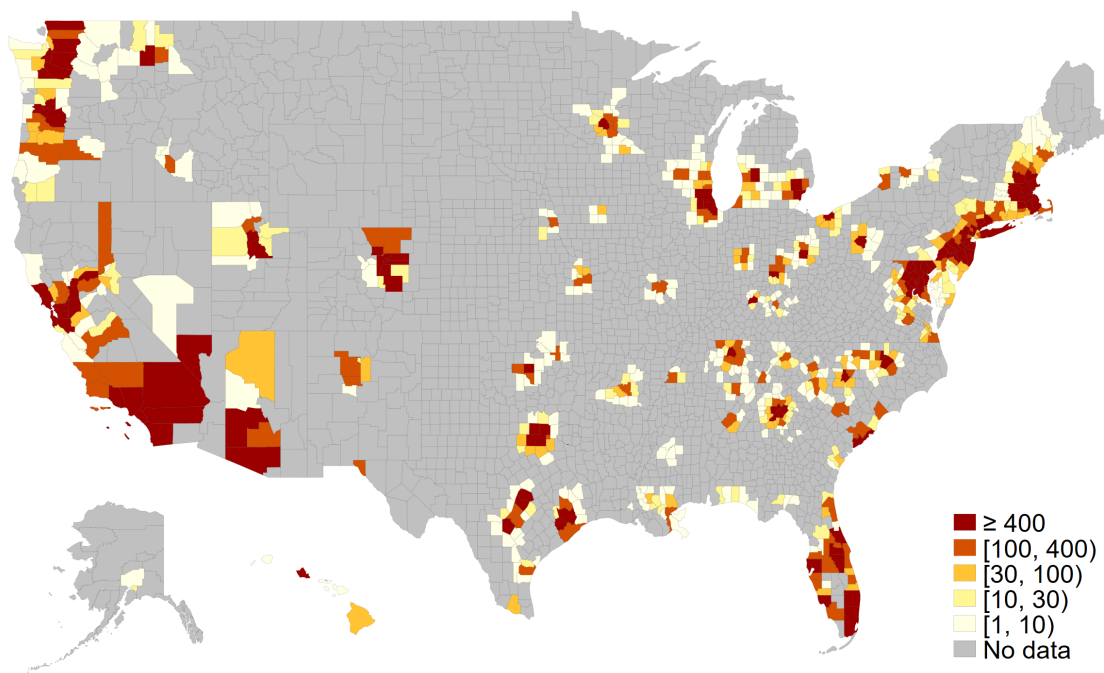
Hi Amber, please help me put together an offer for .

Start An Offer

By continuing, you agree to our [Terms of Use](#) and [Privacy Policy](#)

Notes: This figure shows the “Start an Offer” panel on Redfin. This panel is a Redfin page where buyers start to make offers to properties that they are interested in. Once buyers fill in the required information listed on the page and click the red “Start an Offer” button, they are assigned with Redfin agents and are encouraged to declare their needs on this page.

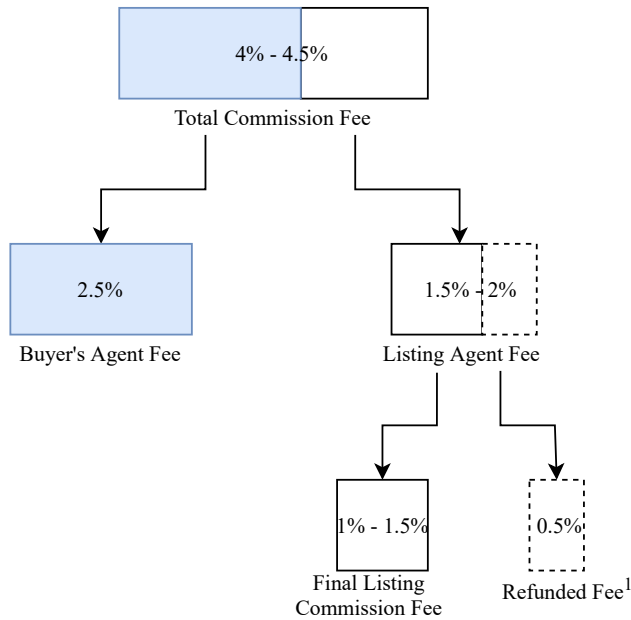
Figure B3: Geographical Distribution of Bargaining Events (2012–2022)



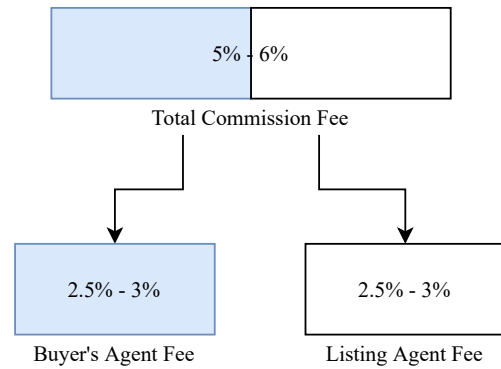
Notes: This map shows the geographical distribution of 293,793 property listing events across 45 states in U.S. that happened between January 2012 and December 2022 in our data. States colored in gray indicate that data in that state is unavailable.

Figure B4: Illustration of Redfin Fee Structure

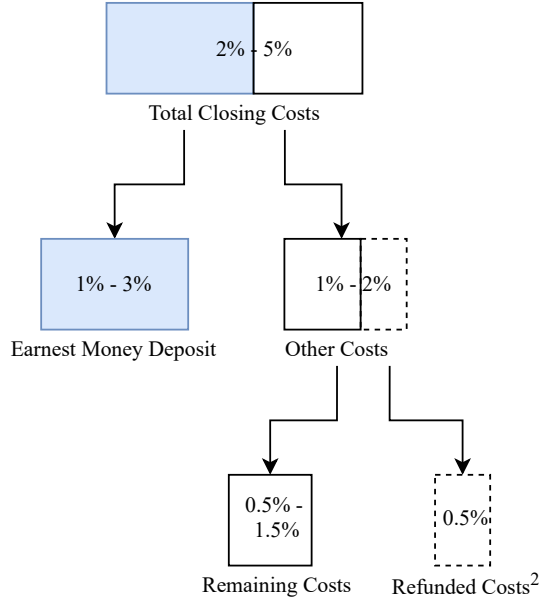
Redfin Charges for Sellers :



Traditional Charges for Sellers :

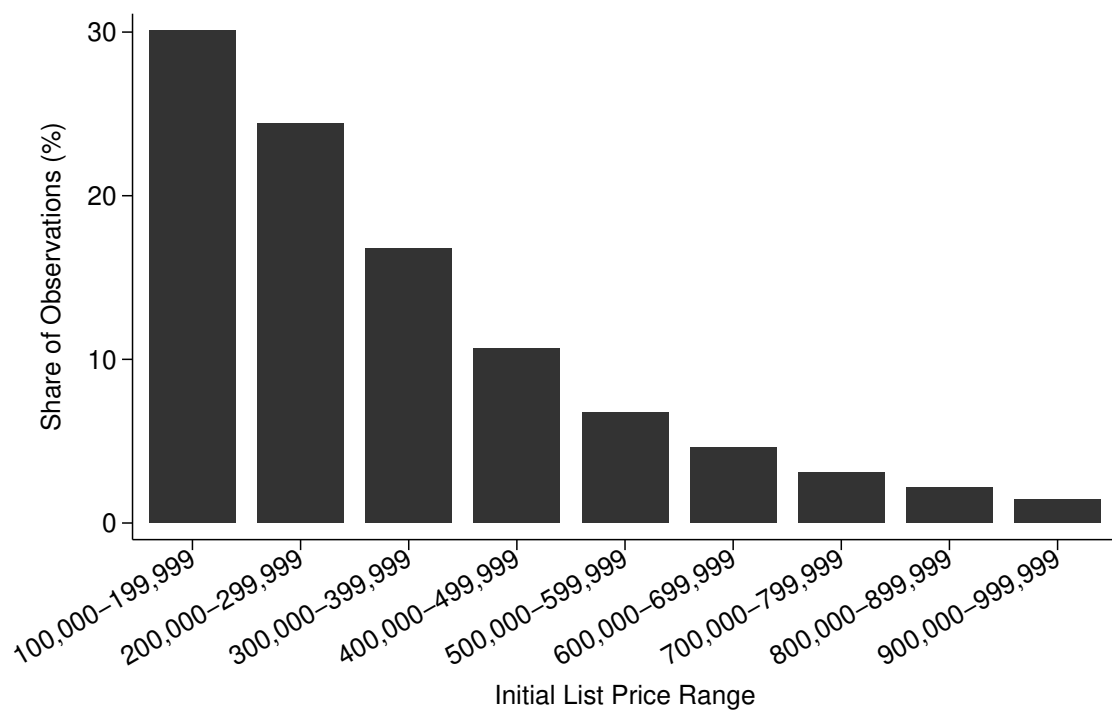


Redfin Charges for Buyers :



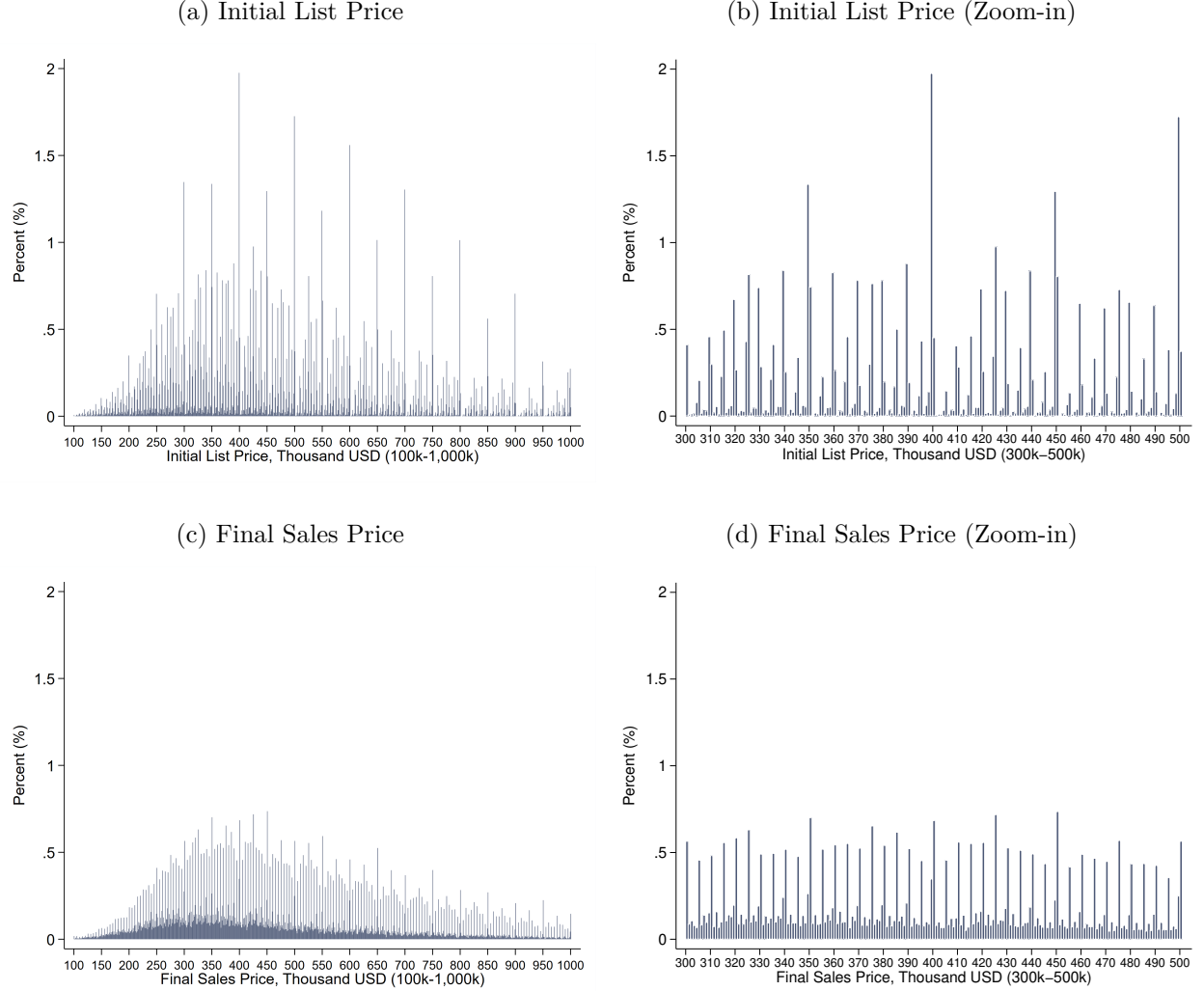
Notes: This figure illustrates fees charged by Redfin on sellers and buyers compared to other institutions. The refunded fee 1 is returned by Redfin if the sellers buy homes on Redfin within one year of their sales. The refunded costs 2 are returned by Redfin if buyers hired Redfin agents.

Figure B5: Share of Observations by Price Range



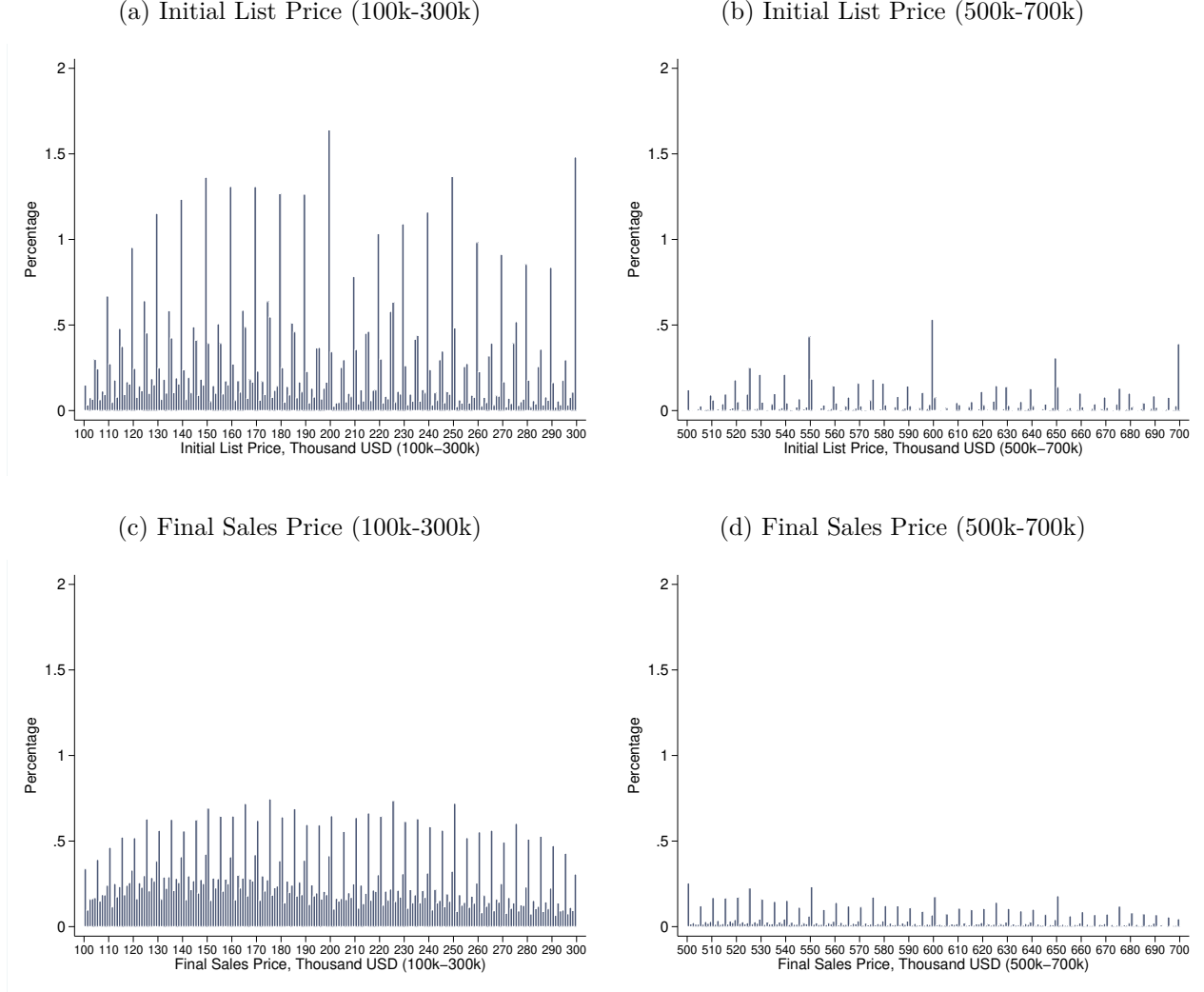
Notes: This figure illustrates the distribution of observations across various price ranges. The scope of this plot is confined to observations with an initial list price ranging from \$100,000 to \$999,999.

Figure B6: Distribution of Event-Level Prices (Redfin)



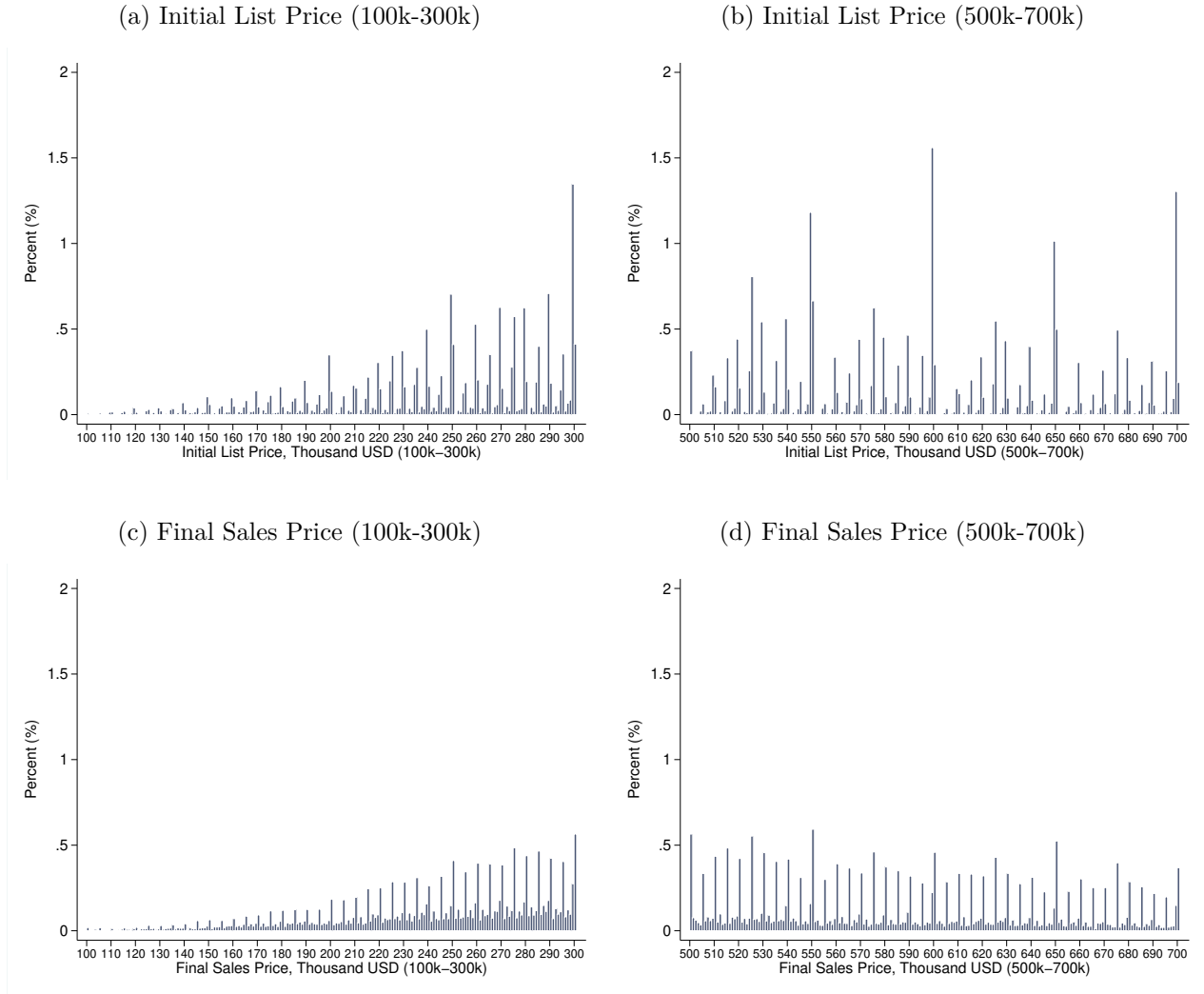
Notes: This figure shows the distribution of the initial list price and final sales price of properties using the Redfin sample. The sample consists of buyer and seller interactions from 147,709 housing bargaining events on Redfin's platform across 45 states in the U.S. from January 2012 to December 2019. Each bar represents a 1k price range. Panels (a) and (c) plots the distribution of the initial list price and final sales price in the price range of 100k-1,000k USD. Panels (b) and (d) are the zoom-in versions of panels (a) and (c), restricted to the price range of 300k-500k USD. Both boundaries are included. For robustness check, figure B8 shows the zoom-in plots over other price ranges.

Figure B7: Distribution of Event-Level Prices (MLS, Robustness Check)



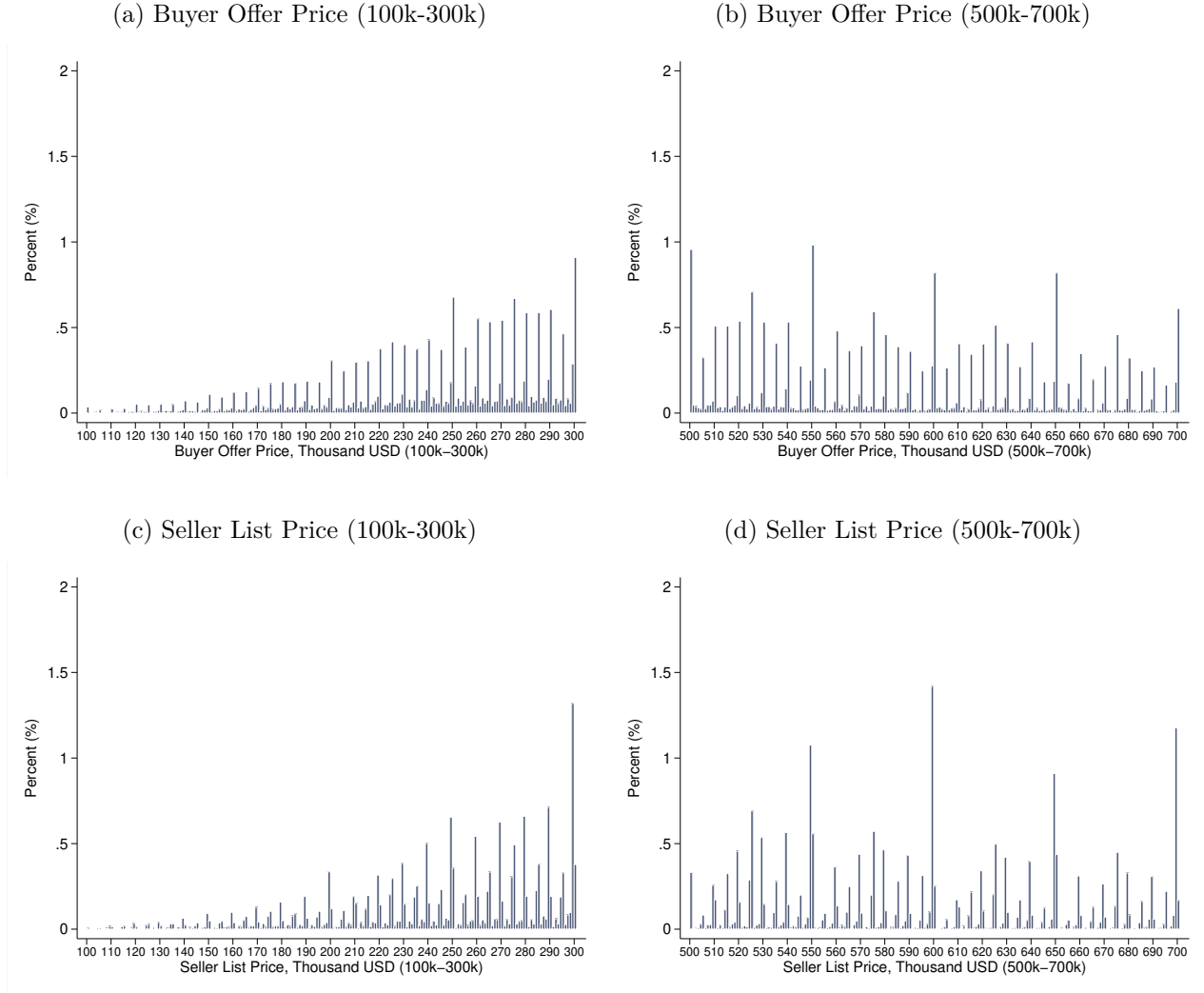
Notes: This figure shows the distribution of the initial list price and final sales price of properties using the MLS sample, with different price ranges in different panels. This table presents summary statistics for our MLS data. The sample consists of 64,820,263 housing bargaining events on MLS data in the U.S. from 2000 to 2022. We restrict our focus to single-family, condos, and townhouses. We only keep observations with a non-missing initial list price and final sale price. We also drop foreclosures and short sales. All prices are in thousand U.S. dollars. Both boundaries are included. Each bar represents a 1k price range.

Figure B8: Distribution of Event-Level Prices (Redfin, Robustness Check)



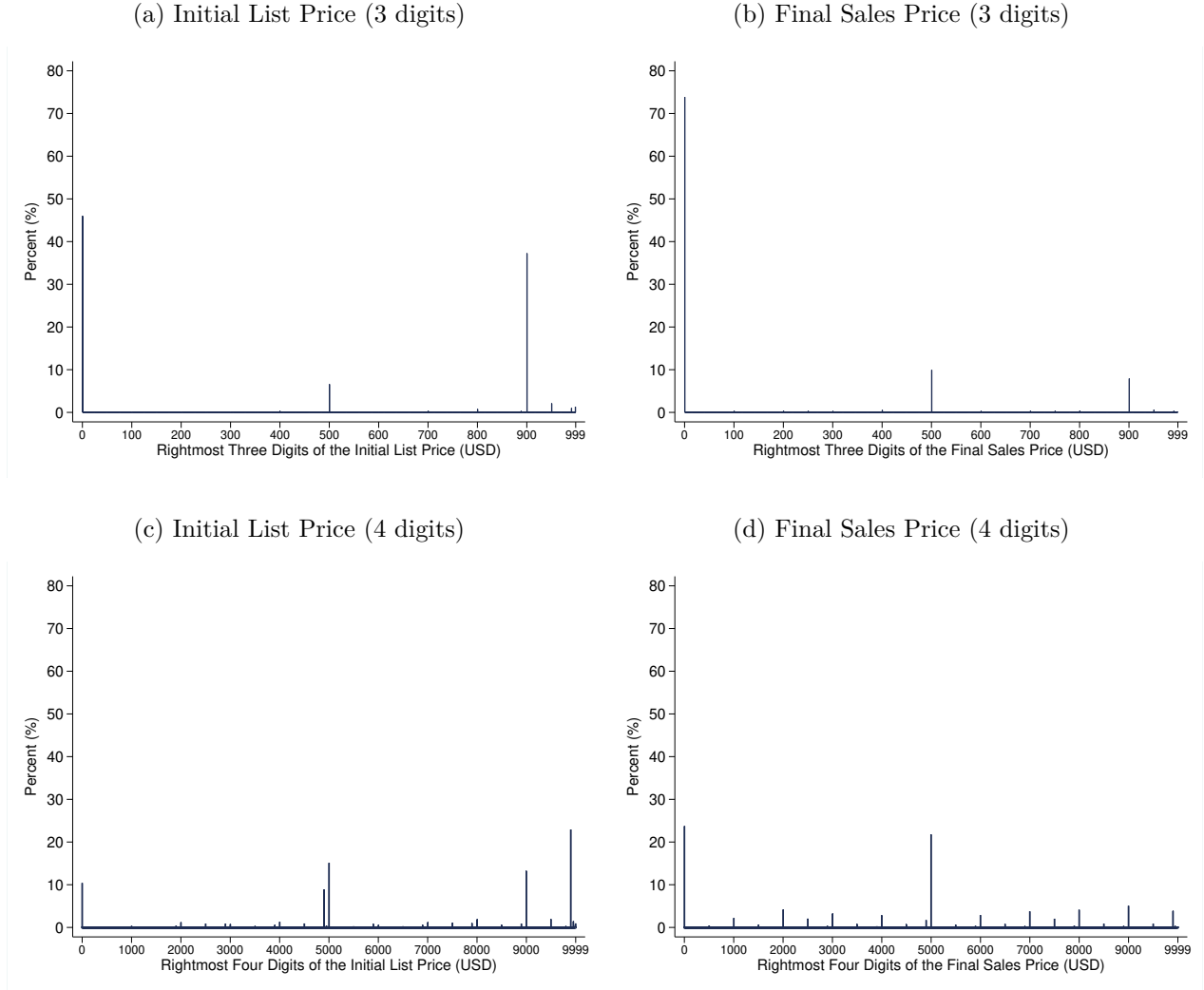
Notes: This figure shows the distribution of the initial list price and final sales price of properties using the Redfin sample, with different price ranges in different panels. The sample consists of buyer and seller interactions from 296,640 housing bargaining events on Redfin's platform across 45 states in the U.S. from January 2012 to December 2022. All prices are in thousand U.S. dollars. Both boundaries are included. Each bar represents a 1k price range.

Figure B9: Distribution of Action-Level Prices (Redfin, Robustness Check)



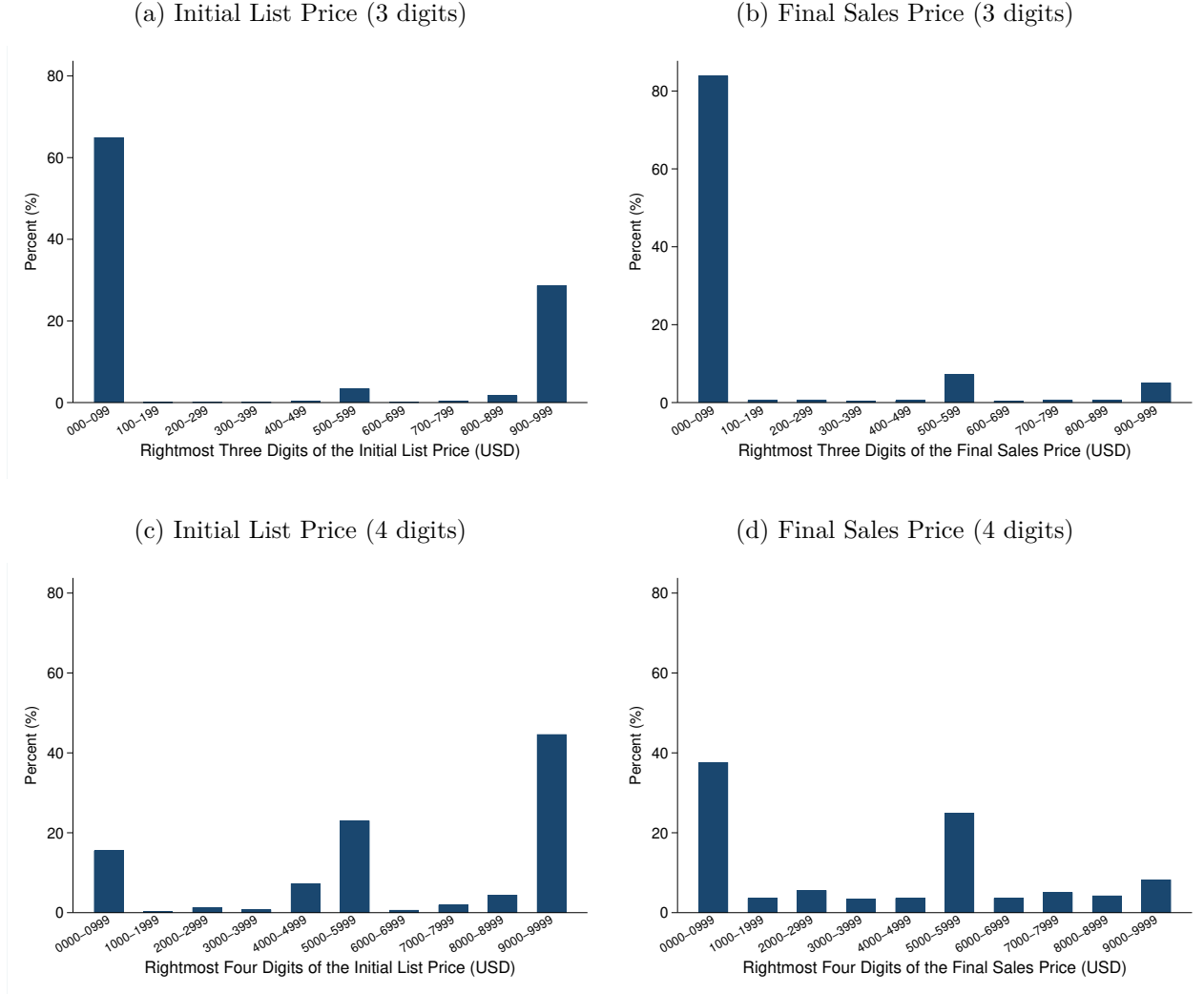
Notes: This figure shows the distribution of the buyer offer price and the seller list price of properties using the Redfin sample, with different price ranges in different panels. The sample consists of buyer and seller interactions from 296,640 housing bargaining events on Redfin's platform across 45 states in the U.S. from January 2012 to December 2022. All prices are in thousand U.S. dollars. Both boundaries are included. Each bar represents a 1k price range.

Figure B10: Event-level Refined Distribution of the Rightmost Digits (MLS)



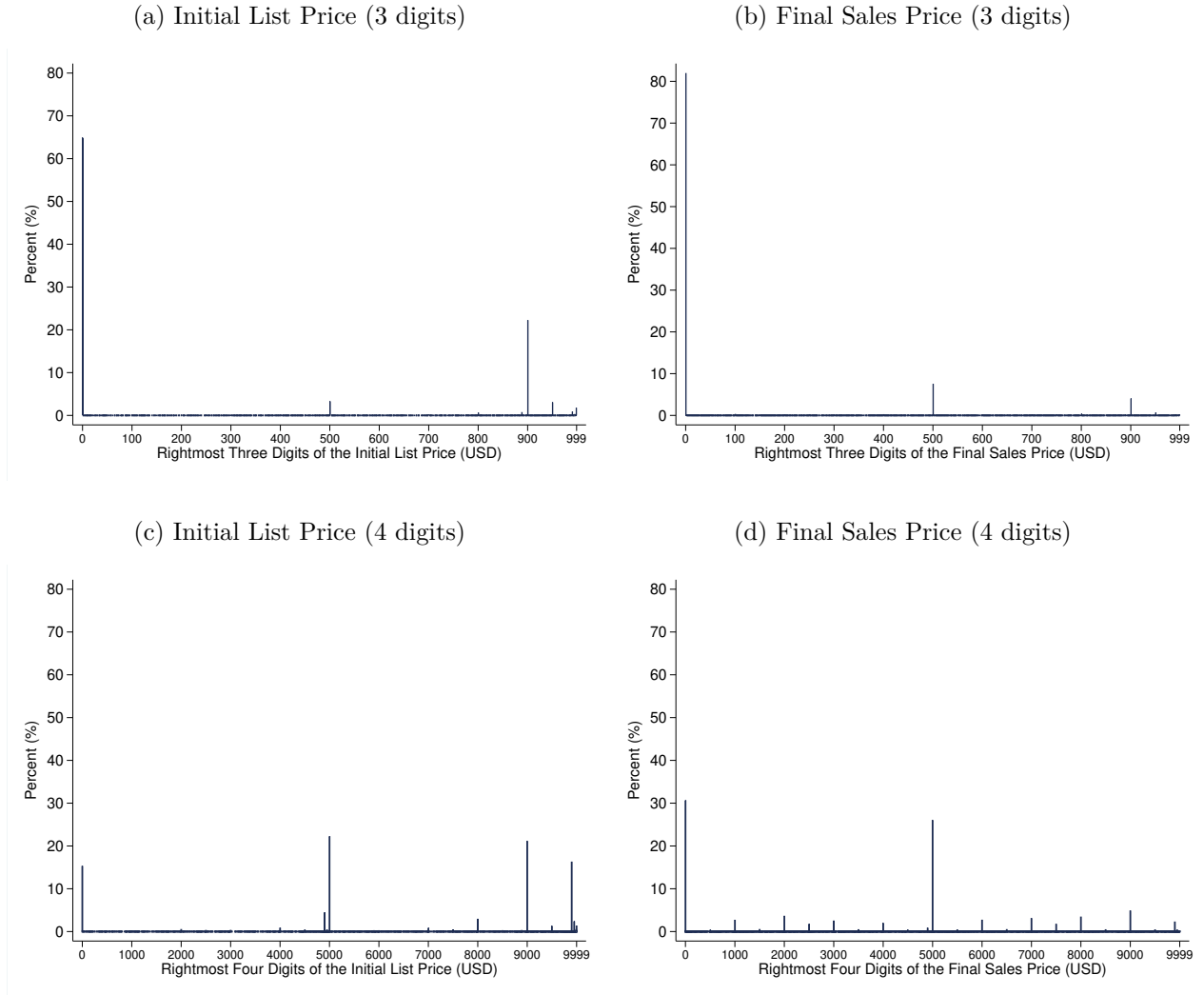
Notes: This figure shows the distribution of the rightmost digits of the initial list price and the final sales price at the event level using the MLS sample. This table presents summary statistics for our MLS data. The sample consists of 64,820,263 housing bargaining events on MLS data in the U.S. from 2000 to 2022. We restrict our focus to single-family, condos, and townhouses. We only keep observations with a non-missing initial list price and final sale price. We also drop foreclosures and short sales. Each bin represents a specific rightmost digit. Panels (a) and (c) show the rightmost-digit distribution of the initial list price. Panels (b) and (d) show the rightmost-digit distribution of the final sales price. Panels (a) and (b) use the 3 rightmost digits while panels (c) and (d) use the 4 rightmost digits.

Figure B11: Event-level Distribution of the Rightmost Digits (Redfin)



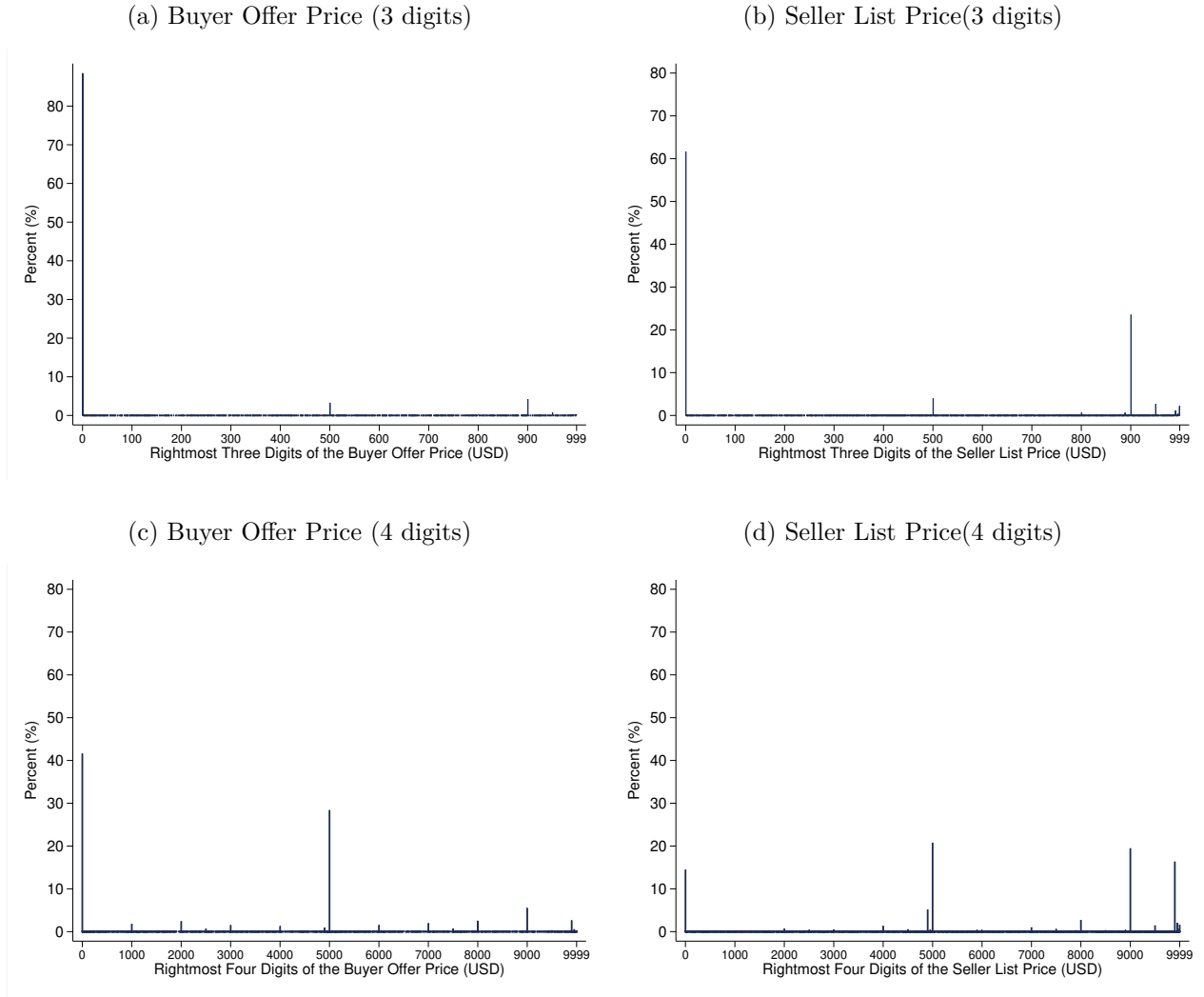
Notes: This figure shows the distribution of the rightmost digits of the initial list price and the final sales price at the event level using the Redfin sample. The sample consists of buyer and seller interactions from 296,640 housing bargaining events on Redfin's platform across 45 states in the U.S. from January 2012 to December 2022. Panels (a) and (c) show the rightmost-digit distribution of the initial list price. Panels (b) and (d) show the rightmost-digit distribution of the final sales price. Panels (a) and (b) use the 3 rightmost digits while panels (c) and (d) use the 4 rightmost digits. Figure B12 shows a more refined version of the distribution.

Figure B12: Event-level Refined Distribution of the Rightmost Digits (Redfin)



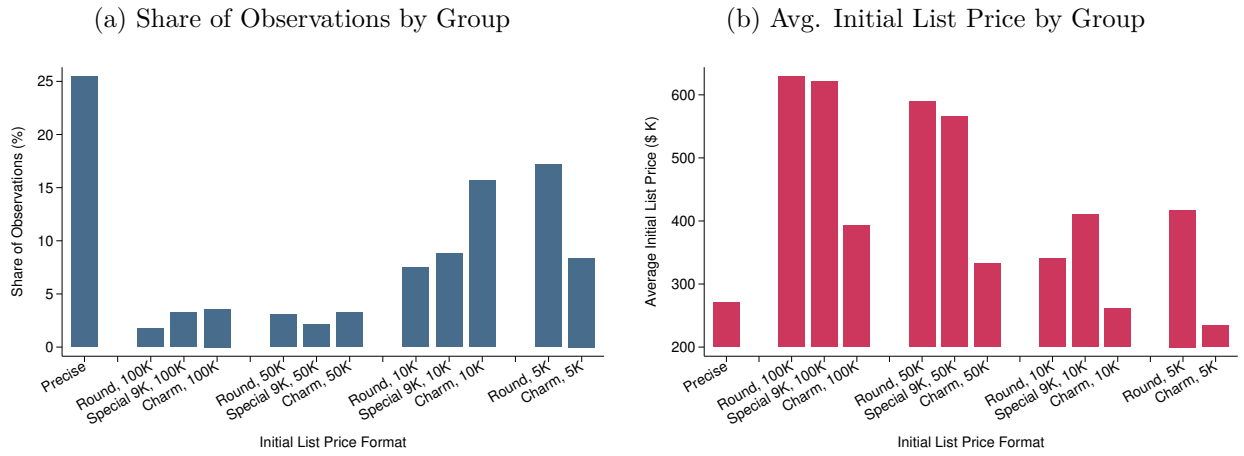
Notes: This figure shows the distribution of the rightmost digits of the initial list price and the final sales price at the event level using the Redfin sample. The sample consists of buyer and seller interactions from 296,640 housing bargaining events on Redfin's platform across 45 states in the U.S. from January 2012 to December 2022. Each bin represents a specific rightmost digit. Panels (a) and (c) show the rightmost-digit distribution of the initial list price. Panels (b) and (d) show the rightmost-digit distribution of the final sales price. Panels (a) and (b) use the 3 rightmost digits while panels (c) and (d) use the 4 rightmost digits.

Figure B13: Action-level Refined Distribution of the Rightmost Digits (Redfin)



Notes: This figure shows the distribution of the rightmost digits of the buyer offer price and the seller list price at the event level using the Redfin sample. The sample consists of buyer and seller interactions from 296,640 housing bargaining events on Redfin's platform across 45 states in the U.S. from January 2012 to December 2022. Each bin represents a specific rightmost digit. Panels (a) and (c) show the rightmost-digit distribution of the buyer offer price. Panels (b) and (d) show the rightmost-digit distribution of the seller list price. Panels (a) and (b) use the 3 rightmost digits while panels (c) and (d) use the 4 rightmost digits.

Figure B14: Comparison by Focal Group (MLS)



Notes: This figure shows the share of observations and average initial list price by focal groups. This table presents summary statistics for our MLS data. The sample consists of 64,820,263 housing bargaining events on MLS data in the U.S. from 2000 to 2022.

C Data Construction

C.1 Illustration of Bargaining Events

Figure 1 (a) shows the situation which one seller bargains with one buyer for multiple rounds. The seller lists the property on the Redfin platform on 2014/05/29 with an initial listing price of \$399,000. Then, on 2014/06/16, the seller revises the price to \$389,000. That constitutes the first round of bargaining. On 2014/07/23, the seller further revises the price as \$379,000. According to our definition, that is the second round of bargaining. On 2014/08/26, the seller revises the price again as \$367,000, which completes the third round of bargaining. On 2014/08/31, one buyer makes an offer with a price of \$365,000. That completes the fourth round of bargaining. On 2014/09/03, the seller takes the property off the Redfin market, and the deal moves to private negotiation stage. After private negotiation, the seller successfully sells the property at \$365,000. This process demonstrates the first situation of a complete event tree.

Figure 1 (b) shows the situation which one seller bargains with multiple buyers for multiple rounds. The seller lists the property on the Redfin platform on 2018/07/12 with an initial listing price of \$269,900. Then, on 2018/08/02, the seller revises the price to \$259,900. That constitutes the first round of bargaining. On 2018/08/30, both buyer 1 and buyer 2 make respective offers with a price of \$245,000. On 2018/09/06, the seller revises the listing price to \$250,000 to bargain with the two buyers. That completes the second round of bargaining. On 2018/09/18, the seller takes the property off the Redfin market, and the deal moves to private negotiation stage. After private negotiation, the seller successfully sells the property at \$247,500 to buyer 1, and rejects buyer 2's offer due to other reason. This process demonstrates the second situation of a complete event tree.

Figure 1 (c) shows the situation which one seller bargains with one buyer for only one round. The seller lists the property on the Redfin platform on 2018/09/25 with an initial listing price of \$450,000. Then, on 2018/10/08, one buyer makes an offer with a price of \$447,500. That completes the first round of bargaining. On 2018/10/28, the seller takes the property off the Redfin market, and the deal moves to private negotiation stage. After private negotiation, the seller rejects the buyer due to failed inspection. This process demonstrates the third situation of a complete event tree.

C.2 Data Processing of MLS Data

To mitigate the impact of outliers, we adjust our sample to exclude data below the 1.5 percentile and above the 99 percentile for the initial list price. Similarly, we adjust the sample for the sales-to-list price ratio, excluding data below the 0.2 percentile and above the 99.9 percentile.

Regarding other variables, we apply a winsorization technique to the Days on Market (DOM) at the 99.5 percentile. We also winsorize the number of bedrooms and bathrooms at the right end of the distribution (above the 99.9 percentile), and apply the same technique to the living area data at the 0.05 and 99.95 percentiles. For the property age, we restrict the year built to be within 1900 to 2022.

C.3 Data Processing of Redfin Data

To align the Redfin dataset with the MLS data, we concentrate on identical property types. Importantly, we implement a more conservative data trimming approach for Redfin, excluding initial list prices below the 0.1 percentile and above the 99.5 percentile. This less aggressive trimming is justified by the reduced presence of outliers in the Redfin sample compared to the MLS dataset. In terms of the sales-to-list price ratio, the dataset is refined by excluding observations below the 0.1 percentile and above the 99.9 percentile. Additionally, the final list price is winsorized at the 0.1 and 99.5 percentiles. However, to maintain consistency with the MLS dataset, we refrain from trimming this segment of the sample.

For other variables, the winsorization technique is applied to the Days on Market (DOM) at the 99.5 percentile. This approach is also extended to the number of revisions, bedrooms, and bathrooms for values above the 99.9 percentile. Living area data is similarly treated at the 0.05 and 99.95 percentiles. Lastly, the property age is constrained, considering only properties built between 1900 and 2022.

D Guide on Redfin Fee Structure

Considering the majority of home-buyers do not fully understand how they pay for their real estate agents from a survey conducted by Redfin, we write this guidebook to summarize fees buyers and sellers pay separately for real properties transactions. For better understanding of fee structures on Redfin, we also compare fees charged for property listings by other brokerages. More details in [B4](#).

Redfin charges the seller for commission fees, which include both buyer's and the listing agent fee. In total, the commission fee on Redfin is 4% – 4.5% of the purchase price, including approximately 2.5% as the buyer's agent fee and 1.5% – 2% as the listing agent fee. In very rare cases, if the buyer is unrepresented by any agents, Redfin charges an extra 1% on listing commission fee for the seller. This 1.5% or 2% listing agent fee depends on the lowest commission fee required by the market where the transaction takes place. The lowest commission is 1.5% in most states while it is 2% in a few other states. The listing commission can be as low as 1% if this seller continues buying a property with a Redfin agent within 365 days of selling her property with Redfin. Under this situation, Redfin would then refund this previous seller (current buyer) with 0.5% of her previous property sales price. Normally with other brokerages, sellers' agents charge 2.5% – 3% of the final sales price as the commission fee while sellers can negotiate with their agents for some discount before signing the contract. Thus, the typical commission fee ranges from 5% to 6% on the housing market. Redfin claims that their sellers' agent fee is lower than the market, thus transparent and non-negotiable.

From a survey in 2020, properties listed with Redfin sell for \$2,800 more than comparable properties listed by other brokerages. Redfin suggests that sellers sometimes account for the fee they will be paying and pass costs along by raising their listing price.

On the buyer's side, Redfin only charges the buyer for closing costs, which are typically 2% - 5% of its purchase price. If the buyer works with a Redfin agent, Redfin would also refund her with 0.5% at the time of closing. These closing costs include:

1. Appraisal: a professional's opinion on the value of the property, which costs around \$300 – \$500 depending on the location and house price;
2. Inspection: an assessment of the conditions of the property, which costs around \$300 – \$500 depending on local rates;

3. Earnest money deposit: a payment from the buyer when there is a mutual acceptance on the purchase, which accounts for 1% – 3% of the purchase price;
4. Taxes, insurance and loan-related fees.