The Numbers Game: Effects of Listing and Counteroffer Pricing Format in Housing Bargaining*

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Abstract

Using confidential offer-level data from the US housing market, this paper analyzes the impact of various listing and counteroffer pricing strategies on the housing bilateral bargaining process. We observe that sellers tend to cluster their listing prices around "charm" numbers (e.g. 349,999) while buyers' counteroffers mainly cluster around round numbers (i.e., 350,000). Through the repeated sales approach, we explore the benefits and costs of these pricing strategies. Compared to listings with precise prices, listings with special prices (i.e., either round prices or charm prices) tend to sell faster but at lower prices than those with more precise prices. Although this indicates "cheap talk" signaling benefits, charm prices systematically dominate round prices. Charm listing prices typically lead to a higher likelihood of sale, achieving higher sales prices, and quicker transactions compared to round listing prices. With respect to the effects of buyer counteroffer pricing strategies, our analysis reveals that round counteroffer prices frequently result in lower sales prices and faster deals, albeit at an increased risk of negotiation breakdown. Furthermore, we identify a "mimicry effect": buyers mirroring the precision level of sellers' charm or precise listing prices significantly lower the risk of impasse, even though it may lead to higher sales prices and longer negotiation periods. Overall, our findings offer novel insights into the strategic effectiveness of different pricing formats in the housing market bargaining process.

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1 Introduction

Bilateral bargaining plays a crucial role in allocating resources and responsibilities in economics (Backus et al., 2020). Among factors influencing bilateral bargaining outcomes, empirical researchers have increasingly recognized the importance of various pricing format strategies (i.e., \$399,999 vs \$400,000 vs \$401,123) across multiple contexts, such as eBay transactions and fashion jewelry sales (Backus et al., 2019; Petrowsky et al., 2023; Mason et al., 2013). However, the effects of these strategies at different stages of the bargaining process in the housing market still remain underexplored due to data limitations (Cardella and Seiler, 2016). Given the high-stakes nature of housing transactions and their substantial impact on the household's balance sheet (Davis and Van Nieuwerburgh, 2015), investigating the effects of pricing format strategies in this market is extremely important. To address this gap, this paper utilizes confidential offer-level data from the US housing market alongside comprehensive nationwide transaction data to reveal novel patterns of pricing format strategies employed by home buyers and home sellers. Importantly, it then examines the impact of these pricing format strategies on outcomes in the bargaining process within the US housing market.

Our analysis relies on two primary datasets. The first dataset provides novel data from Redfin, one of the largest online residential real estate brokerages in the US. Compared to standard datasets, one unique advantage of Redfin data is to offer detailed records of home buyers' actions at the offer level, including counteroffers made by buyers before a sale and the total number of bidders. This rich dataset 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. Our second dataset is the *nationwide* multiple listing service (MLS) data, which provides comprehensive information on the seller side across all US states. By combining these two datasets, we are able to track the detailed bargaining process between buyers and sellers when a property is listed in the US housing market.

We first present several novel patterns in the use of special price formats. Our analysis includes the seller's listing price, the buyer's counteroffer price, and the final sales price, encompassing all the primary prices in housing transactions. By examining the distribution of these prices and their rightmost digits, we observe that prices used in housing transactions are not smoothly distributed. Rather, there is bunching around certain "special numbers."[1] This suggests a common practice of employing special price formats in bargaining. Importantly, these formats cannot be identified by only tallying ending zeroes. Most listing prices bunch just below exact round numbers (what are called "charm numbers", such as 345,900, or "special 9k numbers", such as 349,000). However, most buyer counteroffer prices and final sales prices occur at *exact* round numbers, such as multiples of \$5k. Bunching intensity also differs – the initial listing price set by sellers exhibits higher density mass at bunching points, whereas the final sales price shows lower density, indicating reductions in bunching intensity over the course of bargaining.

Next, we study the impact of varying seller listing price formats in the bargaining process. We explore the effects of using different special listing prices on *transaction-level* outcomes. We utilize a repeat-sales model enriched with a comprehensive set of fixed effects and flexibly controlled initial listing price, to study the costs and benefits of using special prices. Our first set of results concerns charm prices (prices at most \$100 below a rounding level). Charm prices occurred in more than 20 million listings in the period 2000-2022, which is 32% of all listing price observations in the MLS data. Using our repeat-sales model, we find that houses listed at charm listing prices experience faster sales compared to listings with precise prices. For instance, listings with charm listing prices around the same rounding level lead to a reduction in market time, shortening the period by approximately 2.57 days, or 4.09%, compared to the average for listings with precise prices. The trade-off for this shorter time on the market is selling for a lower price. Indeed, houses listed at charm prices around multiples

[1] We use the term "special price" to denote prices that are either round numbers (multiples of \$5k or above), charm numbers (at most \$100 below a round price), or special 9k numbers (ending with "9000"). An exact definition and the explanation for the choice of "special prices" are provided in Section 2.

of \$100K result in a decrease in the final sales price by 0.11% respectively, compared to listings with precise prices.

What about houses listed at round prices? We find again that listings with round prices generally experience faster sales with a shorter time on the market than precise listing prices. However, there is an important difference in performance compared to charm listing prices. Charm prices systematically outperform round prices on many metrics. Charm listing prices generally result in a higher likelihood of final sales, higher sales prices, and shorter time on the market. Taking special prices around \$50K as an example, compared with listings with round prices, charm listing prices at the same rounding level increase the likelihood of final sales by 3.14 percentage points, increase the final sales price by 2.8%, and reduce the time on the market by 0.75 days. This may explain why charm listing prices are so widely used in the housing market. This result is novel in the literature and suggests that charm prices seem to perform a "cheap talk" signaling role in the real estate market, which is present in the eBay setting in (Backus et al., 2019). However, unlike in (Backus et al., 2019), round listing prices are a dominated cheap-talk signaling strategy, and therefore their presence and prevalence raise a puzzle.

We attempt to resolve this puzzle in two steps. We follow the literature (Han and Strange, 2014; Leib et al., 2021) and break down the sample by whether the sales price is above the initial listing price (bidding wars) or if the sales price is below the initial listing price (negotiations).[2] We find that round-priced listings only outperform charm-priced listings in terms of the final sales price in the bidding war scenario. This result is aligned with Leib et al. (2021)'s finding that round prices lead to better sales prices in bidding wars, in the Netherlands housing market. We contribute by noting the importance of measuring special prices not by the number of ending zeroes, since charm prices may have few or no ending zeroes but display systematically different patterns compared to other precise prices. In fact, charm prices outperform precise prices by giving higher sales prices during bidding

[2] The literature has also called these splits seller's market and buyer's market respectively.

wars despite having the same number of ending zeroes, suggesting that the mechanism of a finer-grained pricing scale discussed in Leib et al. (2021) may not be driving the observed behavior.

Second, we leverage our unique data on buyer-side counteroffers to shed light on this puzzle. We examine the effects of listing price formats on *counteroffer-level* outcomes. Our findings indicate that round listing prices tend to elicit a more aggressive bargaining approach from buyers. Consistent with the "weaker anchor" hypothesis, round listing prices often lead to both larger upward adjustments and larger downward adjustments in buyer counteroffers compared to charm or precise listing prices. When considering upward adjustments, listing prices with round figures at multiples of \$100K typically result in an upward adjustment of approximately \$8,277, or 22.65% increase compared to the average upward adjustment associated with precisely priced listings. Similarly, in scenarios involving downward adjustments, round listing prices at multiples of \$100K on average lead to a downward adjustment of approximately \$8,411, equivalent to a 30.16% decrease compared to the typical adjustments associated with precise listing prices. This effect does not hold for the charm prices at the same rounding level, and even if it holds, it has a much smaller magnitude. Such patterns imply that while the weak anchor of round listing prices can lead to price swings in either direction, the greater positive adjustments allow the possibility of some sellers *strategically* choosing round prices in the hope of benefiting from a bidding war.

Importantly, we can rule out the role of search interfaces on popular housing websites. The concern may be that price ranges are selected on the websites in round number buckets of 50k (such as 250k - 400k) that may bias the set of houses visible to home buyers and lead to certain price heuristics doing better. There are a couple of reasons why this is highly unlikely. First of all, we observe the same results for rounding levels of 10k and 5k, while website search ranges are at the 50k level (see Figure B1). Second, round prices are included in the lower end of the search range, while corresponding charm prices are dropped. Therefore, one may think that round prices benefit because they are the cheapest house in the selected range, and will be viewed by buyers with a higher willingness to pay. However, we find the opposite result — on average round prices perform worse than charm prices. Note that there are no such concerns for the upper end of the search range since both round prices and charm prices are included in search results.

Finally, in another set of novel results, we explore how different pricing formats for buyer counteroffers affect the bargaining process. We find that round counteroffers have two main benefits: buyers often secure lower purchase prices, and transactions are completed more quickly. These benefits help to explain why buyers' counteroffers tend to cluster at round numbers. However, there is also a downside to this strategy. We find that using round numbers in counteroffers generally decreases the likelihood of transaction success for buyers. Conversely, charm counteroffers generally yield opposite effects. Specifically, charm counteroffers often increase the chance of a transaction's success for buyers but result in higher purchase prices and slower transactions. The latter effects, however, are mainly driven by charm counteroffers that have a minimal difference from the listing price.

Besides exploring the effects of counteroffer price formats per se, we investigate the impact of buyers mirroring sellers' pricing formats on transaction outcomes (i.e., mimicry effect). This inquiry sheds light on whether adopting the same pricing strategy as the seller influences the success and efficiency of transactions. Our findings reveal that when buyers imitate charm or precise pricing strategies used by sellers, they experience a higher rate of transaction success. However, this mimicry comes with certain trade-offs, including higher purchase prices and longer duration to close deals, compared to adopting counteroffers that do not follow the seller's pricing format. This pattern is robust even after we filter out offers that involve only trivial adjustments to the listing price.

This paper contributes to several strands of literature. First of all, it adds to the literature on the effects of pricing formats in the housing market. Due to data limitations, previous research has primarily focused on analyzing the rounding-off patterns of home sellers' initial listing price formats (Pope et al., 2015) and their impact on final sales prices from regional housing markets (Allen and Dare, 2004b,a; Palmon et al., 2004; Thomas et al., 2010; Beracha and Seiler, 2014). Our paper advances this literature in the following ways. First, instead of relying on local housing market data, this paper analyzes nationwide housing transaction data spanning the most recent decade. This approach enables the investigation of rich heterogeneous effects and helps reconcile inconsistent findings in the literature resulting from small sample sizes. Our results for charm prices having advantages of faster sales at a lower price is novel, to the best of our knowledge. In addition, in accordance with the experimental findings in Leib et al. (2021), our study validates the presence of "anchoring effects" stemming from sellers' round listing prices using large-scale transaction data. Second, by examining detailed real-world bilateral bargaining data in housing transactions, this paper sheds light on the effects of these pricing formats on both buyers' counteroffer behaviors and sellers' revised listing behaviors. By extending our analysis beyond the traditional focus on final sales outcomes, we offer a more detailed and nuanced understanding of the effects associated with these pricing strategies during the bargaining process. Third, we go beyond analyzing initial listing prices by providing the first large-scale empirical evidence on the clustering patterns of buyers' counteroffer price formats and their effects on the bargaining process, utilizing novel Redfin data. Consistent with Petrowsky et al. (2023), we show that "mimicry effects" also exist in the bargaining process of the housing market. Additionally, we document novel empirical evidence on the pros and cons of adopting counteroffers with special prices.

In a paper that is related to ours, Repetto and Solís (2020) analyze house sales in Sweden. They find that houses with list prices rounded at the 1 million SEK and 100,000 SEK level sell for a lower price compared to those below it. They, therefore, find that round prices perform poorly compared to other prices. There are a few important differences between their paper and ours. First, they do not consider charm prices. When choosing just-below prices they choose a bandwidth of 500,000 SEK below the 1 mn SEK rounding level, going down to 5,000 SEK in their robustness, a bandwidth of 0.5%. However, for the 100,000 SEK rounding levels, they take a bandwidth of 50,000 SEK with no reported robustness, a 50% bandwidth. In contrast, we look at charm prices at a bandwidth of 100 USD below the round price at every level (a bandwidth of 0.01% for a 1 mn USD house). We further document why it is important to make this distinction, offering plausible cheap talk benefits of charm prices. Second, Repetto and Solís (2020) do not find similar results for lower rounding levels such as the 10,000 SEK level as they do at higher SEK levels, even though they do observe significant bunching at these levels. Our results, which split rounding patterns in a different manner, are observed at both higher and lower housing values. Last, as the authors themselves note, the public ascending price auction in Sweden is a very different institutional setting compared to the US set-up. In the former, the listing price is the starting value of auctions. In the latter, the listing price can play different roles.[3]

Second, this paper also contributes to the empirical literature on negotiation and sequential bargaining. Backus et al. (2020) note that previous studies mainly examine various aspects of bargaining in theory or in laboratory experiments. Only a few empirical studies examine people's detailed bargaining behaviors in large-scale real-world negotiations, such as eBay transactions (Backus et al., 2020; Petrowsky et al., 2023) and merger and acquisition (M&A) negotiations (Liu et al., 2023). This paper complements the nascent literature by examining the effects of different listing and counteroffer pricing formats on people's bilateral bargaining behaviors and outcomes in another high-stake real-world setting (i.e., the US housing market).[4] The bulk of the studies in house search and bargaining have primarily 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), financ-

[3]Papers argue that the listing price serves as a strategic instrument balancing the trade-off between sales price and duration, as in Yavas and Yang (1995), as an instrument to direct search, as in Chen and Rosenthal (1996a) and Chen and Rosenthal (1996b), as a signal of seller motivation, like in Albrecht et al. (2016), or as a partial commitment device, as in Han and Strange (2016).

[4]Beracha and Seiler (2014) also examines the bargaining process in the US housing market. However, there are several key distinctions between Beracha and Seiler (2014) and our paper. Firstly, while they only analyze the effects of initial listing prices, our paper also investigates the effects of buyers' counteroffer pricing formats. Secondly, Beracha and Seiler (2014) conducts a lab experiment with undergraduate students and primarily focuses on relatively inexpensive houses with market values around $200,000, whereas our analysis is based on real-world large-scale offer-level data covering both relatively inexpensive and expensive houses.

ing (Genesove and Mayer, 1997), and their relationship with the final sales price. However, as noted by (Merlo and Ortalo-Magné, 2004), due to data limitations, few empirical studies have been able to investigate the individual behavioral patterns of the bargaining process in the housing market that takes place between the seller and the buyer. By observing the the entire path of revised listing prices and counteroffer prices, our paper provides novel insights into this important bargaining process.

Lastly, this paper is also closely related to the literature on "rounding-off" behaviors. Economists have long realized the existence of rounding-off behaviors and heuristics in various markets where people tend to use round numbers.[5] Some papers such as Meng (2023) and Wiltermuth et al. (2022) have studied the reference dependence effect of previous sales price on subsequent valuations of houses using repeat sales data. Complementing this literature, our paper systematically documents the presence of rounding-off behavior at the initial listing price, buyer offer price, and final sales price level. Since our rich data allows us to provide a taxonomy of different rounding-off levels chosen in the market, we are able to find the effects of these rounding-off behaviors on a rich set of housing transaction outcomes.

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 prevalent usage of special pricing formats in both home buyers' counteroffer prices and home sellers' listing prices. Section 4 analyzes the impact of various seller listing pricing formats. Section 5 analyzes the impact of various buyer counteroffer pricing formats. Section 6 concludes.

[5] These 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 for using round numbers 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.

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 Appendix Figure B2.[6] Initially, the seller puts up her property for sale, thereby 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.

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 a failure to sell. A failure to sell can result from unsuccessful negotiations between the buyer and seller, or from the absence of an offer from potential buyers. An *action* within an event is defined as either a listing initialization/revision made by the seller, or an offer proposed by a potential buyer.

In each listing event, distinct price concepts are defined for clarity. The term *initial listing price* refers to the price at which the property is initially listed on the market. When a potential buyer submits an offer, the price proposed is termed the buyer's *counteroffer price*. The *current listing price* is the prevailing listing price at the time the buyer makes their counteroffers. Finally, the *final sales price* denotes the amount at which the transaction is ultimately completed.

[6] Appendix C.1 gives a detailed explanation through example transactions.

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 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, prices, listing dates, agent information, and housing characteristics. Furthermore, the MLS serves as a centralized platform for agents to collaborate, sharing information regarding properties, and 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, our 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 drop observations that are rental listings. Second, we restrict our analysis to single-family homes, multi-family homes (2-4 units),[7] condos, coops, and townhouses. Third, we exclude foreclosures and short sales from our sample, as they may have different market dynamics than regular sales. Fourth, since our research primarily centers around housing prices, we have only retained observations with the non-missing initial listing prices. Fifth, we remove observations before the calendar year 2000 or after the calendar year 2022. We choose sample 2000 because of the sample quality. Finally, we remove listings that are still active or under pending status. Based on our selected sample, we further clean the data to remove outliers and fix anomalies, as described in Appendix C.2. After applying the selection and cleaning, our final dataset comprises 36,931,059 unique properties and 76,981,953 events across 50 states and Washington D.C. in the U.S. for the period between 2000 and 2022. Appendix Figure B5 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 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

[7] Multi-family homes (2-4 units) include Duplex, Triplex, Fourplex.

of the seller agent.[8] 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. Appendix Figure B6 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.[9]

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 agents record 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 can see the recorded reason for rejection. Even if the offer is rejected, Redfin records sales price data. We have sales price data for approximately 90.9% of all property listings in the Redfin dataset.

Our Redfin data spans 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 773,508 buyer/seller actions, 314,829 buyer offers, 296,640

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

[9] The 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.

bargaining events, and 293,793 unique properties listed on Redfin. As depicted in Appendix Figure B7 at the counteroffer level,[10] our dataset covers a wide area of major cities, with a notable emphasis on the West Coast, where Redfin was initially founded and expanded. 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.

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 \$334,824. The ensuing average sales price stands at \$307,190, which is 91.75% of the initial listing price.[11] The average days-on-market (DOM) is 59.48. We define a *bidding war* as a scenario where the sales price surpasses the initial listing price by over \$100.[12] Conversely, a *negotiation* is characterized by a sales price that falls more than \$100 below the initial listing price. Within our MLS sample, bidding wars constitute 20% of the listings, whereas negotiations account for approximately 64%. The remaining listings are those with minimal price deviations. The dataset predominantly comprises single-family homes and Condos, representing 94% of all listings. The typical property in the sample is characterized by an average age of 36.09 years, with three bedrooms and two bathrooms, encompassing an average living area of 1,946 square feet.

Table 2 provides summary statistics for the Redfin dataset. Panel A presents the summary statistics after collapsing the action-level data into the event level. The listing price revision history from the Redfin data gives us a more detailed look at the listing price dynamics during the bargaining. The average initial listing price of a property is \$555,149. We can also observe the final listing price of the house before it was taken off the market. The

[10] We show the coverage at the counteroffer level as it is the main one used for Redfin analysis.

[11] This significantly high discount rate is partly due to the exclusion of failed listings, which are generally listed at a higher price.

[12] A detailed rationale behind this definition is discussed subsequently.

average final listing 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 the total 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 listing price revision. Note that the listing 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 listing price. 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. We also observe a higher share of bidding wars compared to that in MLS data.

Panel B of Table 2 shows the summary statistics at the buyer counteroffer level. The total number of buyer offers recorded in our dataset is 314,829. The average buyer counteroffer price is \$552,284, which is \$1,011 higher than the average listing price at the time of making the offer ("current listing price"). In particular, among all offers, 41% of the counteroffers are upward adjustments over the listing price, while 39% of the counteroffers are downward adjustments to the listing price. The remaining share corresponds to the offers that deviate from the listing price by no more than \$100. When a Redfin buyer makes an counteroffer 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 counteroffers have at least one competing offer at the same time. On average, 3.71 additional offers are 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, which accounts for 10% of all offers.

To address potential concerns regarding interactions among competing buyers, we construct a counteroffer-level sample that excludes the presence of competing offers. As illustrated in Panel C of Table 2, the lack of competition leads to counteroffers without competing offers having lower current listing prices, lower counteroffer prices, as well as greater downward adjustments compared to Panel B.

3 Descriptive Patterns in Special-Price Clustering

We start by examining rounding-off behavior at the event level using the comprehensive nationwide MLS data.

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 (Thomas et al., 2010; Leib et al., 2021). Appendix Figure B9 shows the number of ending zeros for each initial listing price bin of $100,000, for prices in the range $100,000 - $999,999.[13] We see a significant fraction of listing prices in each range having 3 or more ending zeroes. As the initial listing price increases, the number of ending zeroes also increases. In other words, people tend to use more rounded listing prices for more valuable homes. This makes it important to control for the listing price in regressions when tracking the effect of these rounding-off behavior.

However, there are several drawbacks to using the number of ending zeroes to characterize the rounding-off behavior in the housing market. First, in a 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, concerning "special price" formats. Second, ending zeroes cannot correctly correctly classify the choice of special price formats. As we will show later with our alternative definition of special prices, some prices with few ending zeros, such as charm

[13]We 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.

prices (e.g. 449,900), are strategically used. However, those special prices are treated as relatively precise prices using ending-zeros definition, and therefore largely ignored.

To address the drawbacks of using the number of ending zeroes, we carefully examine the distribution of prices, of the initial listing price and the final sales price of properties in the MLS sample, as shown in Figure 1.[14] Each bar here represents a $1K price range.[15] Panels (a) and (c) plot the distribution of the initial listing 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.[16]

Based on Figure 1, it is evident that prices are not smoothly distributed. Instead, both the initial listing 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 listing 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, and even more pronounced around multiples of $50K. A similar phenomenon can also be observed in the final sales prices.

While clustering exists in the distributions of both initial listing 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 listing 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 listing price and the final sales price. Specifically, for a given level of initial listing price, we are interested in the resulting final sales price. Figure B14 shows this connection between the initial listing price and the final sales price through heatmaps. We first calculate the "discount" of each observed listing, defined as the difference between the initial listing price and the final sales

[14] For robustness check, Figure B11 shows the same set of plots using Redfin data.
[15] In this paper, "K" is used to represent thousands and "M" is used to denote millions.
[16] In the appendix, Figures B12 and B13 show the zoomed-in plots over other price ranges.

price. Then, for each level of initial listing price, we provide the share of observations at each discount level, normalized within each initial listing 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 listing price level, most final sales prices tend to round down to a special number. This pattern is robust across all price ranges. In Figure B14, this is depicted 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 1 — because we normalize observations *within* each column. However, the heatmap helps us understand the dynamic movement of prices from the initial listing price stage to the final sales price. Another finding from the heatmaps is that, as the initial listing price increases, as we go from panels (a) to (h) of Figure B14, the 45-degree lines crossing the horizontal axis at multiples of \$50K become more salient. This implies that the degree of rounding increases with the initial listing price, consistent with our finding shown in Figure B9.

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 2 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 listing 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 listing prices are around the multiples of \$50K. The second highest set of densities is around multiples of \$5K.

Comparing Figure 1 with Figure 2, 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 listing prices to round numbers in sales price are driven by the strong preference for buyers to choose round numbers.[17]

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 3 and 4 plot the distribution of the three and four rightmost digits of prices.[18] Figure 3 shows the distribution of the rightmost digits of the initial listing price and the final sales price using the MLS sample. Panels (a) and (b) use the three rightmost digits of the price on the 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 listing prices in the MLS have at least three ending zeros. Separately, more than 30% of all observations end with 900. They constitute the "charm" prices, which are the prices slightly below exact round prices, in Figure 1. For the final sales price, Panel (b) shows that approximately three-quarters of the final sales price has at least three ending zeros. However, it should be clear that while a 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.

To expand the granularity of our analysis, we examine the distribution of the four right-

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

[18]No additional patterns are revealed when looking at the 5 rightmost digits.

most 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 listing 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 concentrated mass 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 the rightmost 4 digits is different from the initial listing price distribution of the rightmost 4 digits. Figure 4, which shows the distribution of the rightmost digits of offer prices at the action level using Redfin data, also exhibits a similar pattern as the final sales price.

Given the patterns of "special values" observed empirically, we will focus on round, and charm prices, as well as 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 $\mathcal{X} \coloneqq \{5\text{K}, 10\text{K}, 50\text{K}, 100\text{K}\}$. 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 $x \in \mathcal{X}$,

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

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 $x \in \mathcal{X}$,

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

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 $x \in \mathcal{X}$,

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

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

To make the definition more concrete, Table A2 shows the example classification of prices around \$450K into the format groups we defined above. We term all other prices as **precise price**. Table A3 provides group-wise summary statistics based on the price format and the associated rounding level.

In the next section, we investigate the question of whether the pricing strategy and rounding level of two similar houses produce any effect on various housing transaction outcomes. We run our analysis on a sample of repeat sales, and crucially control for initial listing prices so that the comparison will be between homes with the same fundamental value listed at similar prices but with different price strategies, say round versus charm.

4 Effects of Listing Pricing Format Strategies

4.1 Effects on Success Likelihood, Sales Price, and Duration

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

To study the implications for different listing price formats used by sellers, we utilize the comprehensive MLS dataset of listing events by the sellers. We run the following specification at the event level:

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

where $Y_{i,t}$ is the event-level outcome of property i initially listed at time t. $p_{i,t}$ is the initial listing price of property i initially listed at time t. As defined in Section 3, the variables $R_x\left(p_{i,t}\right)$, $S_x\left(p_{i,t}\right)$, and $C_x\left(p_{i,t}\right)$ are binary variables indicating whether the initial listing price $p_{i,t}$ is a round, special 9k, or charm number, respectively, at the rounding level x. θ_x, ψ_x, and β_x identify the differences in outcome relative to the precise listings. In our descriptive evidence, we find that sellers are more likely to round off at higher listing prices. We therefore have to account for the correlation between the initial listing price and listing price precision formats. Specifically, we use $g\left(p_{i,t}\right)$, which is the restricted cubic spline of log initial listing price, to provide a more robust and flexible control of this correlation.[19] 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

[19] We use the restricted cubic spline of log initial listing price with four knots. The locations of knots are at 5, 35, 65, and 95 percentiles based on recommended percentiles in Harrell et al. (2001).

may affect its sales price. In addition, we also control for the housing characteristics which are potentially time-varying. They include property age, property age squred, number of bedrooms, number of bathrooms, and the area of the property, 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 listing price formats on the outcomes of bargaining, by comparing identical properties sold at different listing events at nearly identical listing prices, with the only difference being whether the sellers use round, charm, special 9k, or precise listing prices which constitute the control group. 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 listing price format. For example, sellers who use round listing prices may tend to overshoot their listing prices. Our estimates may then be biased if we were to compare *different* homes with similar listing prices but with different listing 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 5 presents the analysis of Equation (1) at the event level, leveraging all repeat-sales transactions recorded in the MLS from 2000 to 2022. This analysis primarily investigates the relationship between various listing price formats and the seller's probability of achieving a final sale. Panel (a) of Figure 5 details the regression outcomes when utilizing a variable that denotes whether a listing closed successfully as the dependent variable. The findings indicate that listings priced with round figures are associated with a decreased chance of concluding a sales. Conversely, charm-priced listings have a slightly positive, albeit statistically insignificant, impact on the likelihood of a successful sale. Specifically, a listing with a round price at the \$100K level is shown to reduce the success probability by 2.57 percentage points, whereas the impact of a charm price at a comparable rounding level results in a marginal change of 0.05 percentage points, which is not significant.

Once the listing is successful, there are multiple dimensions through which we can evaluate the outcomes. We start by examining the likelihood of a discount for each listening event. Recall that the discount is the difference between the initial listing price and the sales price. Panel (b) of Figure 5 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. Therefore, at least part of the role special listing 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 listing price. Given that the mean probability that the control group listed price will have a trivial adjustment is 0.162, our estimates imply that round number listing prices at the 100k level increase this probability by 0.052, or by 1/3rd of the baseline. A closer look at trivial adjustments for round prices (not reported here) shows that they are driven by no changes to the final sales price. Charm prices at the 100k level see an increase in probability by 0.013, or by 1/12th of the baseline probability In trivial adjustment cases, charm prices typically see a round-up to the nearest round number in these cases (e.g., 431,900 to 432,000).

While minor price adjustments play a significant role in the negotiation phase of housing transactions, they account for no more than 25% of cases across all price format categories. When focusing on scenarios where the discount applied is substantial, Panel (c) of Figure 5 delves into the likelihood of a transaction escalating into a bidding war, given that the discount is not trivial. We find that both charm and round listing prices generally result in a diminished probability of triggering bidding wars. A notable exception is observed with round listing prices at the \$100K level, which actually increases the likelihood of a bidding war by 0.7 percentage points. Further comparison between round and charm listing prices at equivalent rounding levels reveals that round prices consistently offer a greater potential for bidding wars than charm prices. This distinction suggests a possible strategic advantage of employing round pricing strategies, suggesting that while charm prices might be appealing for other reasons, round prices have a unique capacity to stir competitive bidding, potentially leading to more favorable outcomes for sellers in terms of sales dynamics.

To further examine other event-level outcomes, Panel (d) of Figure 5 plots the coefficients using the 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 listing prices even though both types of price formats lead to lower sales prices compared to precise listing prices. Round prices lead to much lower sales prices at the same rounding level. At the \$100k level, for example, round initial listing prices lead to a 0.36 percentage point decrease in the final sales price. This effect represents a \$842 (0.36% $\times$ \$234,012, the average sales price of events with precise listing prices) lower sales price, compared with the omitted group of precise listing prices. The decrease in sales prices amounts to 11.23% of the typical discount-off events with precise listing prices. In comparison, at the \$100k level, charm initial listing prices only lead to a 0.11 percentage point decrease in the final sales price, which is \$257 or 3.4% decrease in the final sales price than the group with precise listing prices. 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 shorter 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 (e) of Figure 5. We find that special prices in general lead to shorter DOM. If we compare among the special prices, round prices actually take a longer time on the market than charm prices at every rounding level, except for the \$100K level. Round price listings at the \$50K level, for example, spend 1.7 days less on the market than precise price listings, while this number is 2.45 days less for the charm price listings. This accounts for 1.7/62.84 = 2.7% (round $100K) and 2.45/62.84 = 3.9% (charm $100K) faster than the average DOM for precise listings, respectively.

Combining the transaction level outcomes, we find that both round and charm prices decrease the probability of a bidding war, reduce the final sales price, and shorten the time listings spend on the market. This suggests that both round and charm prices leverage some "cheap talk" benefit, as Backus et al. (2019) documented in low-stake eBay market. Backus et al. (2019) document using eBay bargaining that sellers who list items at special prices, especially those at exact multiples of $100, accept a lower price in exchange for a quicker sale. They propose the "cheap-talk" hypothesis which argues that round listing price is a rational strategy by the sellers to signal their weak bargaining position to buyers. Under this interpretation, round listing prices signal that the sellers are impatient and willing to accept a lower sales price in exchange for a faster sale. In the context of the high-stakes real estate market, our findings extend the application of the "cheap talk" theory, indicating that these special prices still perform as a signal even a high stake market. This revelation is particularly novel within the housing market literature, suggesting that such pricing formats can indeed influence transaction dynamics, partly mirroring the bargaining behavior observed in lower-stakes marketplaces like eBay.

Both round and charm listing prices leverage the "cheap-talk" benefits, yet our analysis shows that charm prices outperform round ones in key aspects. Notably, charm-priced listings, when matched with round listings at similar rounding levels, are more likely to achieve a sale, secure higher sale prices, and spend less time on the market. This outcome is particularly fascinating given that the distinction between charm and round pricing often hinges on minor variations—charm prices are set just below round numbers by a slim margin, which is less than $100 by definition. These additional benefits of adopting charm listing prices aligns with observed seller behaviors where listing prices frequently cluster around these so-called charm numbers, as discussed in Section 3. This is significantly different from Backus et al. (2019) in the low-stake market, where they find a similar "cheap-talk" effect for both types of special prices.

Round price as a dominated strategy for sellers leave us a puzzle: why are there still so many sellers choosing round listing prices? As we observe in the data, there is still a salient amount of sellers who choose exact round prices when setting the initial listing price. From the aggregate transaction-level outcomes, the only notable advantage for sellers opting for round prices is a heightened possibility of trivial discounts or initiating a bidding war. These two effects combined imply that the likelihood for the buyer to bargain down the price when the list is a round price is lower. Yet, this benefit at the extensive margin does not translate into tangible gains in the final sales price. To gain a deeper understanding of this phenomenon, we investigate the heterogeneous effect of the pricing strategy from an ex-post perspective by categorizing transactions based on their conclusion —- either as a bidding war or a negotiation. Then, we estimate Equation 1 using the subsamples. This approach allows us to test the magnitude of the price deviation from the initial listing price in different scenarios.

Panel (f) of Figure 5 shows the regression results using log sales price and days-on-market (DOM) as the dependent variable, respectively. The effect of price format on the final sales price diverges in the case of a bidding war and negotiation. The general pattern is that both round and charm prices lead to a higher sales price in a bidding war while they lead to a lower price in a negotiation. More closely, we see that round prices perform more poorly than charm prices in negotiations. In bidding wars, round prices do significantly better than precise prices and outperform charm prices at the $100K level. Combining these observations, there is an advantage to using round prices in the bidding war scenario. This particular result is related to Leib et al. (2021)'s finding that round prices lead to better sales prices in bidding wars, in the Netherlands housing market. There are also a few notable differences when we compare our paper with their corresponding observational data for Amsterdam in 2017. First, their regressor is the number of zeroes on the selling price. While we do look at rounding levels with increasing zeroes, our results are more granular on the level of rounding, and we make the important distinction of separating out charm prices. Charm prices, in fact, also outperform precise prices and give higher sales prices during bidding wars, something that goes against the mechanism of a finer-grained pricing scale offered for the results in Leib et al. (2021). This is because charm prices have the same number of ending zeroes as those in the control group. Yet, they have a higher price during bidding wars compared to the control group. Second, for results on negotiations, as the authors note (pp 1054), the Amsterdam market in 2017 is not ideal for studying the effect of rounding-off behavior on sales price during negotiations. More generally speaking, for bidding wars we have the benefit of a much larger sample — we have 16 million bidding war observations over 2000-2022 for the entire U.S. compared to about 8,000 observations for 2017 for Amsterdam — allowing us to look at other outcomes given in other panels of Figure 5.

Next, we study counteroffer-level data from Redfin to examine how the rounding-off behavior affects outcomes during the bargaining process. We note at the outset that since the percentage of bidding wars in this sample is 56%, more than double that in the MLS sample, the results are more representative of bidding wars. We use the following regression specification at the buyer-counteroffer level:

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

Here, $Y_{j,t}$ is the dependent variable of counteroffer j in response to the current listing price at time t. The variables $R_x\left(p_{j,t}\right)$, $S_x\left(p_{j,t}\right)$, and $C_x\left(p_{j,t}\right)$ are binary variables indicating whether the current listing price $p_{j,t}$ is a round, special 9k, or charm number, respectively, at the rounding level x. Similar to Equation 1, we control for potential confounding variables, including the cubic spline of log current listing price $p_{j,t}$, and a set of housing characteristics in $X_{j,t}$ including property type, age, 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 counteroffer 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 buyer-agent fixed effect $\xi_{a(j)}$ to control for time-invariant characteristics of the buyer agents.[20]

Figure 6 shows the estimating results of Equation (2) using counteroffer outcomes and competition measures as dependent variables. The dependent variable in Panel (a) is a binary variable indicating whether the counteroffer directly leads to a successful house purchase. The regression results of Panel (a) show that generally, both the round and the charm current listing prices are negatively associated with a buyer's success probability. On average, a round current listing 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 is observed for the \$5k level as well. For other levels, the point estimates suggest a similar story but their confidence bands overlap.

The second interesting result is in Panel (b) of Figure 6. We find that round prices consistently lead to more competing counteroffers, compared to precise listing prices and charm listing prices. Each house receives on average 3.15 competing counteroffers. For homes listed at rounding level 100k, these counteroffers increase to 3.89. For homes listed at charm prices at the 100k level, the counteroffers increase to 3.35. The increase in the number of competing counteroffers for round prices and to some extent, for charm prices, is consistent with results in Panel (a).

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

[20]Since Redfin data is buyer-side, we cannot directly observe the corresponding seller agent.

the reasons for counteroffer failures. Conditional on the sample where the counteroffer failed, the mechanism that drives the negative correlation between the buyer's success rate and the round listing price should be consistent with the corresponding reason for failure as the dependent variable. Panel (c) of 6 shows that i) both round and charm prices lead to a higher share of counteroffers 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 an unsatisfactory price. Finally, the hypothesis can be tested more directly from Panel (b) of Figure 6 which uses the total number of counteroffers as the dependent variable. It confirms the competition story.

4.2 Effects on Buyers' Counteroffers

So far, we have shown that both round and charm listing prices lead to lower sales prices and faster sales compared to precise listing prices. Round listing prices lead to lower sales prices without a faster speed of sale than charm listing prices during negotiations, but during bidding wars, round listing prices lead to higher sales prices than precise listing prices. Round listing prices induce more buyer counteroffers and lead to a lower success probability per buyer counteroffer.

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

To answer this question, Table 3 presents the regression results of Equation (2) using the indicator of the round counteroffer price at a specific level as the dependent variable. This implementation helps us to identify, at a given level of round/charm current listing 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 counteroffer 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. This suggests that when the current listing price is a round or charm number at a certain level, the buyer is more likely to make a round-price counteroffer at that same level. For example, the first coefficient in Column (1) implies that having a round current listing price at multiples of $100k increases the probability of the counteroffer 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 listing price indicators are also significantly positive. However, this effect is not evident for charm prices.

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 listing price. This would be consistent with results on trivial adjustments using our listing data. Formally, we define buyer price adjustment as the difference between the buyer counteroffer price and the current listing price.[21] There are two cases of particular interest.

1. Case 1: A current listing price is a round number, and the buyer proposes a counteroffer with zero price adjustment. Then, the buyer counteroffer price will mechanically be a round number.

2. Case 2: A current listing price is a charm number, and the buyer makes a trivial upward adjustment such that the counteroffer is the nearest round number of the listing 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.[22] Comparing Table 3 with Table 4, removing

[21]The current listing price is the listing price at the time of buyer counteroffer.

[22]We use $100 in absolute value so that the exclusion is symmetric. However, a breakdown in A4 shows

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 listing price drive most of the coordination in rounding between buyers and sellers during bargaining that we observed before.

Anchoring Effect 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 counteroffer prices are closer to the listing prices in general when sellers use round/charm listing 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 counteroffer price is above the current listing price of the property. On the other hand, a downward adjustment signals bargaining, where the buyer is negotiating down the listing 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 listing price. The table is divided into three panels, each representing a different type of current listing price: round current listing price, charm current listing price, and the control group of precise current listing 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 listing price, approximately 44% of the buyer counteroffers have a downward adjustment of more than 100, while 40% have an upward adjustment of more than 100. On the other hand, around 16% of the observations

that most of the non-zero trivial (i.e., adjustment is no more than \$100 in modulus) adjustments correspond to Case 2.

have a downward adjustment equal to 100. Each row sums up to \$100.

Regarding non-trivial upward adjustments, while there is no significant difference between panel A and panel C, the share of buyer counteroffers with a non-trivial upward adjustment conditional on the current listing price being a charm number is much lower (about 10% depending on the rounding level). Overall, these results suggest that a round listing price will reduce the chance for a buyer to make a non-trivial downward adjustment, while a charm current listing 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 listing price. Therefore, the overall effects are ambiguous.

To formally test the correlation between the magnitude of adjustment and sellers' rounding-off behavior, Figure 7 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 listing 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. Quantitatively, when listing prices are exact multiples of \$100k, the positive adjustment in counteroffer prices is by \$8,411 dollars, compared to similar counteroffers with precise listing prices. When listing prices are exact multiples of \$100k, the negative adjustment in counteroffer prices is by \$8,277 dollars, compared to similar non-round and non-charm listing prices. The magnitude of this extra adjustment is sizable, and a similar phenomenon exists when listing prices are multiples of \$50k, \$10k, and \$5k. 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 therefore weaker than for other prices.

4.3 Discussion of Potential Mechanisms

To better understand the result, we must dig into the mechanisms that potentially lead to people's rounding-off behavior. Specifically, we can group all mechanisms into two types: rational and irrational mechanisms.

Many mechanisms have been considered in the literature. One type of rational mechanism is cognitive shortcuts. It refers to the case where people deliberately adopt round numbers as cognitive shortcuts to save cognitive energy. This mechanism commonly exists in many low-stake environments. However, it is unlikely to be a dominant reason in the housing market, which is under high-stake situations. The potential cost of cognitive shortcuts can be huge by choosing a round number at multiples of \$50k. The second type of rational mechanism is lack of information (Herrmann and Thomas, 2005; Ormerod et al., 2007; Whynes et al., 2007; Kleven and Waseem, 2013). It is usually difficult to precisely estimate the value of a property because of heterogeneity and lack of information. Therefore, people might only be able to provide a proxy for the property's value. This means that when more information is available, less rounding-off behavior should be observed. However, this mechanism may not explain why listing prices are more likely to cluster around special values than counteroffer prices if we think sellers in general have more private information than the buyer. Still, we cannot rule out a lack of information driving at least some of the results we observe. The third mechanism is the "overshooting" of sellers and the "undershooting" of buyers. This mechanism refers to people's tendency to round prices in a certain direction in order to extract extra surplus from the negotiation. Specifically, the "overshooting" of sellers refers to sellers' tendency to round up listing prices, while the "undershooting" of buyers refers to buyers' tendency to round down counteroffer prices. In order to test this mechanism, we need to elicit truthful valuation first (Kessler et al., 2019). The final type of rational mechanism is the strategic channel. If a similar bargaining style leads to a higher probability of reaching a deal, people might strategically mimic each other. This is certainly a viable explanation for why charm prices are used so widely in the housing market in the U.S. offering a strategic cheap talk signaling advantage.

The existing literature on irrational mechanisms primarily focuses on people's cognitive limitations (Rosch, 1975; Lacetera et al., 2012; Kuo et al., 2015; Lin and Pursiainen, 2021; D'Acunto et al., 2019). People with low cognitive ability tend to round off more frequently without realizing that it is costly. There are two aspects we can test this mechanism. The first aspect is that people with cognitive limitations may perform worse in other settings. The second aspect is that experience can help to improve cognitive ability and therefore mitigate this behavioral bias.

5 Effects of Counteroffer Pricing Format Strategies

5.1 Effects on Buyers' Success Rate, Purchase Price, Duration

This segment of the study pivots our examination toward the dynamics of buyer price rounding behavior during bargaining, probing its influence on the bargaining outcomes. We extend our model from equation 2 to incorporate buyer rounding-off behavior through the augmented equation as follows:

$$\begin{aligned} Y_{j,t} = &\sum_{m \in \{s,b\}} \sum_{x \in \mathcal{X}} \left[\theta_{m,x} R_x\left(p_{m,j,t}\right) + \psi_{m,x} S_x\left(p_{m,j,t}\right) + \beta_{m,x} C_x\left(p_{m,j,t}\right)\right] + g\left(p_{s,j,t}\right) + X_{j,t}\gamma \\ &+ \tau_{l(j),t} + \xi_{a(j)} + \varepsilon_{j,t} \end{aligned} \tag{3}$$

where subscripts $m \in \{s, b\}$ denote either seller s or buyer b.

In this augmented model, $p_{b,j,t}$ signifies the counteroffer price proposed by the buyer, while $p_{s,j,t}$ denotes the seller's listing price for the respective counteroffer. Compared to Eq.(2), this model incorporates dummy variables to indicate the occurrence of special counteroffer prices by the buyer, akin to the definitions employed for categorizing listing prices as special. The coefficients of interest are $\theta_{b,x}, \psi_{b,x}, \beta_{b,x}$. Despite the absence of notable clustering around charm prices or specific 9k counteroffer prices, these indicators are integrated into the regression to maintain analytical consistency. Although the counteroffer-level data doesn't show significant clustering around charm or special 9k counteroffer prices, we still include these indicators in the regression for consistency. The model also uses special listing price indicators as control variables to account for the interactive rounding behaviors. Beyond the controls applied in Eq. (2), this model further controls for the buyer's adjustment from the listing price, which reflects the buyer's bargaining intent's direction and intensity. The set of fixed effects remains consistent with that of the baseline model.

A key concern in our analysis is if the differences we see are actually because of how the price of the main offer is shown, and not because of other offers we might not know about. To avoid the issue of these unknown competing offers, we only look at cases where there is just one offer, meaning there are no other offers to consider. By doing this and making sure we account for a usual set of factors along with how the price is listed, we make sure that any differences we find are really because of the way the offer's price is presented.

Figure 8 outlines the results of our regression analysis based on Eq. (3), focusing on various outcomes related to counteroffers. We begin by examining the impact of different price formats on a counteroffer's likelihood of success. Specifically, Panel (a) of Figure 8 showcases the effects of price formatting on the probability of a counteroffer being successful. The findings reveal distinct impacts for round and charm price formats. Generally, counteroffers with round prices, such as those ending in multiples of \$100k, are associated with a lower chance of success for the buyer, decreasing by an average of 5.3 percentage points. This drop translates to a success rate approximately 8.82% lower than that for counteroffers with precise price points. The adverse impact of round prices diminishes with less aggressive rounding. On the other hand, charm prices, particularly at the 10K and 5K rounding levels, significantly increase the likelihood of a buyer's counteroffer succeeding. For instance, setting a charm price at a 5K level boosts the success rate by an average of 5.0 percentage points, equivalent to 8.31% higher than the success rate for counteroffers priced precisely.

Upon securing a successful offer, our analysis extends to explore how rounding-off strategies influence two additional dimensions: the final transaction price and the speed of sale. With regard to the transaction price, we study the impact of rounding behavior on the ultimate sale price of the property. Panel (b) in Figure 8 details the regression outcomes from Eq. (3), taking the logarithm of the final purchase price (i.e., a seller's sales price) as the outcome variable. The analysis indicates that counteroffers rounded to whole numbers are generally associated with a non-positive effect on the final purchase price, showing significantly negative impacts at the \$10k and \$5k rounding levels. This suggests that although rounded counteroffers might face lower acceptance rates, when accepted, they tend to position the buyer favorably in negotiations, leading to a lower sale price. For example, a round counteroffer priced at \$10k typically results in a sale price reduction of about 0.3%, or \$1,274. In contrast, charm pricing strategies do not negatively affect purchase prices, and can even result in positive effects. Specifically, a charm-priced counteroffer at the \$10K level, on average, achieves a 0.5% reduction in the final purchase price, equating to a decrease of \$2,123.

The analysis further demonstrates a favorable outcome for round prices in the context of transaction speed. Specifically, we assess the speed of transactions by calculating the number of days required to finalize the deal, defined as the time span from when the buyer presents the counteroffer to the closure of the transaction. Panel (b) in Figure 8 presents the regression findings from Eq. (3), with the duration to complete the deal serving as the dependent variable. The data reveal that counteroffers featuring round prices lead to a more expedient agreement on the final deal compared to precise pricing strategies. In contrast, charm-priced counteroffers tend to prolong the negotiation and closing process. For instance, counteroffers that utilize a round price at the \$100K level are concluded 2.14 days faster on average, whereas deals involving charm prices typically extend the transaction by an additional 4.93 days.

A potential issue with our current sample selection is the possibility that the subset of cases featuring a single counteroffer might be inherently linked to less active market conditions, characterized by a lower volume of buyer proposals. This correlation could introduce bias into our findings, particularly if the effects under scrutiny vary significantly across different market hotness. To validate the reliability of our outcomes against such concerns, Figure B21 incorporates results from a comprehensive sample regression that explicitly accounts for the quantity of competing offers. This approach ensures that our previous conclusions remain robust even when adjusting for market competition levels.

Our analysis sheds light on a sophisticated balancing act embedded in buyer rounding-off strategies. Although rounding-off in counteroffers may initially hinder their acceptance, once accepted, these counteroffers often lead to faster negotiations and can enhance the buyer's financial position. This intricate dynamic highlights the strategic depth behind buyers' use of round counteroffers, as they weigh the chances of acceptance against the benefits of more favorable negotiation terms and a streamlined transaction process.

To address the nuanced differences observed in the outcomes associated with round and charm counteroffer prices, we conduct an in-depth analysis focusing on the extent of counteroffer-price adjustments based on different pricing formats. The detailed data presented in Appendix Table A5 reveal significant disparities in the magnitude of price adjustments for round versus charm counteroffer prices. Specifically, for counteroffers employing round prices, about 80% exhibit an adjustment magnitude exceeding $100, whereas less than 20% of charm price counteroffers reach this threshold. This substantial difference underscores a systematic variation in how the differences in counteroffer formats are associated with the magnitude of price adjustments.

Motivated by these systematic differences, we further explore the impact of these pricing formats in scenarios where buyers have made non-trivial adjustments to their counteroffers, aiming to determine the persistence of the observed effects. Appendix Figure B22 presents regression outcomes after filtering out counteroffers that involve only trivial adjustments.

The results from this refined analysis confirm that the impacts associated with round counteroffer prices continue to be evident, while the effects linked to charm counteroffer prices diminish. This suggests that the strategic implications of utilizing round pricing formats in counteroffers are robust, even when considering only more substantial adjustments.

The persistent effects of buyers using round numbers with non-trivial adjustments warrant a closer examination of the underlying causes and their broader implications on the bargaining process. Two primary hypotheses emerge to explain this phenomenon. Receiving a round counteroffer price can lead to sellers' doubt about the seriousness and thoughtfulness of the counteroffer. Counteroffers that deviate from rounded figures, such as \$501,234 versus \$500,000, are often perceived as more deliberate and well-considered. This perception could lead sellers to view precise counteroffers as more serious, thereby affecting their willingness to negotiate. The regression outcomes suggest that coarser rounding magnifies the negative impact on counteroffer success rates, supporting the notion that the degree of rounding influences seller perceptions. However, once the counteroffer is accepted, the round counteroffer price provides a better common ground for buyers and sellers to negotiate and achieve a final agreement.

5.2 Mimicry Effect

The difference in adjustment magnitude associated with price formats also motivates us to test a slightly different question: Does the buyers' mimicry of sellers' price format affect the transaction outcomes? To test this question, we change our previous model using the following specifications:

$$Y_{j,t} = \omega_P RM_{jt} + \omega_S SM_{jt} + \omega_C CM_{jt} + \omega_P PM_{jt} + g\left(p_{s,j,t}\right) + X_{j,t}\gamma + \tau_{l(j),t} + \xi_{a(j)} + \varepsilon_{j,t} \quad (4)$$

where $RM_{j,t}, SM_{j,t}, CM_{j,t}$, and $PM_{j,t}$ are dummies indicating whether buyers' counteroffer price mimicking sellers' listing price as a round, special 9k, charm, or precise number, respectively. For example, $RM_{jt} = 1$ if and only if the price format of both the seller's current listing price $p_{s,j,t}$ and the buyer's counteroffer price $p_{b,j,t}$ are round numbers. The control group of the equation is those counteroffer price formats deviating from the listing price format, regardless of the price type.

Figure 9 presents the regression outcomes of Equation (4) utilizing a dataset comprising only single-offer situations. Panel (a) of Figure 9 highlights that buyers who mirror the charm or precise pricing strategies of sellers typically achieve a higher success rate in transactions. Specifically, when a buyer's counteroffer emulates the seller's listing price using a charm pricing format, the probability of the counteroffer culminating in a successful sale increases by 6.6 percentage points, which corresponds to a 12.62% enhancement over the average success rate observed for counteroffers that do not mimic the listing price.

However, engaging in such mimicry involves certain concessions. As depicted in Panels (b) and (c) of Figure 9, adopting charm or precise price mimicry not only leads to higher purchase prices but also prolongs the duration needed to finalize transactions, compared with counteroffers that diverge from the seller's pricing strategy. Specifically, charm price mimicry results in an average increase of 0.6% in the final purchase price and extends the deal completion time by 4.10 days. This trend is consistently observed across different analyses, including those employing the full dataset and those excluding counteroffers with trivial adjustments relative to the listing price, as illustrated in Figures B23 and B24.

5.3 Discussion of Potential Mechanisms

The effects of buyers' counteroffer pricing formats can be potentially attributed to either rational or irrational behavioral mechanisms. Regarding rational mechanisms, our findings align most closely with the "under-shooting" mechanism. As outlined in Lin and Pursiainen (2021), buyers have an incentive to round down counteroffer prices. Consequently, using round counteroffer prices increases the risk of impasse but results in lower purchase prices, consistent with our observations. This finding discounts other hypotheses that generate opposing predictions. For instance, the "cheap-talk" hypothesis suggests that buyers use round counteroffers to signal their weak bargaining positions, leading to higher purchase prices (Backus et al., 2019). Similarly, the "flexibility" hypothesis proposes that round counteroffers signal buyers' flexibility in the bargaining process, potentially increasing the likelihood of reaching an agreement. Lastly, the "completion" hypothesis suggests that round counteroffers induce a sense of closure, thereby enhancing the likelihood of agreement (Yan and Pena-Marin, 2017). Given the benefits of using round counteroffers, including lower purchase prices and faster transactions, it is unlikely that buyers resort to round numbers due to cognitive limitations alone. As shown in Kuo et al. (2015), "cognitive limitation" channel predicts poorer financial performance among decision makers who tend to use round numbers.

6 Conclusion

Utilizing confidential offer-level data from the US housing market alongside comprehensive nationwide transaction data, this paper reveals novel patterns of pricing format strategies adopted by home buyers and home sellers, and also examines the impact of these pricing format strategies on the bargaining process within the US housing market. Our dataset includes over 60 million listings and approximately 300,000 interactions between buyers and sellers in the US, providing a significant advance over previous research.

We first document the common usage of special numbers in seller's listing prices, buyer's counteroffer prices, and the final sales prices. Specifically, most listing prices cluster at charm numbers or special 9k numbers. On the contrary, most buyer counteroffer prices and final sales price prices occur at exact round numbers. To justify the usage of these special prices, we next examine the impact of varying seller listing price formats in the bargaining process. Results show that on average, charm listing prices outperform round listing prices and precise listing prices across several metrics, such as final sales price, speed of the sales, and the likelihood of successful sales. Lastly, we further examine the impact of varying buyer counteroffer price formats in this bargaining process. Results show that despite a potential higher impasse risk, using round counteroffer prices often lead to lower purchase prices and faster purchases compared to using charm or precise counteroffer prices.

Future research could expand on our work by exploring how different pricing format strategies impact bargaining outcomes in other high-stakes contexts, such as commercial real estate transactions, business mergers, or luxury goods markets. Additionally, replicating our study with data from other countries could provide valuable insights into the external validity of our findings, offering a broader perspective on how universal these pricing strategies are across various cultural and economic landscapes.

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Table 1: Descriptive Statistics for the MLS Sample

	Mean	SD	P10	Median	P90	N
Successful Listing	0.66	0.47	0	0	1	76,981,953
Initial List Price	334,824	292,397	90,000	249,900	664,900	76,981,953
Sales Price	307,190	263,651	85,000	235,500	603,000	50,382,905
Discount	11,684	41,053	-7,500	5,000	39,000	50,382,905
Days on Market (DOM)	59.48	74.50	3	32	153	48,180,118
Bidding War	0.20	0.40	0	0	1	50,382,905
Under-Listing	0.64	0.48	0	1	1	50,382,905
Property Age (Years)	36.09	29.49	3	30	80	74,658,448
Number of Bedrooms	3.21	1.00	2	3	4	75,448,614
Number of Bathrooms	2.22	1.02	1	2	3.1	76,834,459
Living Area (Square Feet)	1,946	975.7	1,006	1,718	3,169	57,362,286
Single Family	0.84	0.37	0	1	1	76,981,953
Condo	0.10	0.30	0	0	1	76,981,953
Coop	0.002	0.041	0	0	0	76,981,953
Townhouse	0.030	0.17	0	0	0	76,981,953
Multi-Family (2-4 Units)	0.027	0.16	0	0	0	76,981,953

Notes: This table presents summary statistics for our MLS data. The sample consists of 76,981,953 housing bargaining events on MLS data in the U.S. from 2000 to 2022. The data cleaning 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
Panel A: Event Level						
Initial Listing Price	555,149	322,373	254,900	475,000	940,000	298,529
Final Listing 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
Under-Listing	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
Panel B: Buyer Counteroffer Level						
Buyer Counteroffer Price	552,284	320,730	250,000	470,000	941,000	314,829
Current Listing 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 Counteroffer	0.29	0.46	0	0	1	314,829
Failed Counteroffer due to Competition	0.45	0.50	0	0	1	314,829
Failed Counteroffer due to Unsatisfactory Price	0.10	0.30	0	0	1	314,829
Days to Complete Deal	49.17	33.56	26	40	80	103,329
Panel C: Buyer Counteroffer Level without Competing Offers						
Buyer Counteroffer Price	505,986	289,059	238,500	430,000	850,000	112,253
Current Listing Price	525,271	303,025	249,900	449,000	885,000	112,253
Price Adjustment	-19,287	44,284	-50,900	-10,000	5,000	112,253
Adjustment Rate	-0.04	0.06	-0.10	-0.03	0.01	112,253
Upward Adjustment	0.13	0.34	0	0	1	112,253
Downward Adjustment	0.67	0.47	0	1	1	112,253
Successful Counteroffer	0.54	0.50	0	1	1	112,253
Failed Counteroffer due to Competition	0.01	0.09	0	0	0	112,253
Failed Counteroffer due to Unsatisfactory Price	0.18	0.38	0	0	1	112,253
Days to Complete Deal	51.13	35.86	27	41	84	66,084

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 counteroffer level. Panel C summarizes a subsample of buyer counteroffers where there is no competing offers. We winsorize the initial listing price, final listing price, final sales price, buyer counteroffer 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%. Appendix 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)
	$x = 100$K	$x = 50$K	$x = 10$K	$x = 5$K
Round, 100K	0.177***	0.002	0.016***	0.028***
	(0.005)	(0.004)	(0.006)	(0.006)
Round, 50K	-0.012***	0.190***	0.008*	0.031***
	(0.003)	(0.004)	(0.005)	(0.005)
Round, 10K	0.003	0.000	0.205***	0.016***
	(0.002)	(0.002)	(0.004)	(0.004)
Round, 5K	-0.001	-0.003	-0.001	0.226***
	(0.002)	(0.002)	(0.003)	(0.003)
Special 9K, 100K	0.010***	0.002	0.024***	0.039***
	(0.003)	(0.003)	(0.005)	(0.005)
Special 9K, 50K	-0.019***	0.008**	0.006	0.028***
	(0.004)	(0.004)	(0.006)	(0.006)
Special 9K, 10K	-0.009***	-0.002	0.011***	0.007*
	(0.002)	(0.002)	(0.004)	(0.004)
Charm, 100K	0.049***	-0.012***	0.024***	0.026***
	(0.003)	(0.003)	(0.005)	(0.005)
Charm, 50K	-0.026***	0.064***	0.010*	0.020***
	(0.003)	(0.004)	(0.006)	(0.005)
Charm, 10K	-0.006***	-0.002	0.045***	0.008**
	(0.002)	(0.002)	(0.004)	(0.004)
Charm, 5K	-0.010***	-0.002	0.001	0.062***
	(0.003)	(0.003)	(0.005)	(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 × Month FE	✓	✓	✓	✓
Year × Zip-Code FE	✓	✓	✓	✓
Year × Buyer Agent FE	✓	✓	✓	✓

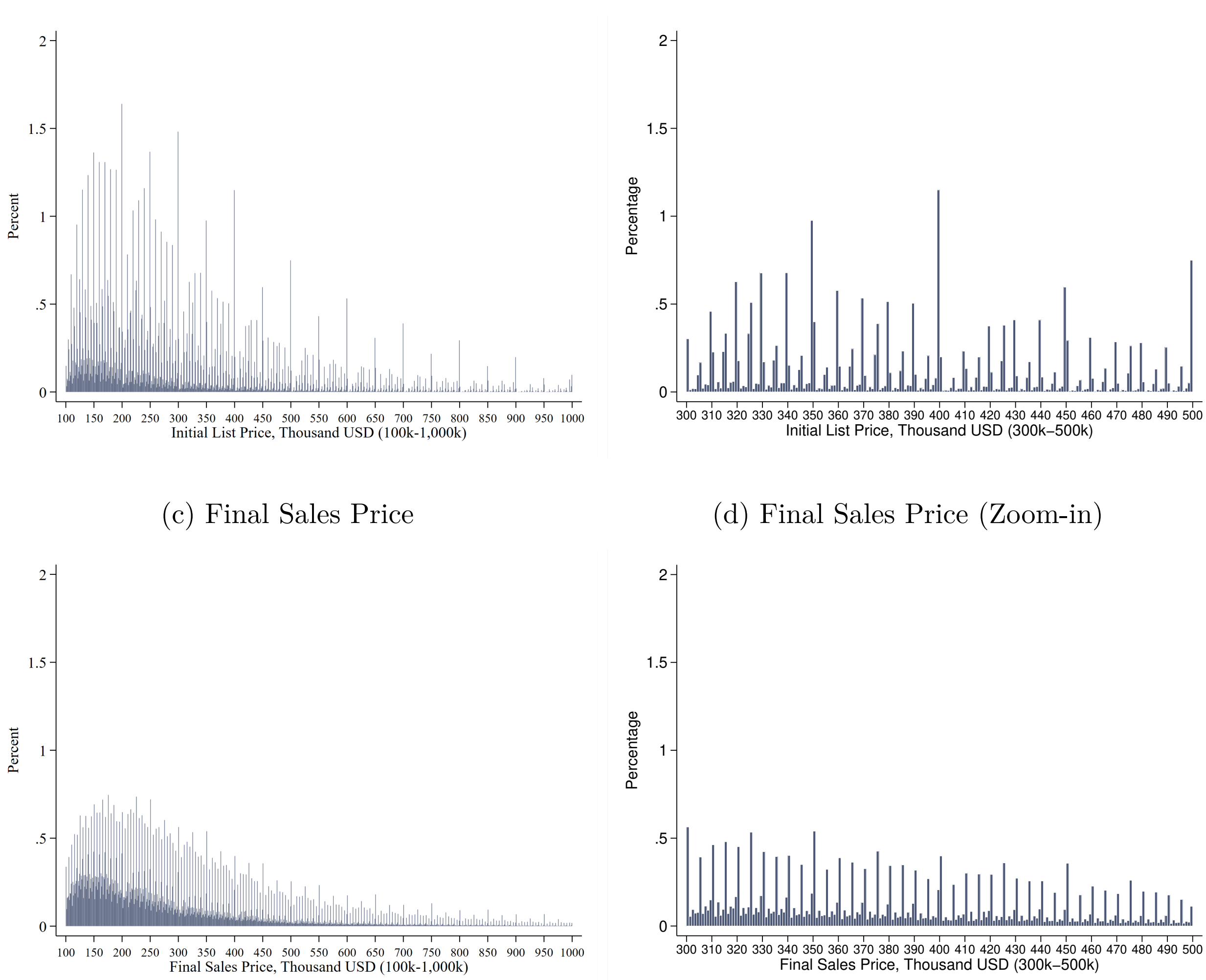
Notes: This table presents the effect of current list price format on the buyer offer formats. This table presents summary statistics for our Redfin data. The sample consists of buyer and seller interactions from 296,640 housing bargaining events on Redfin's platform across 45 states in the U.S. from 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)	(2)	(3)	(4)
	x = 100K	x = 50K	x = 10K	x = 5K
Round, 100K	-0.050***	0.013***	0.048***	0.058***
	(0.004)	(0.005)	(0.007)	(0.007)
Round, 50K	0.000	-0.055***	0.041***	0.067***
	(0.004)	(0.003)	(0.006)	(0.006)
Round, 10K	0.013***	0.006**	0.003	0.039***
	(0.003)	(0.003)	(0.005)	(0.005)
Round, 5K	0.007***	0.004*	0.020***	0.027***
	(0.002)	(0.002)	(0.004)	(0.004)
Special 9K, 100K	0.008**	-0.004	0.020***	0.031***
	(0.004)	(0.004)	(0.005)	(0.005)
Special 9K, 50K	-0.020***	0.009*	0.008	0.028***
	(0.004)	(0.005)	(0.007)	(0.007)
Special 9K, 10K	-0.007**	-0.003	0.019***	0.012**
	(0.003)	(0.003)	(0.005)	(0.005)
Charm, 100K	-0.068***	-0.009***	0.053***	0.059***
	(0.003)	(0.003)	(0.006)	(0.006)
Charm, 50K	-0.021***	-0.063***	0.045***	0.058***
	(0.004)	(0.003)	(0.007)	(0.007)
Charm, 10K	0.001	0.004	-0.033***	0.030***
	(0.003)	(0.003)	(0.005)	(0.005)
Charm, 5K	-0.002	0.004	0.020***	-0.012**
	(0.003)	(0.003)	(0.006)	(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 × Month FE	✓	✓	✓	✓
Year × Zip-Code FE	✓	✓	✓	✓
Year × 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 1: Distribution of Event-Level Prices (MLS)



(a) Initial List Price

(b) Initial List Price (Zoom-in)

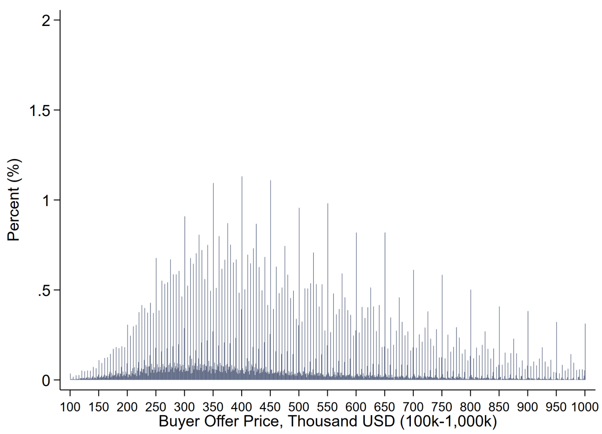
(c) Final Sales Price

(d) Final Sales Price (Zoom-in)

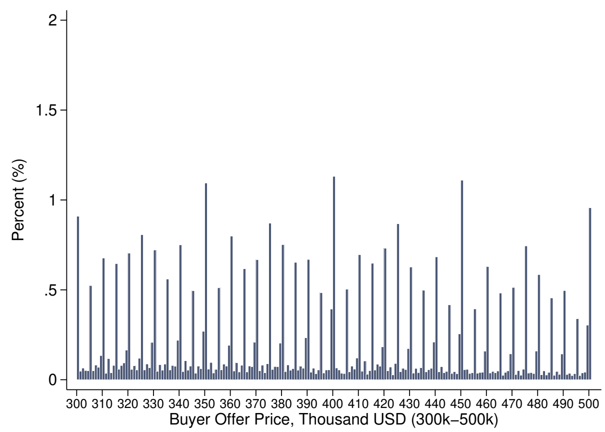
Notes: This figure shows the distribution of the initial list price and final sales price of properties using the MLS sample. This table presents summary statistics for our MLS data. The sample consists of 76,981,953 housing bargaining events on MLS data in the U.S. from 2000 to 2022. We restrict our 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 B11 shows the same set of plots using Redfin data. Figures B12 and B13 show the zoom-in plots over other price ranges.

Figure 2: Distribution of Action-Level Prices (Redfin)

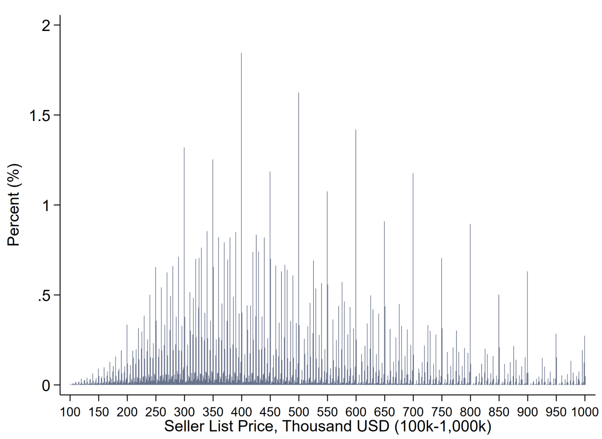
(a) Buyer Offer Price



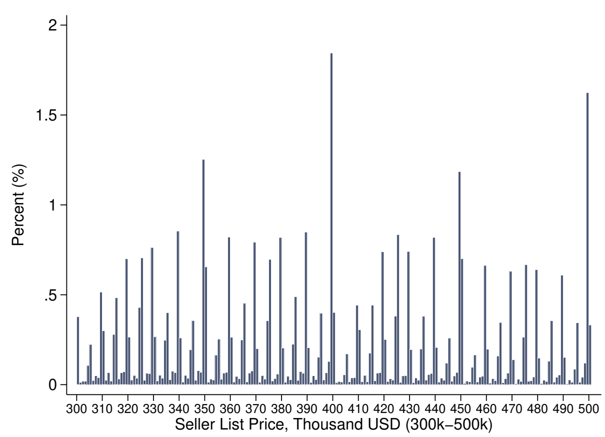
(b) Buyer Offer Price (Zoom-in)



(c) Seller List Price



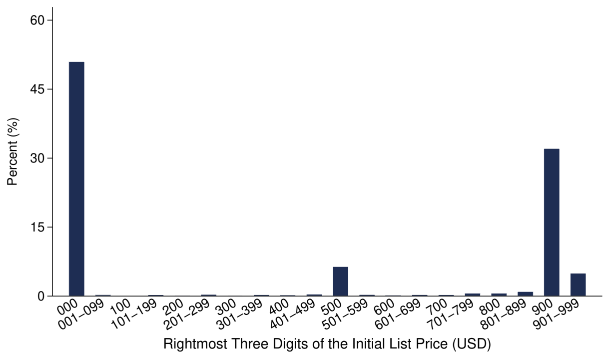
(d) Seller List Price (Zoom-in)



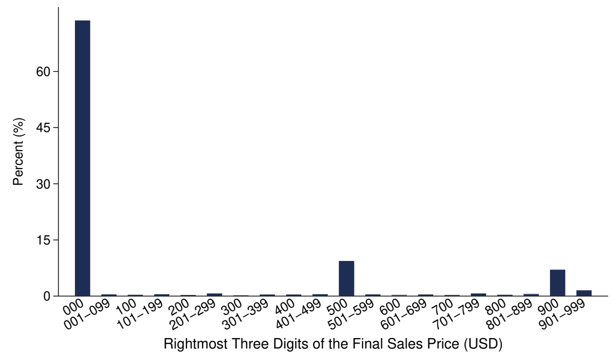
Notes: This figure shows the distribution of the buyer offer price and the seller list price of properties using the Redfin sample. The sample consists of buyer and seller interactions from 296,640 housing bargaining events on Redfin's platform across 45 states in the U.S. from January 2012 to December 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 B15 shows the zoom-in plots over other price ranges.

Figure 3: Event-level Distribution of the Rightmost Digits (MLS)

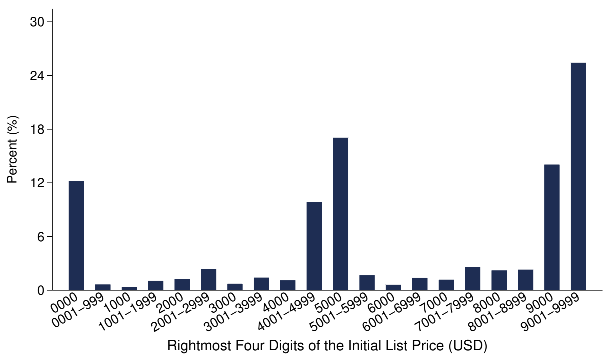
(a) Initial List Price (3 digits)



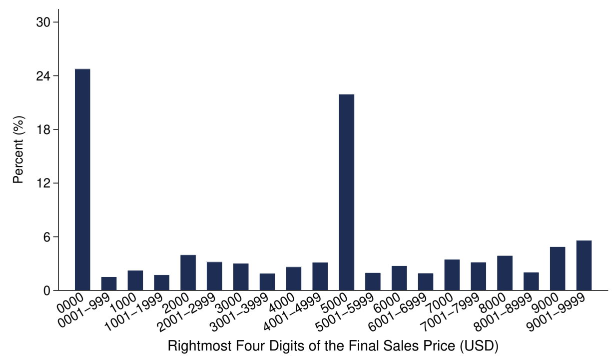
(b) Final Sales Price (3 digits)



(c) Initial List Price (4 digits)



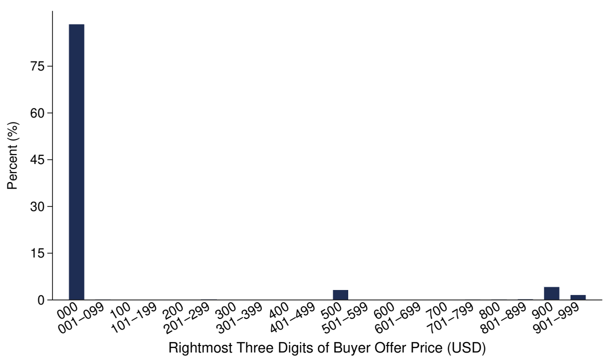
(d) Final Sales Price (4 digits)



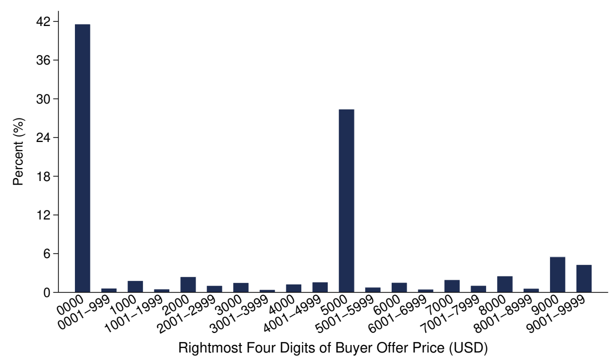
Notes: This figure shows the distribution of the rightmost digits of the initial list price and the final sales price at the event level using the MLS sample. The sample consists of 76,981,953 housing bargaining events on MLS data in the U.S. from 2000 to 2022. We restrict our focus to single-family, 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 B16 shows a more refined version of the distribution. For robustness check, figure B17 shows the same set of plots using Redfin data.

Figure 4: Action-level Distribution of the Rightmost Digits (Redfin)

(a) Buyer Offer Price (3 digits)

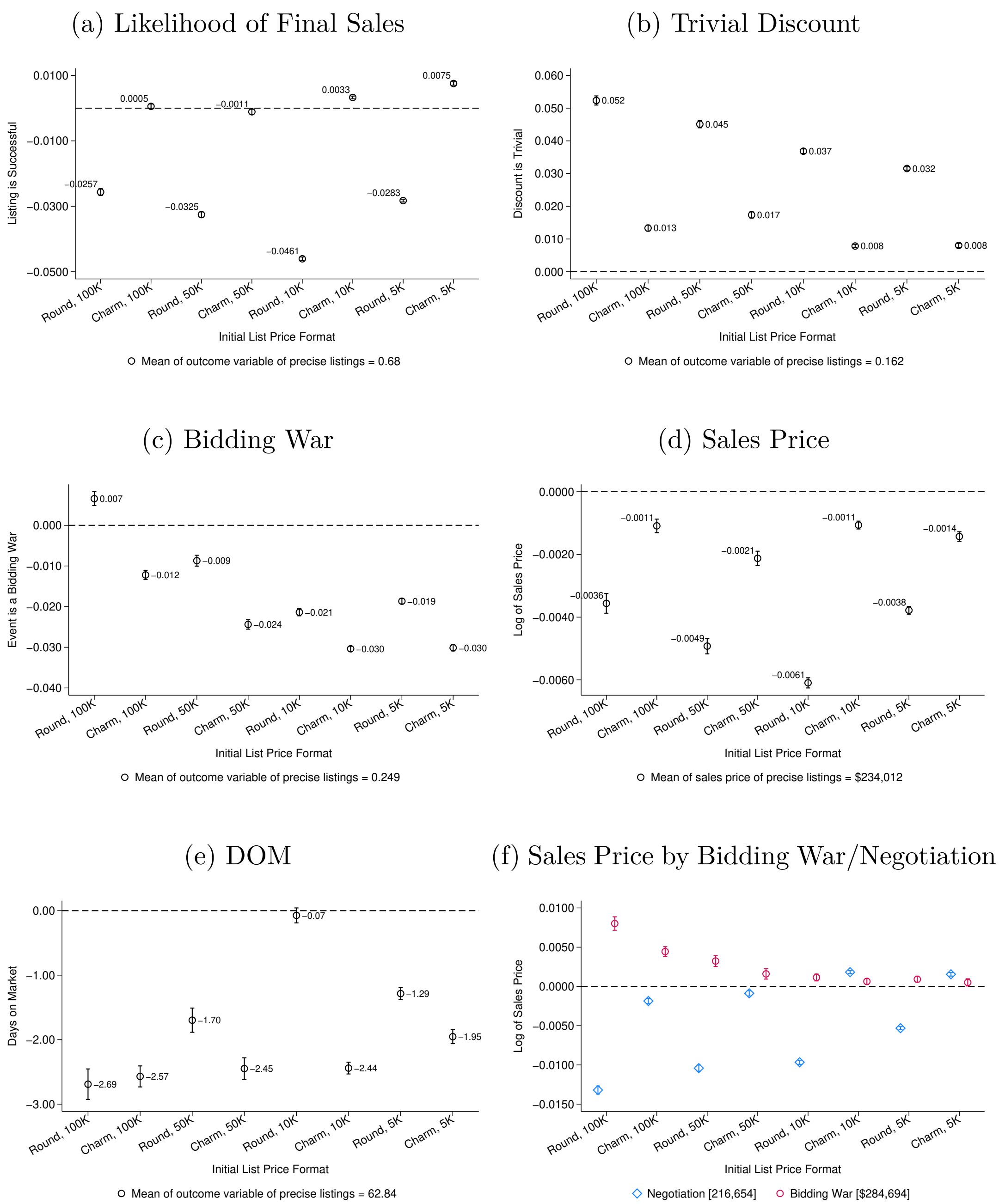


(b) Buyer Offer Price (4 digits)



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 B19 shows a more refined version of the distribution.

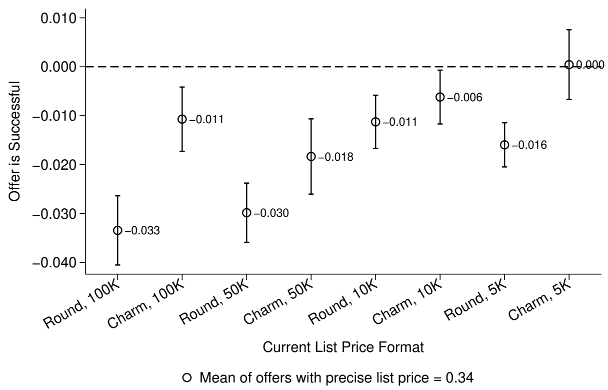
Figure 5: Effects of Initial List Price on Event-Level Outcomes



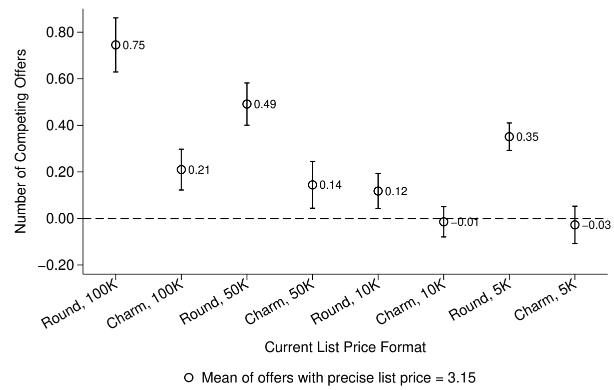
Notes: This set of figures plots the effect of the initial list price format on the event-level outcomes along with 90% CI. The results are estimated using Eq. (2). The control means are reported in the legends. The sample consists of 76,981,953 housing bargaining events on MLS data in the U.S. from 2000 to 2022. The dependent variables are the dummy indicating whether the listing is closed successfully in Panel (a), trivial adjustment dummy in Panel (b), bidding war indicator in Panel (c), log of sales price in Panels (d) and (f), and DOM in panel (e). The independent variables of interest are dummies indicating whether the initial list price is a number of special formats. In particular, the sample used in Panel (a) utilizes full sample, while Panels (b) to (f) are conditional on successful listings. Panel (c) excludes the observations with a trivial discount. Panel (f) splits the sample into bidding wars and negotiations. Standard errors are clustered at the property level. For better illustration, we omit the results on special 9k. The full set of results on the equivalent regressions are reported in Table A6.

Figure 6: Effects of Current List Price on Competition

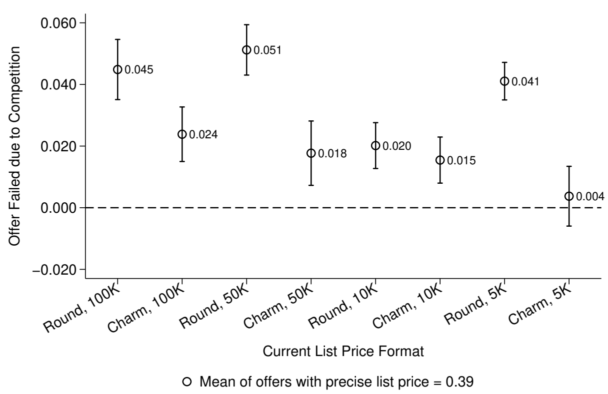
(a) Buyer Success Rate



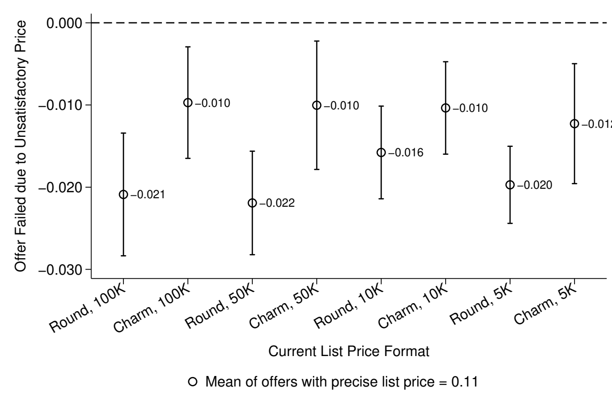
(b) Number of Competing Offers



(c) Failure due to Competing Offers



(d) Failure due to Unsatisfactory Price

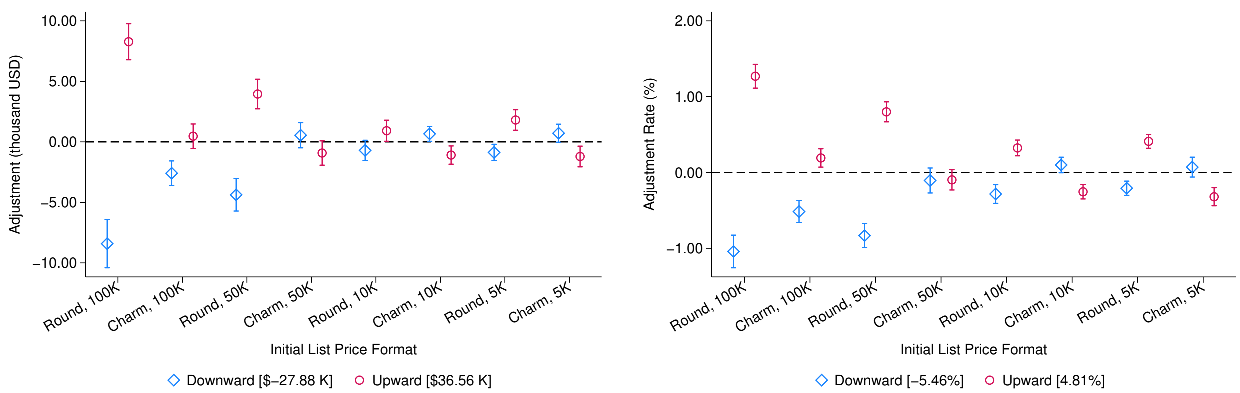


Notes: This set of figures plots the effect of the current list price format on offer outcomes and the competition, along with 90% CI. The results are estimated using Eq. (2). The control means are reported in the legends. The sample consists of buyer and seller interactions from 296,640 housing bargaining events on Redfin's platform across 45 states in the U.S. from January 2012 to December 2022. The dependent variables are the buyer success indicator in Panel (a), number of competing offers in Panel (b), dummies indicating whether the offer is failed due to competing offers in Panel (c) or faild due to unsatisfactory price in Panel (d). The independent variables of interest are dummies indicating whether the current list price is a number of special format. In particular, the sample used in Panels (c) and (d) includes only failed offers. All regressions control for the restricted cubic spline of log list price, housing characteristics, number of competing offers and buyer adjustment. Housing characteristics include the property age, property type, log of square foot, number of bedrooms, and number of bathrooms. We also impose Year $\times$ Month, Year $\times$ Zipcode, and Buyer Agent fixed effects. Robust standard errors are reported in parentheses. For better illustration, we omit the results on special 9k. The full set of results on the equivalent regressions are reported in Table A7.

Figure 7: Anchoring Effect

(a) Adjustment

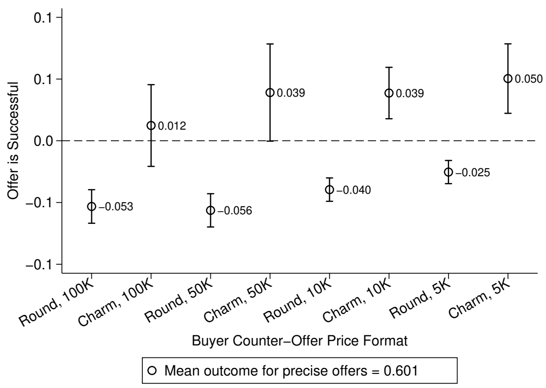
(b) Adjustment Rate



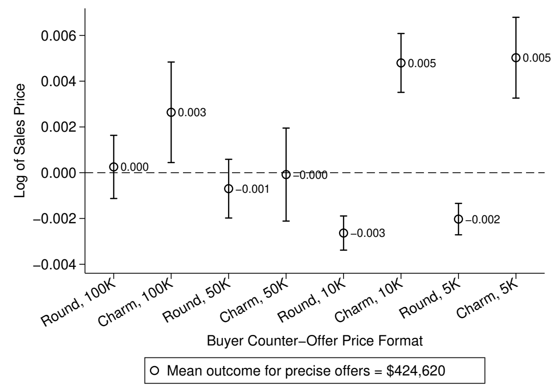
Notes: This set of figures presents the anchoring effect of the special current list prices along with 90% CI. The results are estimated using Eq. (2). The control means are reported in the legends. The sample consists of buyer and seller interactions from 296,640 housing bargaining events on Redfin's platform across 45 states in the U.S. from January 2012 to December 2022. The dependent variables are the buyer's adjustment in Panel (a), and the adjustment rate in Panel (b). The adjustment is defined as the difference between buyer offer price and seller current list price. An upward (positive) adjustment implies the offer price to be higher than the seller list price. The adjustment rate is defined as the ratio of the adjustment to current list price. The independent variables of interest are dummies indicating whether the current list price is a number of special format. In each panel, we split the sample by upward and downward adjustment. All regressions control for the restricted cubic spline of log list price, housing characteristics, number of competing offers and buyer adjustment. Housing characteristics include the property age, property type, log of square foot, number of bedrooms, and number of bathrooms. We also impose Year × Month, Year × Zipcode, and Buyer Agent fixed effects. Robust standard errors are reported in parentheses. For better illustration, we omit the results on special 9k. The full set of results on the equivalent regressions are reported in Table A8.

Figure 8: Effects of Counteroffer Price Format on Outcomes

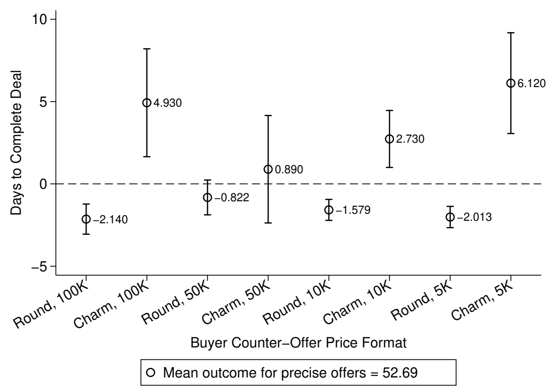
(a) Buyer Success Rate



(b) Log of Sales Price



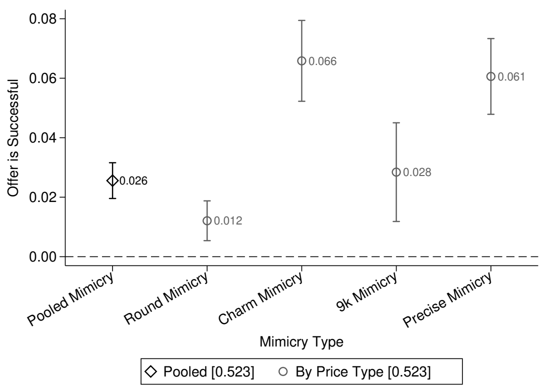
(c) Days to Complete Deal



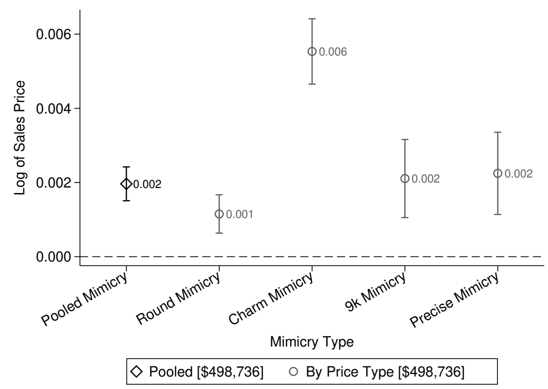
Notes: This set of figures presents the effects of buyer counteroffer format on counteroffer outcomes using the specification shown in Eq. (3), along with 90% CI. The control means are reported in the legends. The sample consists of buyer and seller interactions with single counteroffers from 112,253 buyer offers in 109,684 housing bargaining events on Redfin's platform across 45 states in the U.S. from January 2012 to December 2022. The dependent variables are a dummy indicating whether the offer is successful in Panel (a), log of the sales price in Panel (b), and days to complete deal Panel (c). Days to complete deal is defined as the sum of acceptance time and private negotiation time. The acceptance time is defined as the days from the counteroffer submission to counteroffer acceptance. The private negotiation time is defined as the days from the counteroffer acceptance to final sales. The independent variables of interest are dummies indicating whether the buyer counteroffer price is a round number. The sample used in Panel (a) includes all counteroffers. The sample used in Panels (b) and (c) includes only successful offers. All regressions control for the restricted cubic spline of log list price, housing characteristics, number of competing counteroffers and buyer adjustment. Housing characteristics include the property age, property type, log of square foot, number of bedrooms, and number of bathrooms. We also impose Year × Month, Year × Zipcode, and Buyer Agent fixed effects. Robust standard errors are reported in parentheses. The full set of results on the equivalent regressions are reported in Table A9.

Figure 9: Effects of Mimicry Type on Outcomes

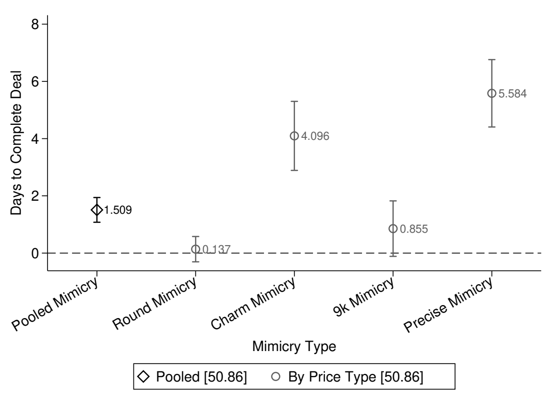
(a) Buyer Success Rate



(b) Log of Sales Price



(c) Days to Complete Deal



Notes: This set of figures presents the effects of mimicry type on counteroffer outcomes using the specification shown in Eq. (4), along with 90% CI. The control means are reported in the legends. The sample consists of buyer and seller interactions with single counteroffers from 112,253 buyer counteroffers in 109,684 housing bargaining events on Redfin's platform across 45 states in the U.S. from January 2012 to December 2022. The dependent variables are a dummy indicating whether the counteroffer is successful in Panel (a), log of the sales price in Panel (b), and days to complete deal Panel (c). Days to complete deal is defined as the sum of acceptance time and private negotiation time. The acceptance time is defined as the days from the counteroffer submission to offer acceptance. The private negotiation time is defined as the days from the counteroffer acceptance to final sales. The independent variables round mimicry, 9k mimicry and precise mimicry are dummies indicating whether the list price and the counteroffer price both belong to one of the price types by *Round Price*, *Special 9k Price*, *Charm Price* and *Precise Price*. The independent variable pooled mimicry is a dummy indicating whether list price and the counteroffer price belong to round mimicry, 9k mimicry or precise mimicry. The sample used in Panel (a) includes all counteroffers. The sample used in Panels (b) and (c) includes only successful counteroffers. All regressions control for the restricted cubic spline of log list price, housing characteristics, number of competing counteroffers and buyer adjustment. Housing characteristics include the property age, property type, log of square foot, number of bedrooms, and number of bathrooms. We also impose Year × Month, Year × Zipcode, and Buyer Agent fixed effects. Robust standard errors are reported in parentheses. The full set of results on the equivalent regressions are reported in Table A10.

Appendices

A Additional Tables

Table A1: Dictionary of Variables

Variable	Definition
Panel A: Event Level	
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 minuses 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
Panel B: Buyer Offer Level	
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 minuses 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"
Days to complete deal	Number of days from offer offer submission date to the final sales date

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

	N	Initial List Price ($)	Sales Price ($)	Unit Sales Price ($/sqft)	DOM (Days)	Bidding War (%)	Negotiation (%)
Panel A: Round Initial List Prices							
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
Panel B: Special 9k Initial List Prices							
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
Panel B: Charm Initial List Prices							
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
Panel C: Precise Initial List Prices							
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				
	$\lvert$Adjustment$\rvert > 100$		$\lvert$Adjustment$\rvert \leq 100$		
	Downward	Upward	Downward	Zero	Upward
Panel A: Round Current List Price					
Round Current List Price (100k)	30.54	47.20	0.03	22.17	0.07
Round Current List Price (50k)	31.74	44.55	0.01	23.67	0.03
Round Current List Price (10k)	35.30	42.98	0.02	21.66	0.05
Round Current List Price (5k)	34.85	43.37	0.00	21.76	0.02
Panel B: Special 9k List Price					
Special 9k List Price (100k)	36.38	52.15	0.00	11.46	0.02
Special 9k List Price (50k)	37.38	48.59	0.00	14.02	0.01
Special 9k List Price (10k)	42.61	41.13	0.00	16.23	0.01
Panel C: Charm Current List Price					
Charm Current List Price (100k)	38.32	39.92	0.12	10.95	10.70
Charm Current List Price (50k)	38.71	37.57	0.16	12.25	11.32
Charm Current List Price (10k)	43.35	34.82	0.17	13.42	8.24
Charm Current List Price (5k)	44.74	32.32	0.18	13.99	8.76
Panel D: Control Group					
Precise List Price	44.01	39.64	0.07	15.77	0.51

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 296,640 housing bargaining events on Redfin's platform across 45 states in the U.S. from January 2012 to December 2022.

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

	% of Observations with				
	$\lvert$Adjustment$\rvert > 100$		$\lvert$Adjustment$\rvert \leq 100$		
	Downward	Upward	Downward	Zero	Upward
Panel A: Round Offer Price					
Round Offer Price (100k)	40.61	43.56	0.01	8.94	6.89
Round Offer Price (50k)	39.50	38.62	0.00	16.83	5.06
Round Offer Price (10k)	45.93	43.36	0.00	7.17	3.54
Round Offer Price (5k)	40.09	40.61	0.00	17.72	1.57
Panel B: Special 9k Offer Price					
Special 9k Offer Price (100k)	18.78	8.79	0.04	72.21	0.18
Special 9k Offer Price (50k)	20.90	8.21	0.00	70.85	0.05
Special 9k Offer Price (10k)	31.15	16.58	0.01	52.06	0.21
Panel C: Charm Offer Price					
Charm Offer Price (100k)	5.06	5.74	1.01	86.81	1.38
Charm Offer Price (50k)	4.54	4.10	1.26	89.48	0.63
Charm Offer Price (10k)	9.92	6.67	1.09	81.88	0.45
Charm Offer Price (5k)	12.40	10.35	0.99	76.00	0.26
Panel D: Control Group					
Precise Offer Price	33.48	54.80	0.05	11.25	0.42

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 296,640 housing bargaining events on Redfin's platform across 45 states in the U.S. from January 2012 to December 2022.

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

	Likelihood of Final Sales	Trivial Discount	Bidding War	Days on Market	Log of Sales Price		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Round, 100K	-0.0257***	0.0524***	0.0066***	-2.6908***	-0.0036***	-0.0132***	0.0080***
	(0.0006)	(0.0008)	(0.0010)	(0.1440)	(0.0002)	(0.0003)	(0.0005)
Round, 50K	-0.0325***	0.0451***	-0.0087***	-1.6980***	-0.0049***	-0.0104***	0.0032***
	(0.0005)	(0.0007)	(0.0008)	(0.1141)	(0.0002)	(0.0002)	(0.0004)
Round, 10K	-0.0461***	0.0368***	-0.0214***	-0.0734	-0.0061***	-0.0097***	0.0011***
	(0.0003)	(0.0004)	(0.0005)	(0.0703)	(0.0001)	(0.0002)	(0.0003)
Round, 5K	-0.0283***	0.0316***	-0.0187***	-1.2863***	-0.0038***	-0.0053***	0.0009***
	(0.0003)	(0.0003)	(0.0004)	(0.0561)	(0.0001)	(0.0001)	(0.0002)
Special 9K, 100K	-0.0198***	-0.0202***	0.0064***	-1.0921***	-0.0026***	-0.0050***	0.0032***
	(0.0005)	(0.0006)	(0.0008)	(0.1207)	(0.0002)	(0.0002)	(0.0004)
Special 9K, 50K	-0.0198***	-0.0148***	-0.0064***	-0.5533***	-0.0030***	-0.0027***	0.0003
	(0.0006)	(0.0007)	(0.0009)	(0.1428)	(0.0002)	(0.0003)	(0.0005)
Special 9K, 10K	-0.0212***	-0.0117***	-0.0176***	-1.2858***	-0.0025***	-0.0002*	-0.0016***
	(0.0003)	(0.0004)	(0.0005)	(0.0734)	(0.0001)	(0.0001)	(0.0003)
Charm, 100K	0.0005	0.0133***	-0.0122***	-2.5700***	-0.0011***	-0.0019***	0.0044***
	(0.0004)	(0.0006)	(0.0007)	(0.0990)	(0.0001)	(0.0002)	(0.0004)
Charm, 50K	-0.0011**	0.0174***	-0.0244***	-2.4485***	-0.0021***	-0.0009***	0.0016***
	(0.0005)	(0.0006)	(0.0007)	(0.1018)	(0.0001)	(0.0002)	(0.0004)
Charm, 10K	0.0033***	0.0078***	-0.0304***	-2.4409***	-0.0011***	0.0018***	0.0006***
	(0.0003)	(0.0003)	(0.0004)	(0.0553)	(0.0001)	(0.0001)	(0.0002)
Charm, 5K	0.0075***	0.0080***	-0.0301***	-1.9538***	-0.0014***	0.0015***	0.0005*
	(0.0003)	(0.0004)	(0.0005)	(0.0659)	(0.0001)	(0.0001)	(0.0003)
Obs.	48,732,491	24,037,191	18,241,103	22,694,544	24,037,191	11,073,126	1,216,339
Control Mean	0.68	0.162	0.249	62.84	234,012	216,654	284,694
R^2	0.522	0.516	0.656	0.628	0.994	0.995	0.999
Sample	All	Successful Listings	Successful Listings with Non-Trivial Discount	Successful Listings	Successful Listings	Successful Listings with Negotiation	Successful Listings with Bidding War
g(list price)	YES	YES	YES	YES	YES	YES	YES
Property Characteristics	YES	YES	YES	YES	YES	YES	YES
Year-Month-Zipcode FE	YES	YES	YES	YES	YES	YES	YES
Property FE	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 and Round/Charm Current List Price

	Success	N. of Competing Offers	Failure Competition	Failure Price
	(1)	(2)	(3)	(4)
Round, 100K	-0.0335***	0.7456***	0.0448***	-0.0209***
	(0.0043)	(0.0707)	(0.0059)	(0.0045)
Round, 50K	-0.0298***	0.4915***	0.0512***	-0.0219***
	(0.0037)	(0.0552)	(0.0050)	(0.0038)
Round, 10K	-0.0113***	0.1177***	0.0202***	-0.0158***
	(0.0033)	(0.0456)	(0.0045)	(0.0034)
Round, 5K	-0.0160***	0.3513***	0.0411***	-0.0197***
	(0.0027)	(0.0359)	(0.0037)	(0.0029)
Special 9K, 100K	-0.0254***	0.4756***	0.0338***	-0.0092**
	(0.0039)	(0.0564)	(0.0052)	(0.0041)
Special 9K, 50K	-0.0193***	0.2179***	0.0339***	-0.0242***
	(0.0050)	(0.0662)	(0.0066)	(0.0051)
Special 9K, 10K	-0.0100***	0.0627	0.0176***	-0.0101***
	(0.0035)	(0.0423)	(0.0047)	(0.0036)
Charm, 100K	-0.0107***	0.2099***	0.0238***	-0.0097**
	(0.0040)	(0.0533)	(0.0054)	(0.0041)
Charm, 50K	-0.0183***	0.1442**	0.0177***	-0.0100**
	(0.0047)	(0.0609)	(0.0063)	(0.0047)
Charm, 10K	-0.0062*	-0.0145	0.0155***	-0.0104***
	(0.0033)	(0.0396)	(0.0045)	(0.0034)
Charm, 5K	0.0004	-0.0272	0.0037	-0.0123***
	(0.0043)	(0.0487)	(0.0059)	(0.0044)
Obs.	272,100	238,547	190,810	190,810
Control Mean	0.34	3.15	0.39	0.11
R^2	0.418	0.460	0.381	0.318
Sample	All	All	Failed Offers	Failed Offers
g(list price)	YES	YES	YES	YES
Property Characteristics	YES	YES	YES	YES
Year-Month FE	YES	YES	YES	YES
Year-Zipcode FE	YES	YES	YES	YES
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: Anchoring Effect around Round/Charm Prices

	Adjustment ($ K)		Adjustment Rate (%)	
	(1)	(2)	(3)	(4)
Round, 100K	-8.4110***	8.2773***	-1.0417***	1.2699***
	(1.2113)	(0.9056)	(0.1308)	(0.0955)
Round, 50K	-4.3753***	3.9553***	-0.8324***	0.8000***
	(0.8144)	(0.7438)	(0.0965)	(0.0801)
Round, 10K	-0.7023	0.9213*	-0.2839***	0.3241***
	(0.5084)	(0.5304)	(0.0749)	(0.0631)
Round, 5K	-0.8716**	1.8104***	-0.2078***	0.4109***
	(0.4091)	(0.5146)	(0.0570)	(0.0555)
Special 9K, 100K	-4.0274***	0.3000	-0.6815***	0.3894***
	(0.7768)	(0.7953)	(0.0887)	(0.0836)
Special 9K, 50K	1.7252**	-0.4695	-0.0045	0.1495
	(0.8161)	(0.9304)	(0.0993)	(0.1021)
Special 9K, 10K	0.7372*	-1.4535***	-0.0051	-0.1248*
	(0.4323)	(0.5567)	(0.0644)	(0.0649)
Charm, 100K	-2.5915***	0.4675	-0.5154***	0.1920***
	(0.6193)	(0.6147)	(0.0882)	(0.0734)
Charm, 50K	0.5481	-0.9201	-0.1055	-0.0967
	(0.6315)	(0.6104)	(0.1001)	(0.0814)
Charm, 10K	0.6634*	-1.0891**	0.0991	-0.2539***
	(0.3746)	(0.4580)	(0.0624)	(0.0578)
Charm, 5K	0.7180	-1.2071**	0.0710	-0.3198***
	(0.4525)	(0.5203)	(0.0797)	(0.0724)
Obs.	92,206	116,163	92,206	116,163
Control Mean	-27.88	36.56	-5.46	4.81
R^2	0.620	0.600	0.438	0.462
Sample	Downward	Upward	Downward	Upward
g(list price)	YES	YES	YES	YES
Property Characteristics	YES	YES	YES	YES
Year-Month FE	YES	YES	YES	YES
Year-Zipcode FE	YES	YES	YES	YES
Buyer Agent FE	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 A9: Effects of Buyer Counteroffer Format on Outcomes

	Success (1)	ln(Sales Price) (2)	Days to Complete Deal (3)
Round, 100K	-0.0532***	0.0003	-2.1403***
	(0.0083)	(0.0008)	(0.5562)
Round, 50K	-0.0563***	-0.0007	-0.8224
	(0.0082)	(0.0008)	(0.6439)
Round, 10K	-0.0396***	-0.0026***	-1.5787***
	(0.0058)	(0.0005)	(0.3874)
Round, 5K	-0.0253***	-0.0020***	-2.0125***
	(0.0057)	(0.0004)	(0.3934)
Special 9K, 100K	-0.0044	-0.0008	-1.5891
	(0.0202)	(0.0015)	(1.2913)
Special 9K, 50K	0.0171	0.0001	-1.2297
	(0.0231)	(0.0014)	(1.3469)
Special 9K, 10K	-0.0109	0.0011	-0.3232
	(0.0111)	(0.0007)	(0.6714)
Charm, 100K	0.0124	0.0026**	4.9298**
	(0.0201)	(0.0013)	(1.9920)
Charm, 50K	0.0391	-0.0001	0.8903
	(0.0239)	(0.0012)	(1.9834)
Charm, 10K	0.0387***	0.0048***	2.7303***
	(0.0127)	(0.0008)	(1.0518)
Charm, 5K	0.0504***	0.0050***	6.1204***
	(0.0171)	(0.0011)	(1.8615)
Obs.	84,603	41,143	37,309
Control Mean	0.601	$424,620	52.65
R^2	0.441	0.998	0.404
Sample	Single Offers	Single & Successful Offers	Single & Successful Offers
g(list price)	YES	YES	YES
Property Characteristics	YES	YES	YES
N. of Additional Offers	YES	YES	YES
Buyer Adjustment	YES	YES	YES
Year-Month FE	YES	YES	YES
Year-Zipcode FE	YES	YES	YES
Buyer Agent FE	YES	YES	YES

Notes: This table presents the effects of buyer offer format on counteroffer outcomes using the specification shown in Eq. (3). The sample uses observations with single counteroffer and consists of buyer and seller interactions with single counteroffer from 112,253 buyer offers in 109,684 housing bargaining events. The dependent variables are a dummy indicating whether the counteroffer is successful in Columns (1), log of the sales price in Columns (2), and days to complete deal in Columns (3). Days to complete deal is defined as the sum of acceptance time and private negotiation time. The acceptance time is defined as the days from the counteroffer submission to counteroffer acceptance. The private negotiation time is defined as the days from the counteroffer acceptance to final sales. The independent variables of interest are dummies indicating whether the buyer's counteroffer price is a round number. The sample used in Column (1) includes all offers of the corresponding sample. The samples used in Columns (2) to (3) include only successful counteroffers of the corresponding sample. All regressions control for the restricted cubic spline of log list price, housing characteristics, number of competing offers, and buyer adjustment. Housing characteristics include the property age, property type, log of square foot, number of bedrooms, and number of bathrooms. We also impose Year × Month, Year × Zipcode, and Buyer Agent fixed effects. Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

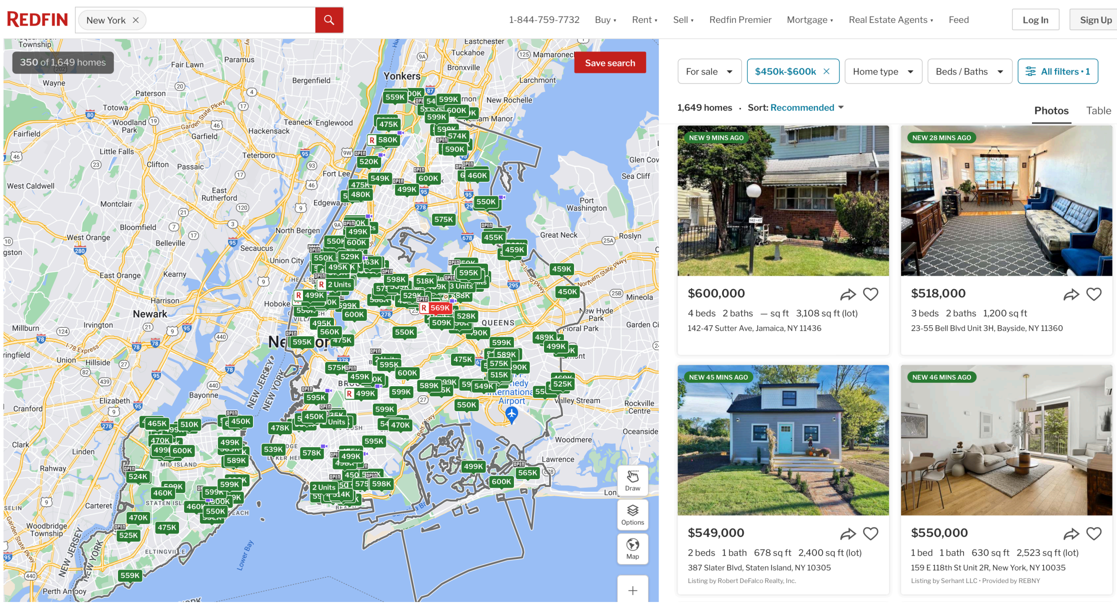
Table A10: Effects of Mimicry Type on Outcomes

	Success	In(Sales Price)	Days to Complete Deal
	(1)	(2)	(3)
Panel A: Pooled Mimicry			
Pooled Mimicry	0.0256***	0.0020***	1.5094***
	(0.0037)	(0.0003)	(0.2626)
R^2	0.440	0.998	0.400
Panel B: 4 Mimicry Types			
Round Mimicry	0.0121***	0.0012***	0.1366
	(0.0041)	(0.0003)	(0.2687)
9k Mimicry	0.0284***	0.0021***	0.8546
	(0.0101)	(0.0006)	(0.5892)
Charm Mimicry	0.0658***	0.0055***	4.0956***
	(0.0083)	(0.0005)	(0.7331)
Precise Mimicry	0.0606***	0.0022***	5.5838***
	(0.0077)	(0.0007)	(0.7159)
R^2	0.441	0.998	0.404
Obs.	84,603	41,143	37,309
Control Mean	0.523	$498,736	50.84
g(list price)	YES	YES	YES
Property Characteristics	YES	YES	YES
N. of Additional Offers	YES	YES	YES
Buyer Adjustment	YES	YES	YES
Year-Month FE	YES	YES	YES
Year-Zipcode FE	YES	YES	YES
Buyer Agent FE	YES	YES	YES

Notes: This table presents the effects of mimicry type on counteroffer outcomes using the specification shown in Eq. (4). The sample uses observations with single counteroffer and consists of buyer and seller interactions with single counteroffer from 112,253 buyer offers in 109,684 housing bargaining events. The dependent variables are a dummy indicating whether the counteroffer is successful in Columns (1), log of the sales price in Columns (2), and days to complete deal in Columns (3). Days to complete deal is defined as the sum of acceptance time and private negotiation time. The acceptance time is defined as the days from the counteroffer submission to offer acceptance. The private negotiation time is defined as the days from the counteroffer acceptance to final sales. The independent variables round mimicry, 9k mimicry and precise mimicry are dummies indicating whether the list price and the counteroffer price both belong to one of the price types by *Round Price*, *Special 9k Price*, *Charm Price* and *Precise Price*. The independent variable pooled mimicry is a dummy indicating whether list price and the counteroffer price belong to round mimicry, 9k mimicry or precise mimicry. The sample used in Column (1) includes all counteroffers of the corresponding sample. The samples used in Columns (2) to (3) include only successful counteroffers of the corresponding sample. All regressions control for the restricted cubic spline of log list price, housing characteristics, number of competing counteroffers and buyer adjustment. Housing characteristics include the property age, property type, log of square foot, number of bedrooms, and number of bathrooms. We also impose Year × Month, Year × Zipcode, and Buyer Agent fixed effects. Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

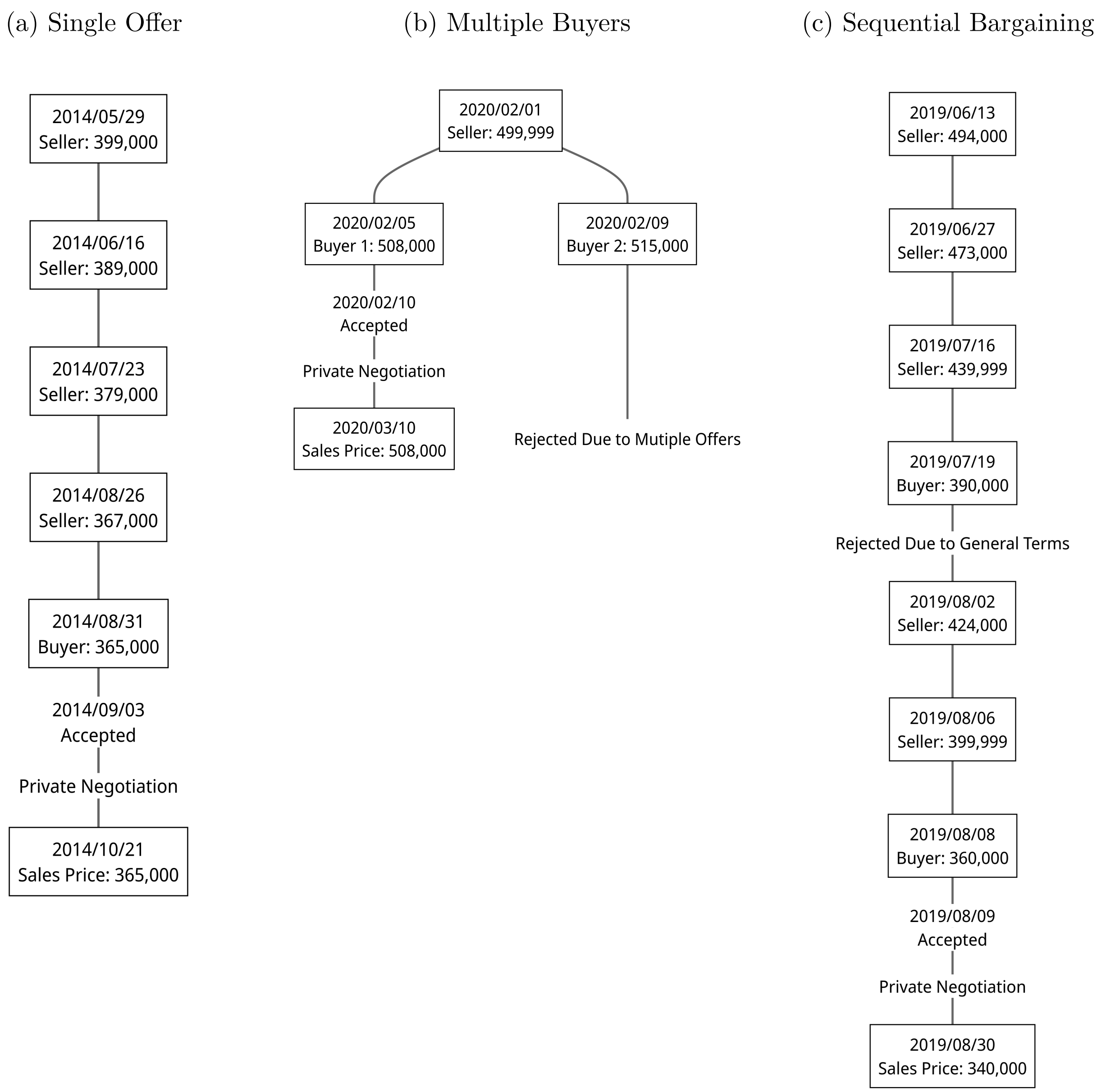
B Additional Figures

Figure B1: Redfin Search Interface



Notes: This figure shows the search interface of the Redfin platform.

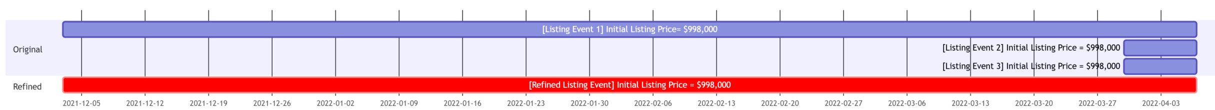
Figure B2: Illustration of Bargaining Events



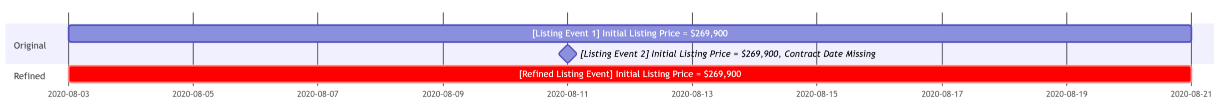
Notes: This figure shows three real bargaining events we observe in Redfin data to illustrate the bargaining events.

Figure B3: Refinement of Duplicated Successful Listings

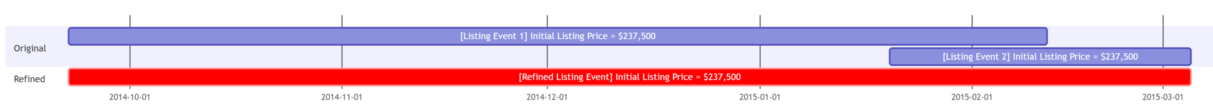
(a) Different Initial Listing Date



(b) Missing Contract Date



(c) Different Initial Listing Date and Contract Date

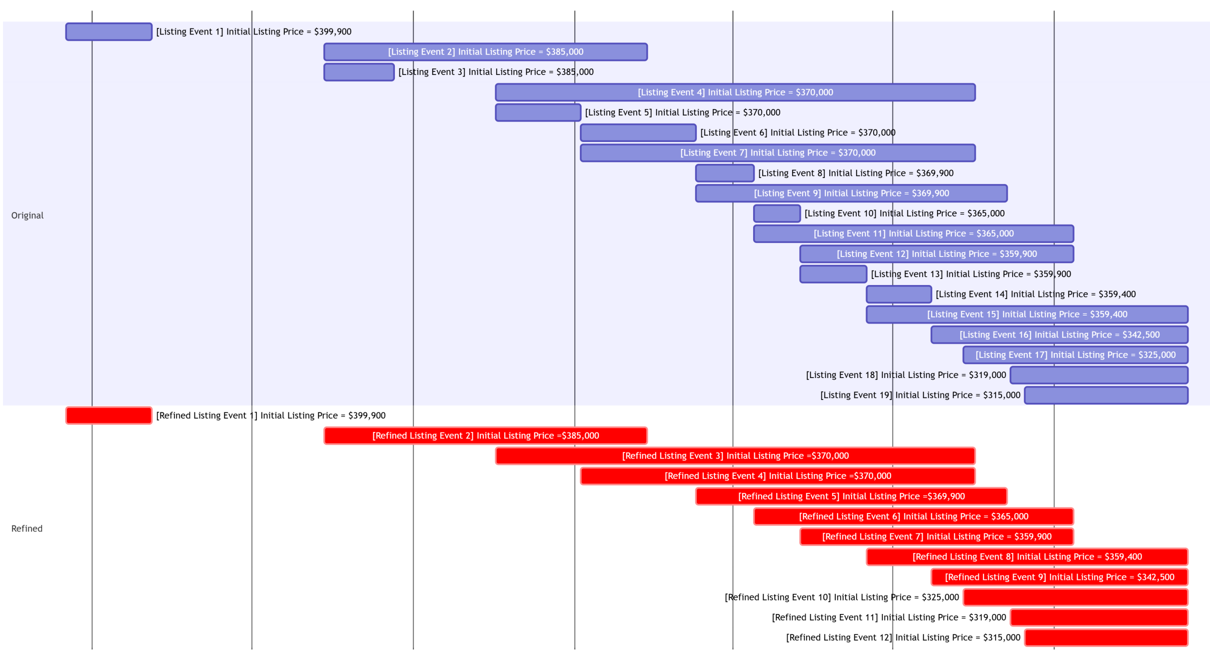


Notes: This figure shows the example refinement of duplicated successful listings in MLS data. Each subfigure shows an example of duplicating listing records for the same property. Each bar plots the period of a listing event in our sample from the initial listing date until the contract date. The blue bars refer to the transaction period in the raw data and the red bars refer to the transaction period after refinement.

Figure B4: Refinement of Duplicated Failed Listings

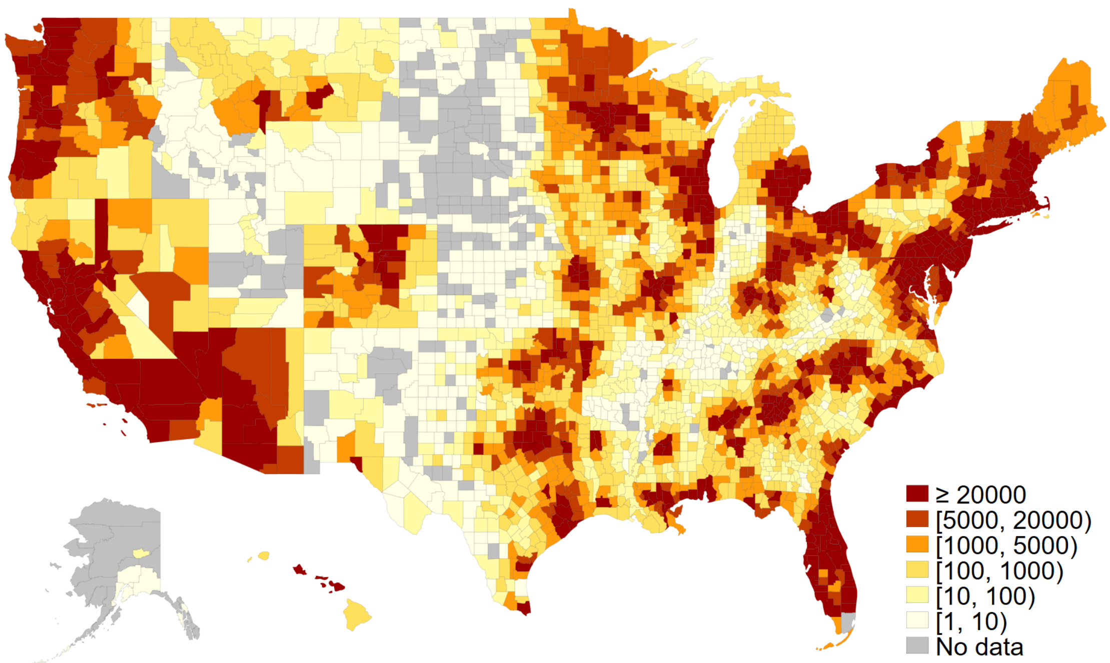
(a) Simple Listing History

(b) Complex Listing History



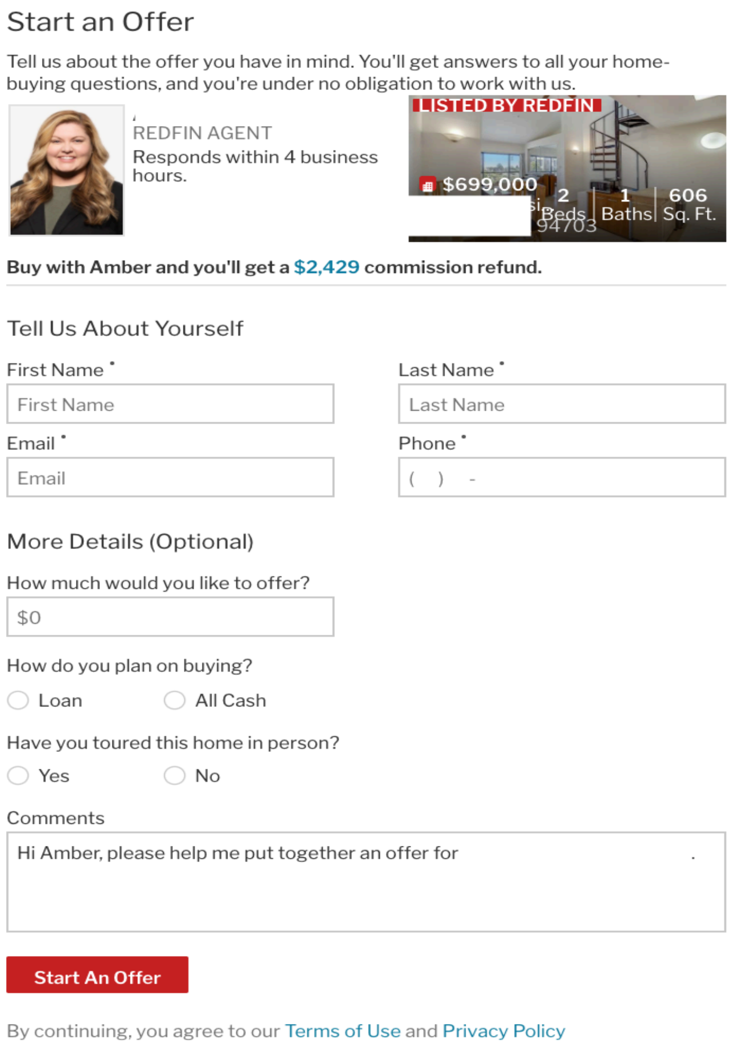
Notes: This figure shows the example refinement of duplicated failed listings in MLS data. Each subfigure shows an example of duplicating listing records for the same property. Each bar plots the period of a listing event in our sample from the initial listing date until the off-market date. The blue bars refer to the transaction period in the raw data and the red bars refer to the transaction period after refinement.

Figure B5: Geographical Distribution of MLS Listing Events (2000–2022)



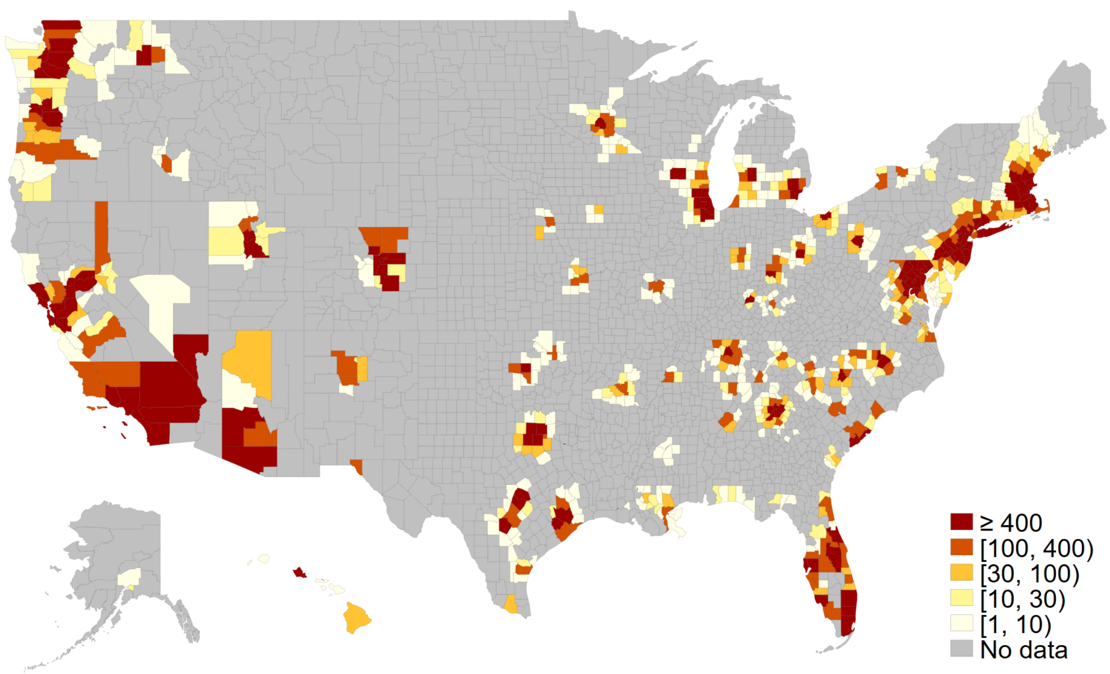
Notes: This map shows the geographical distribution of 76,981,953 transactions across 50 states and Washington D.C. in the U.S. from 2000 to 2022 from our selected MLS data. The sample includes both successful and failed listings.

Figure B6: Start an Offer Panel



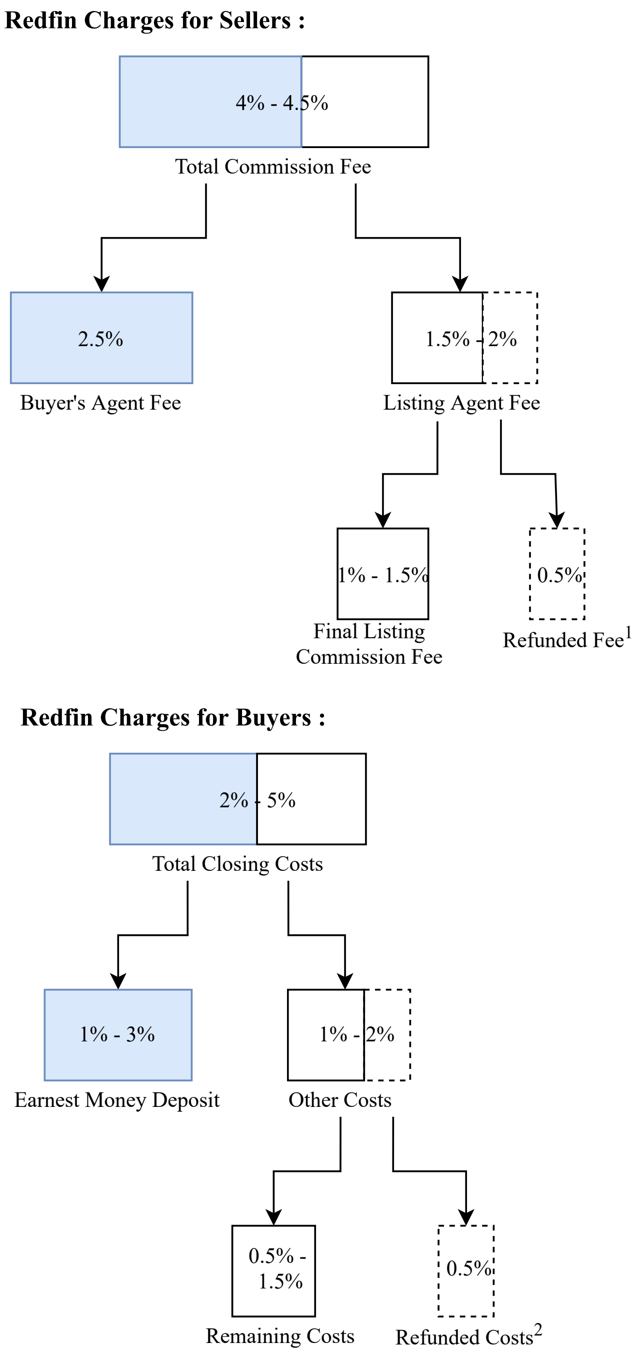
Notes: This figure shows the "Start an Offer" panel on Redfin. This panel is a Redfin page where buyers start to make offers to properties that they are interested in. Once buyers fill in the required information listed on the page and click the red "Start an Offer" button, they are assigned with Redfin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

Figure B7: Geographical Distribution of Redfin Buyer Counteroffers (2012–2022)



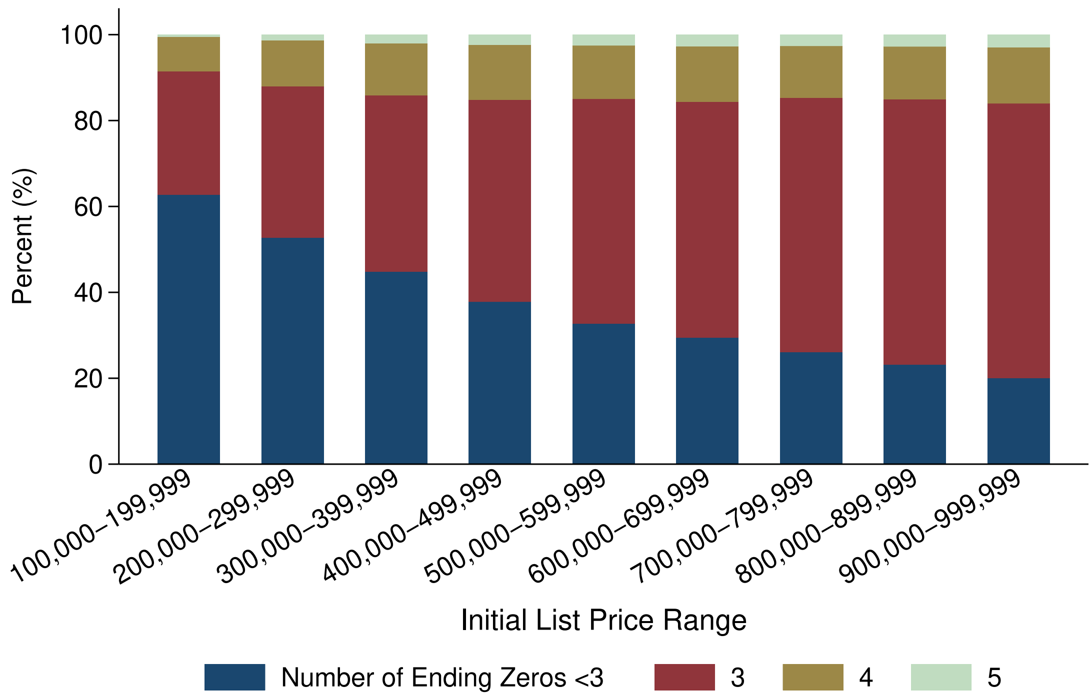
Notes: This map shows the geographical distribution of 314,829 buyer counteroffers using Redfin data across 45 states in U.S. that happened between January 2012 and December 2022 in our data.

Figure B8: Illustration of Redfin Fee Structure



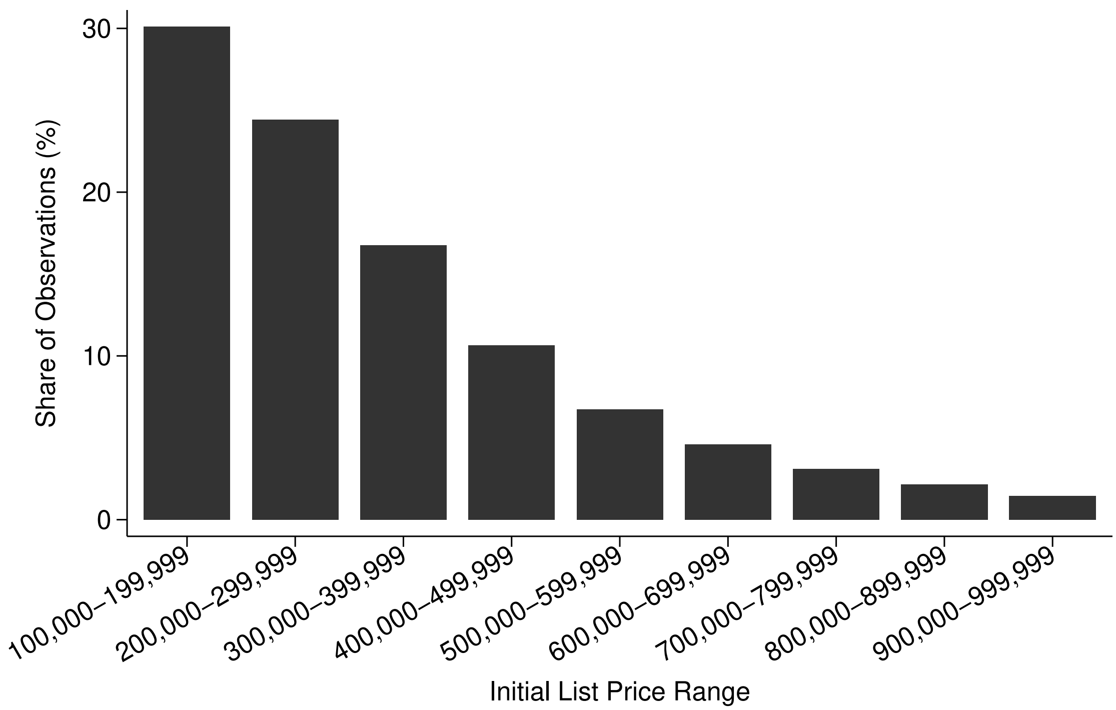
Notes: This figure illustrates fees charged by Redfin on sellers and buyers compared to other institutions. The refunded fee 1 is returned by Redfin if the sellers buy homes on Redfin within one year of their sales. The refunded costs 2 are returned by Redfin if buyers hired Redfin agents.

Figure B9: 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 B10 shows the share of observations across price ranges.

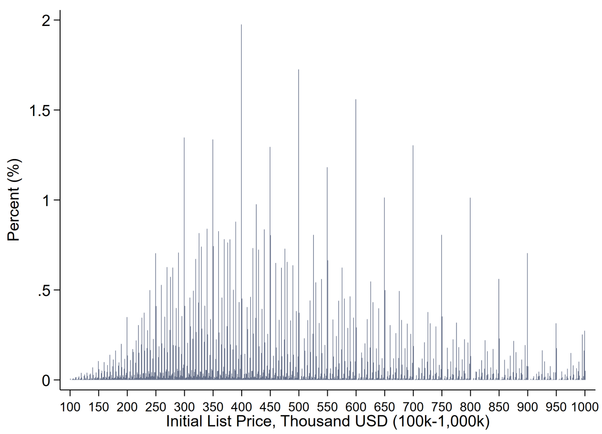
Figure B10: Share of Observations by Price Range



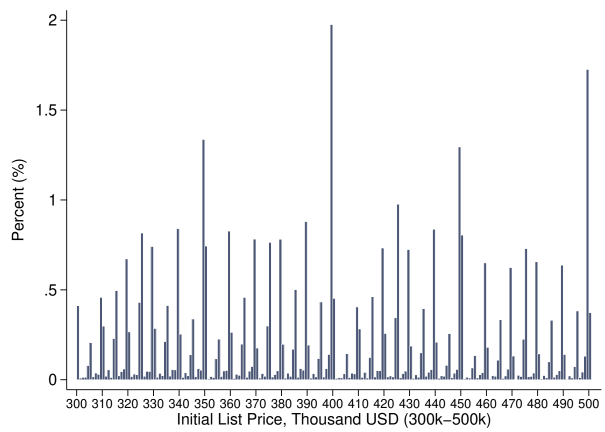
Notes: This figure illustrates the distribution of observations across various price ranges. The scope of this plot is confined to observations with an initial list price ranging from $100,000 to $999,999.

Figure B11: Distribution of Event-Level Prices (Redfin)

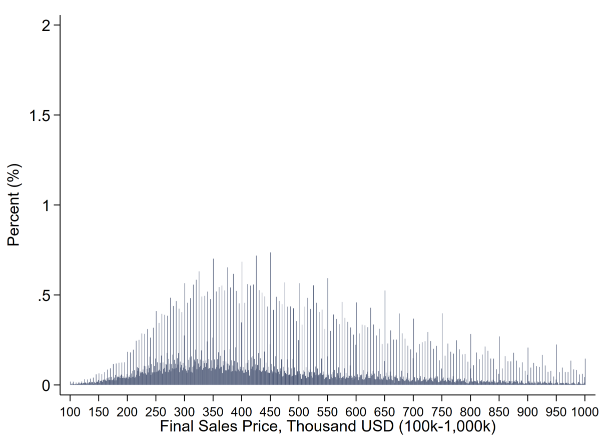
(a) Initial List Price



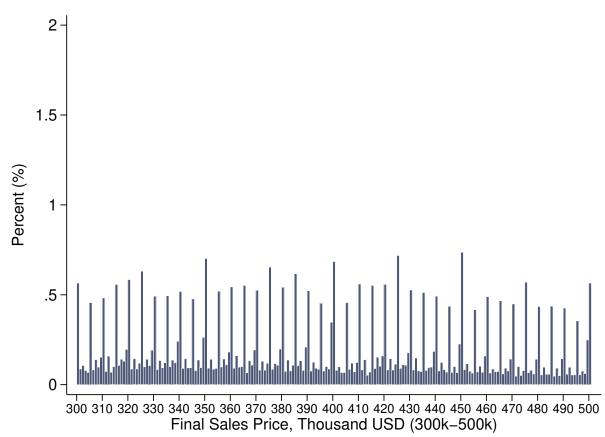
(b) Initial List Price (Zoom-in)



(c) Final Sales Price



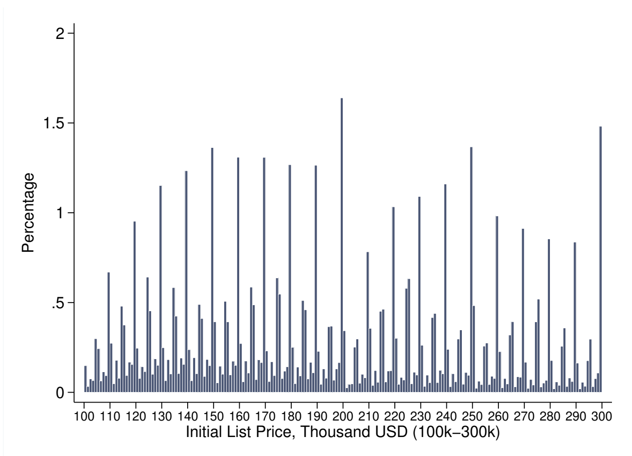
(d) Final Sales Price (Zoom-in)



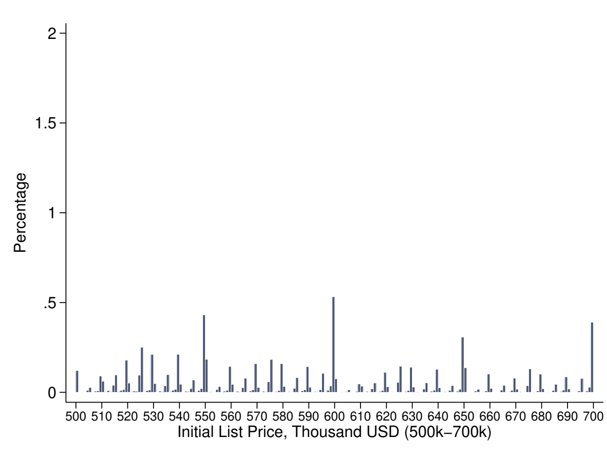
Notes: This figure shows the distribution of the initial list price and final sales price of properties using the Redfin sample. The sample consists of buyer and seller interactions from 147,709 housing bargaining events on Redfin's platform across 45 states in the U.S. from January 2012 to December 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 B13 shows the zoom-in plots over other price ranges.

Figure B12: Distribution of Event-Level Prices (MLS, Robustness Check)

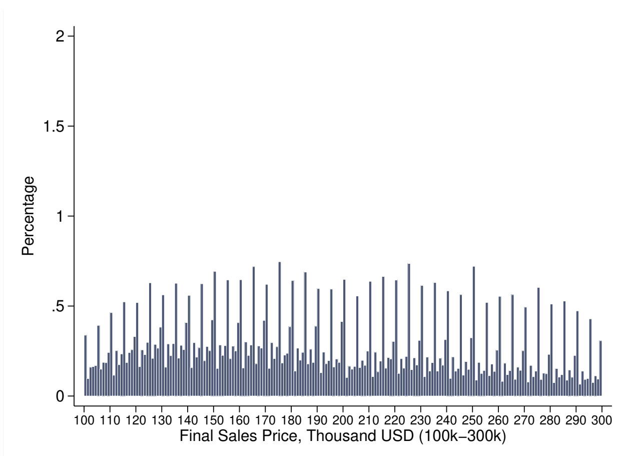
(a) Initial List Price (100k-300k)



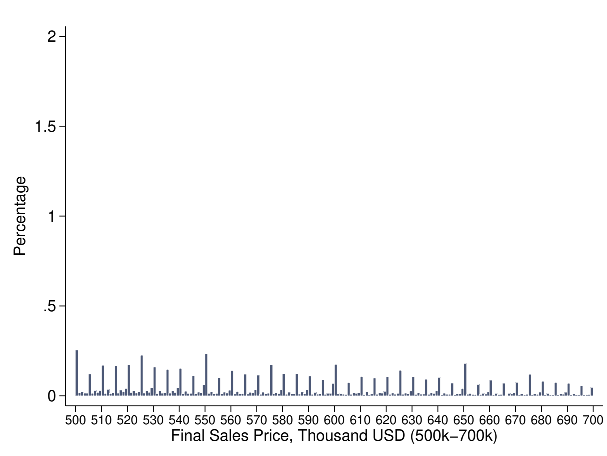
(b) Initial List Price (500k-700k)



(c) Final Sales Price (100k-300k)



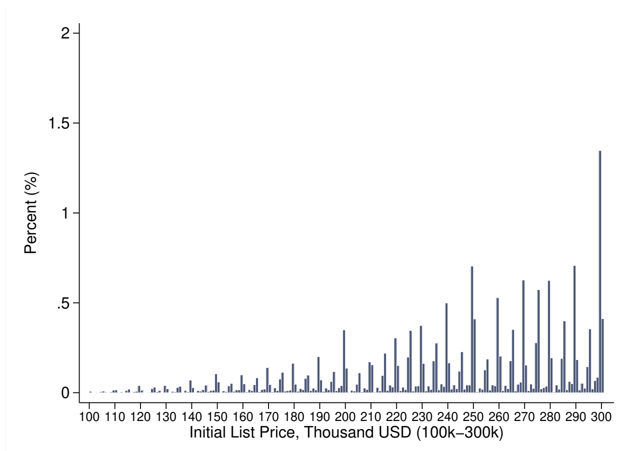
(d) Final Sales Price (500k-700k)



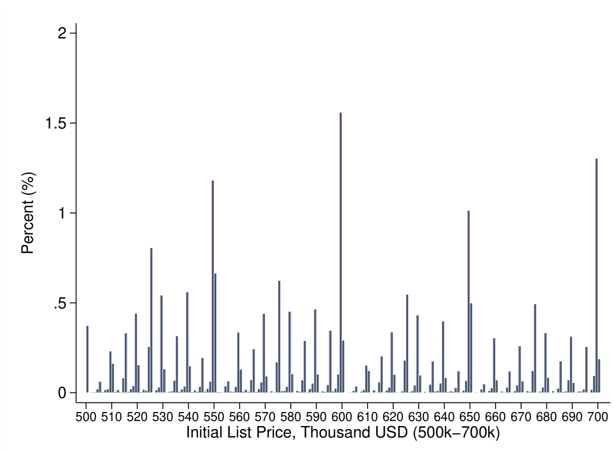
Notes: This figure shows the distribution of the initial list price and final sales price of properties using the MLS sample, with different price ranges in different panels. This table presents summary statistics for our MLS data. The sample consists of 76,981,953 housing bargaining events on MLS data 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 B13: Distribution of Event-Level Prices (Redfin, Robustness Check)

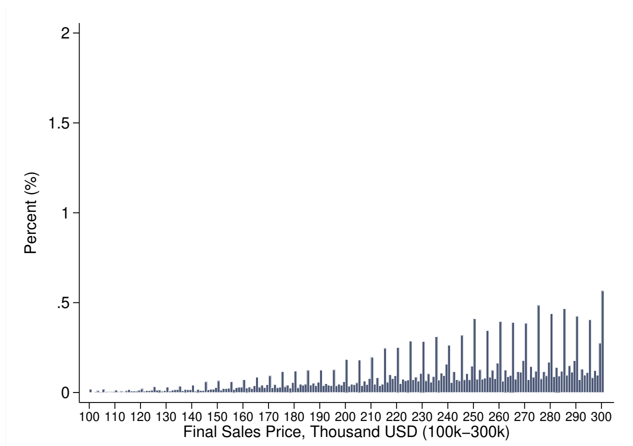
(a) Initial List Price (100k-300k)



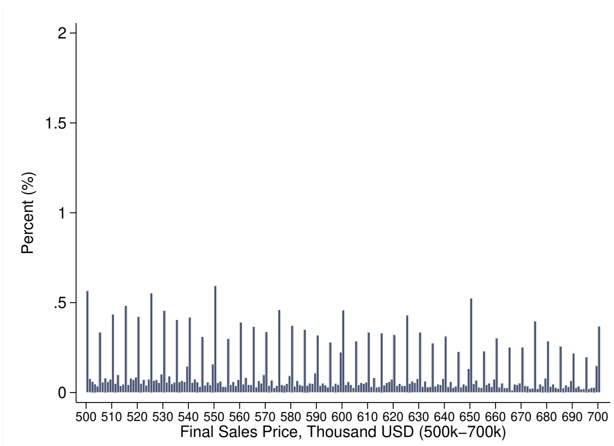
(b) Initial List Price (500k-700k)



(c) Final Sales Price (100k-300k)



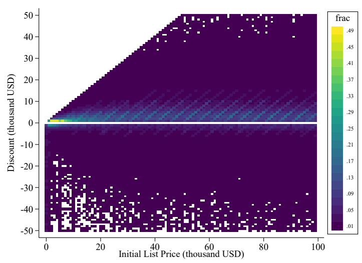
(d) Final Sales Price (500k-700k)



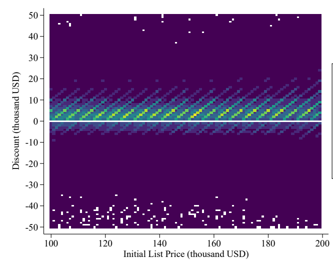
Notes: This figure shows the distribution of the initial list price and final sales price of properties using the Redfin sample, with different price ranges in different panels. The sample consists of buyer and seller interactions from 296,640 housing bargaining events on Redfin's platform across 45 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 B14: Heatmap of Discount against Initial List Price Cont. (Column-Normalized)

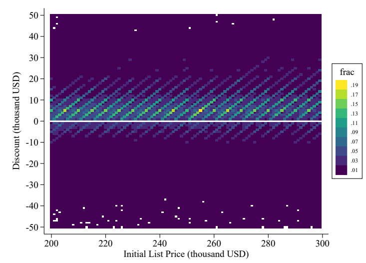
(a) [$0k,$100k)



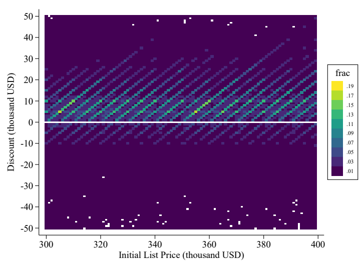
(b) [$100k,$200k)



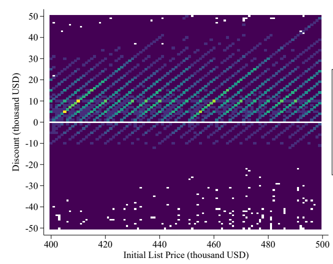
(c) [$200k,$300k)



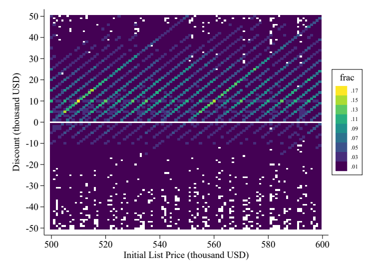
(d) [$300k,$400k)



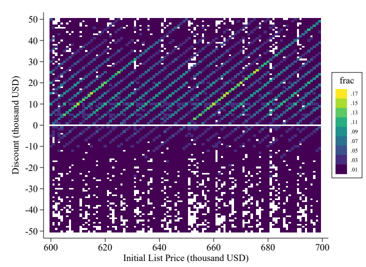
(e) [$400k,$500k)



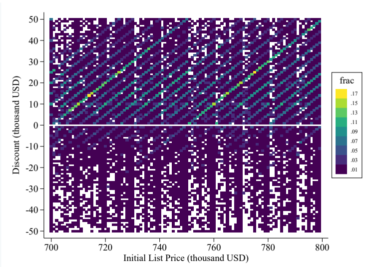
(f) [$500k,$600k)



(g) [$600k,$700k)



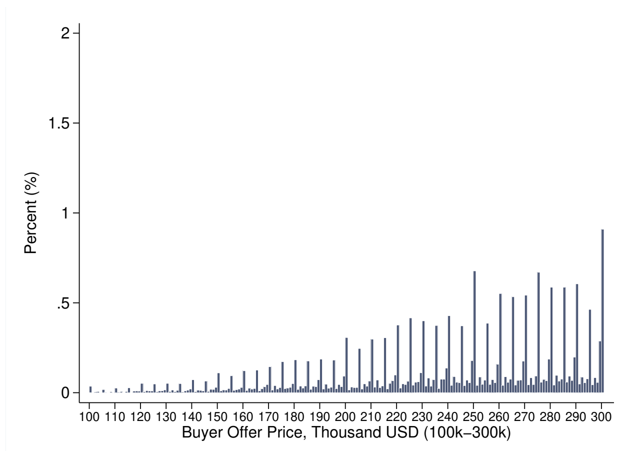
(h) [$700k,$800k)



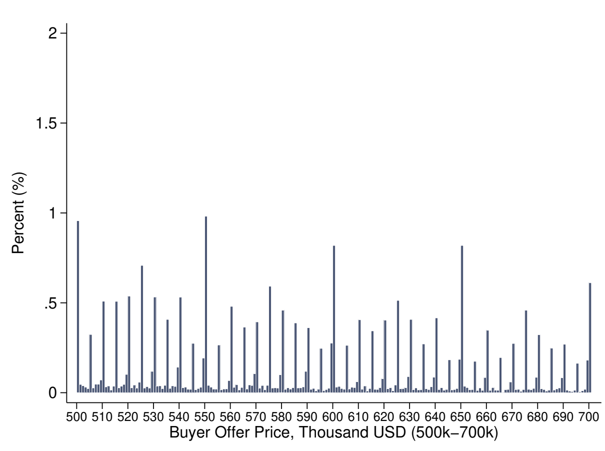
Notes: This figure shows the heatmaps of the discount against the initial list price in our selected MLS dataset. This table presents summary statistics for our MLS data. The sample consists of 76,981,953 housing bargaining events on MLS data in the U.S. from 2000 to 2022. We restrict our focus on single-family, 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 thousands 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 equal 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 a 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 B15: Distribution of Action-Level Prices (Redfin, Robustness Check)

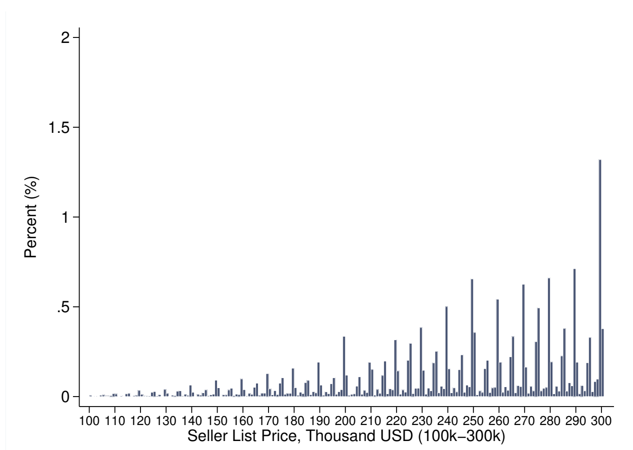
(a) Buyer Offer Price (100k-300k)



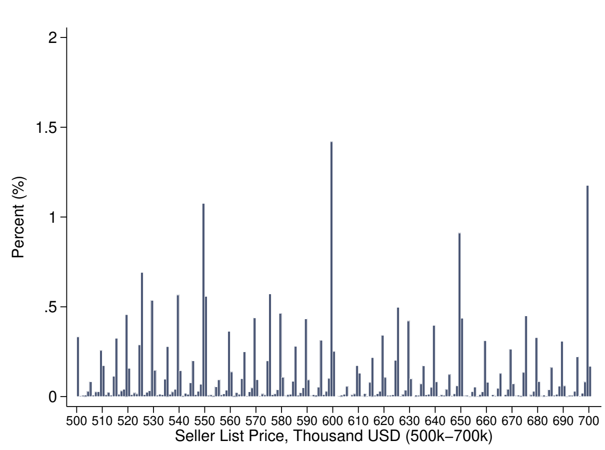
(b) Buyer Offer Price (500k-700k)



(c) Seller List Price (100k-300k)



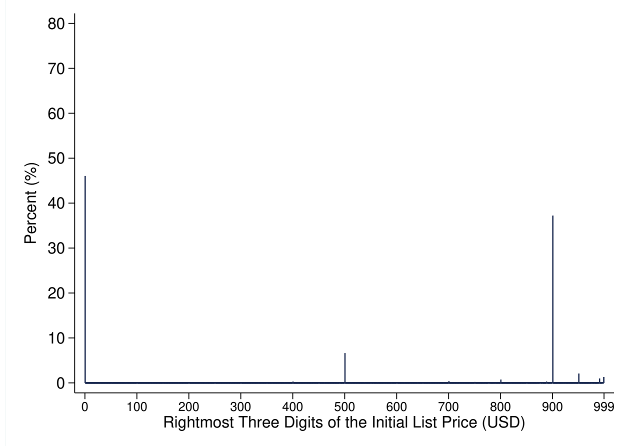
(d) Seller List Price (500k-700k)



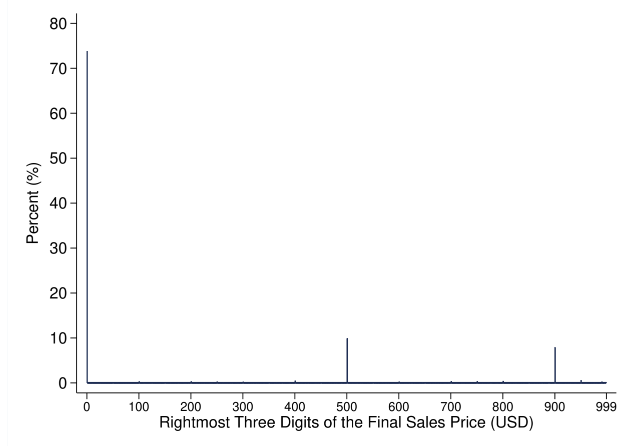
Notes: This figure shows the distribution of the buyer offer price and the seller list price of properties using the Redfin sample, with different price ranges in different panels. The sample consists of buyer and seller interactions from 296,640 housing bargaining events on Redfin's platform across 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 B16: Event-level Refined Distribution of the Rightmost Digits (MLS)

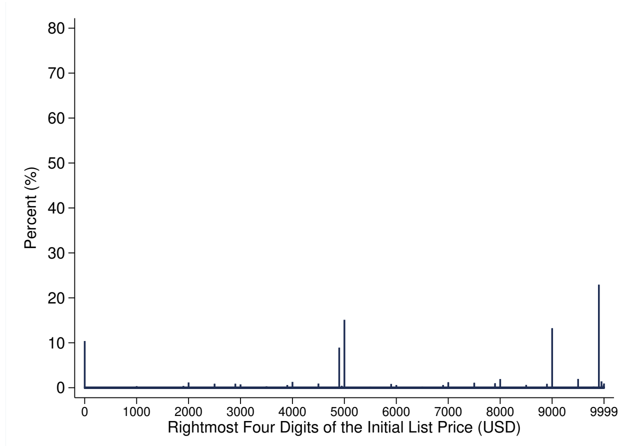
(a) Initial List Price (3 digits)



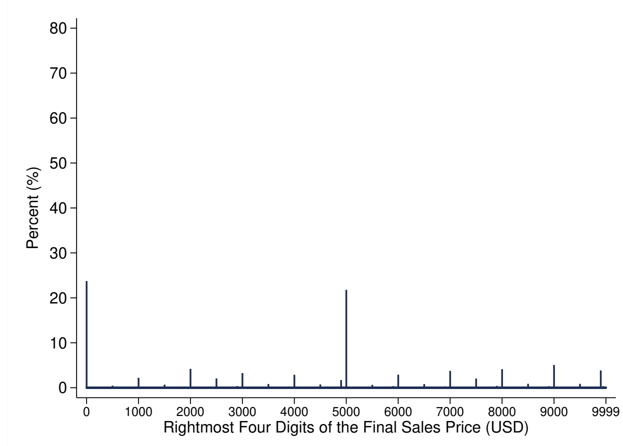
(b) Final Sales Price (3 digits)



(c) Initial List Price (4 digits)



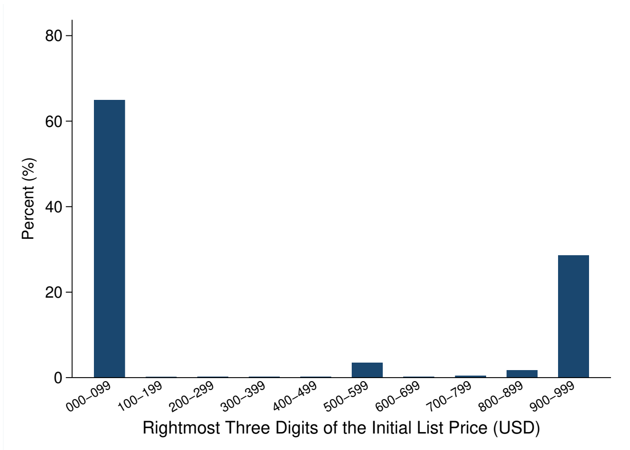
(d) Final Sales Price (4 digits)



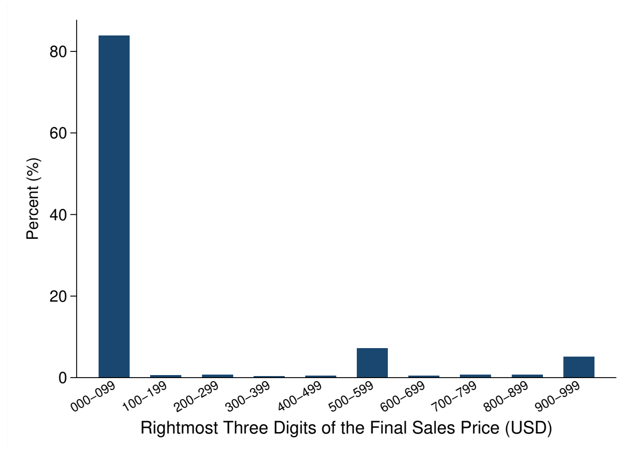
Notes: This figure shows the distribution of the rightmost digits of the initial list price and the final sales price at the event level using the MLS sample. This table presents summary statistics for our MLS data. The sample consists of 76,981,953 housing bargaining events on MLS data in the U.S. from 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 B17: Event-level Distribution of the Rightmost Digits (Redfin)

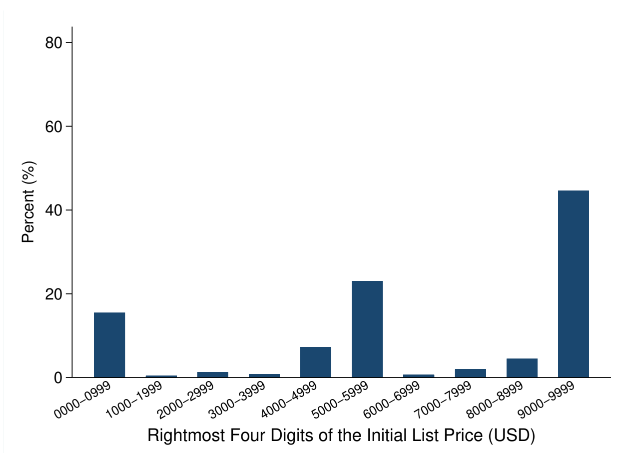
(a) Initial List Price (3 digits)



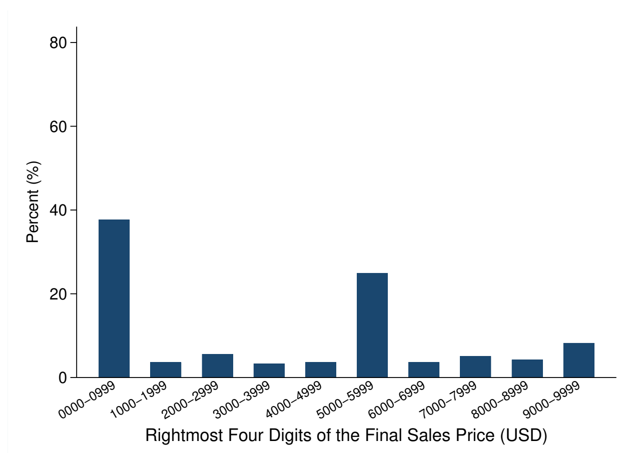
(b) Final Sales Price (3 digits)



(c) Initial List Price (4 digits)



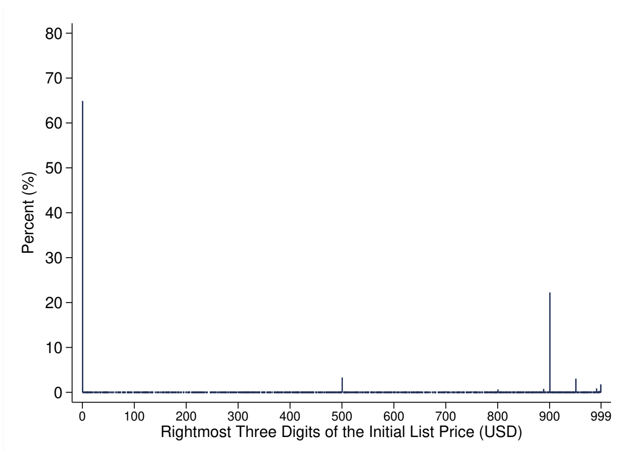
(d) Final Sales Price (4 digits)



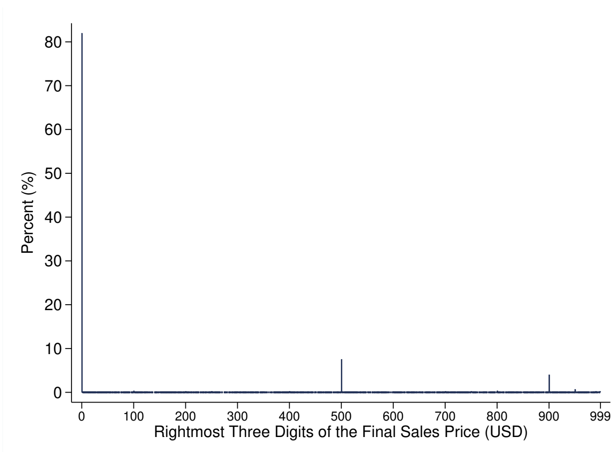
Notes: This figure shows the distribution of the rightmost digits of the initial list price and the final sales price at the event level using the Redfin sample. The sample consists of buyer and seller interactions from 296,640 housing bargaining events on Redfin's platform across 45 states in the U.S. 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 B18 shows a more refined version of the distribution.

Figure B18: Event-level Refined Distribution of the Rightmost Digits (Redfin)

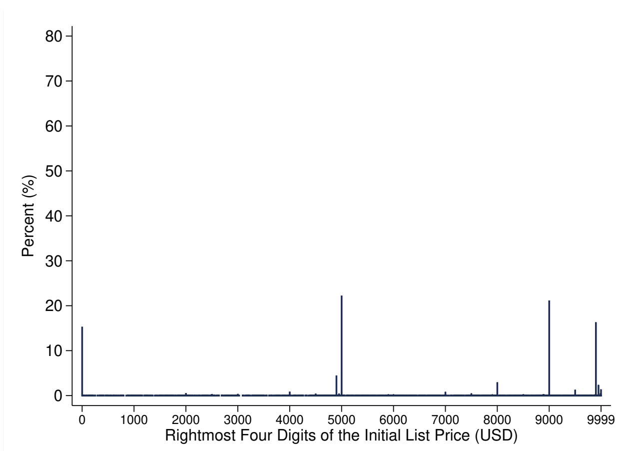
(a) Initial List Price (3 digits)



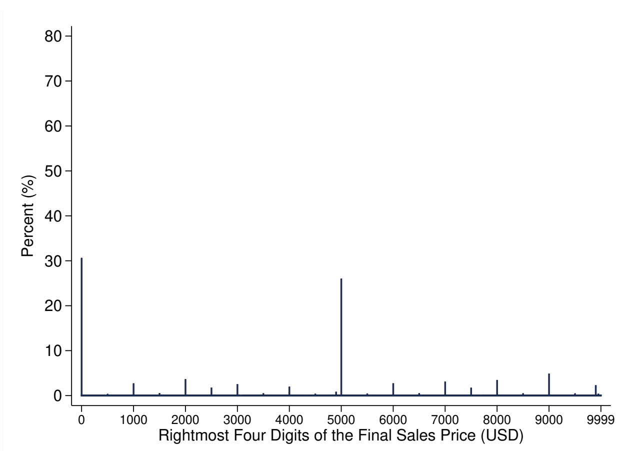
(b) Final Sales Price (3 digits)



(c) Initial List Price (4 digits)



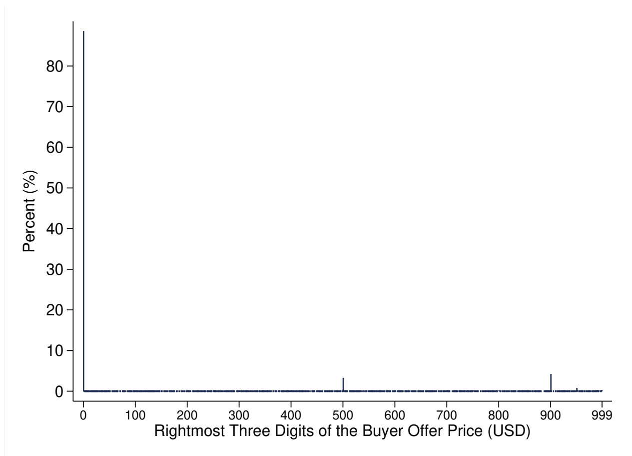
(d) Final Sales Price (4 digits)



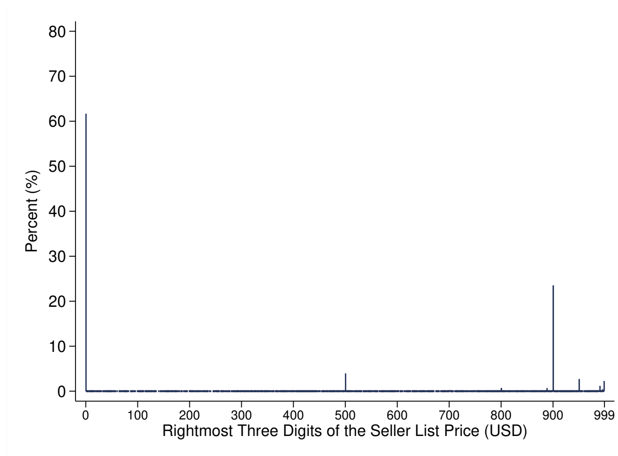
Notes: This figure shows the distribution of the rightmost digits of the initial list price and the final sales price at the event level using the Redfin sample. The sample consists of buyer and seller interactions from 296,640 housing bargaining events on Redfin's platform across 45 states in the U.S. 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 B19: Action-level Refined Distribution of the Rightmost Digits (Redfin)

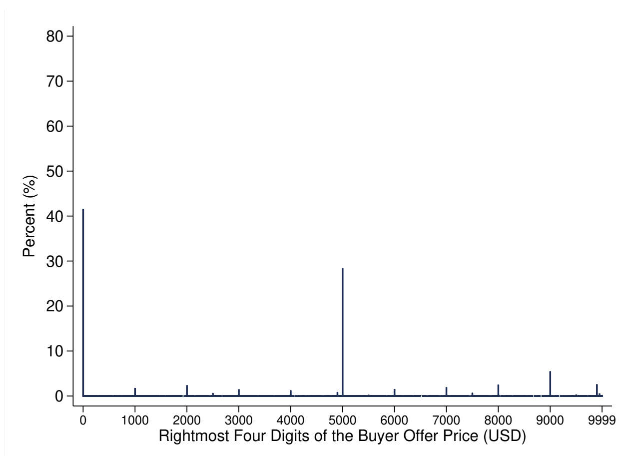
(a) Buyer Offer Price (3 digits)



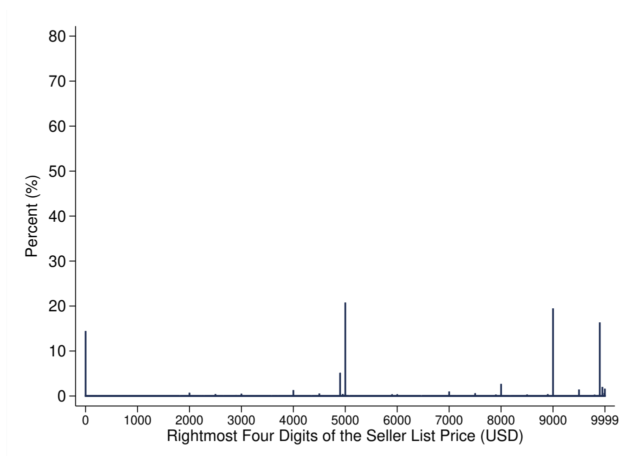
(b) Seller List Price(3 digits)



(c) Buyer Offer Price (4 digits)



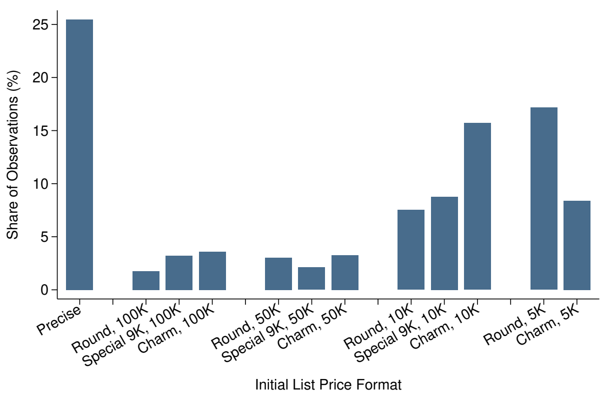
(d) Seller List Price(4 digits)



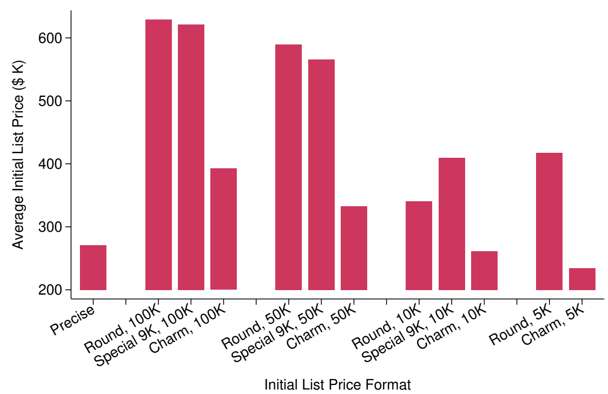
Notes: This figure shows the distribution of the rightmost digits of the buyer offer price and the seller list price at the event level using the Redfin sample. The sample consists of buyer and seller interactions from 296,640 housing bargaining events on Redfin's platform across 45 states in the U.S. 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 B20: Comparison by Focal Group (MLS)

(a) Share of Observations by Group



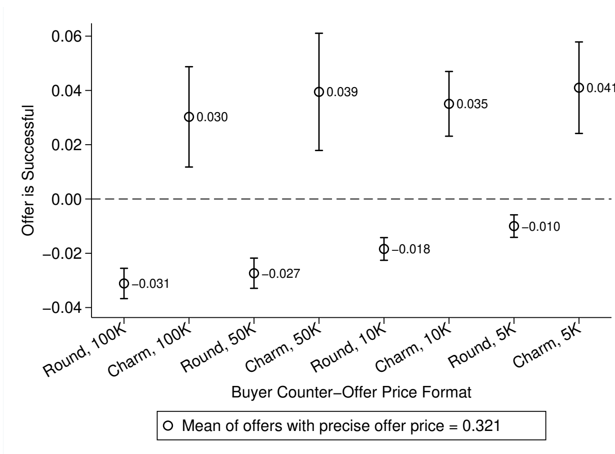
(b) Avg. Initial List Price by Group



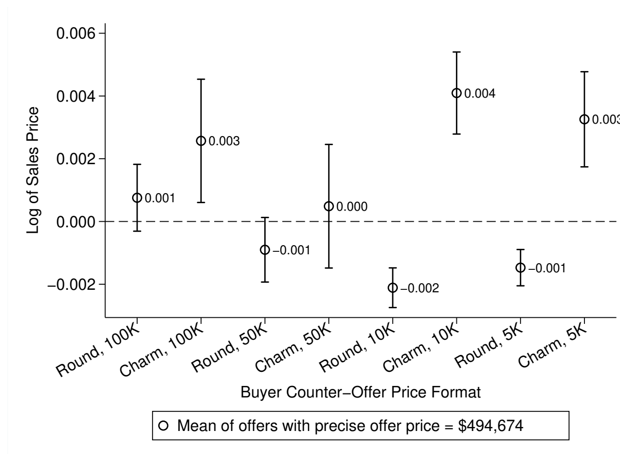
Notes: This figure shows the share of observations and average initial list price by focal groups. This table presents summary statistics for our MLS data. The sample consists of 76,981,953 housing bargaining events on MLS data in the U.S. from 2000 to 2022.

Figure B21: Effects of Counteroffer Price Format on Outcomes (Full Sample)

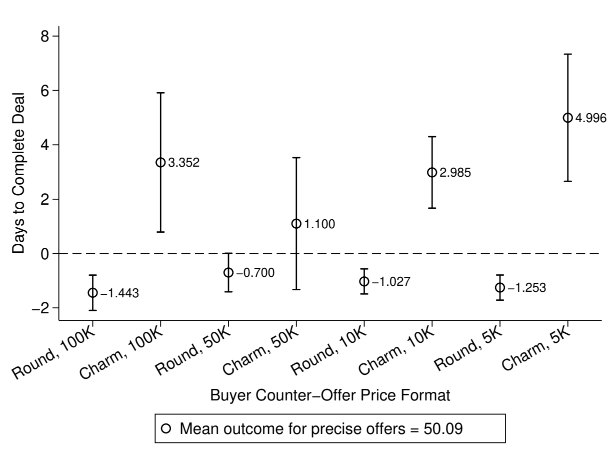
(a) Buyer Success Rate



(b) Log of Sales Price



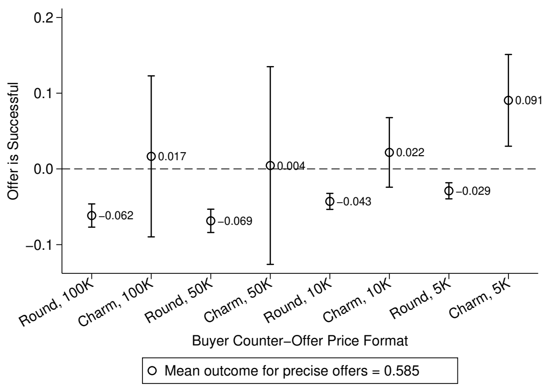
(c) Days to Complete Deal



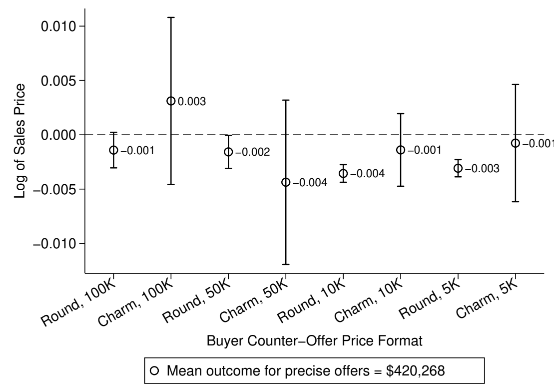
Notes: This set of figures presents the effects of buyer counteroffer format on counteroffer outcomes using the specification shown in Eq. (3), along with 90% CI. The control means are reported in the legends. The sample consists of 314,829 buyer counteroffers using Redfin data across 45 states in the U.S. from January 2012 to December 2022. The dependent variables are a dummy indicating whether the counteroffer is successful in Panel (a), log of the sales price in Panel (b), and days to complete deal Panel (c). Days to complete deal is defined as the sum of acceptance time and private negotiation time. The acceptance time is defined as the days from the counteroffer submission to offer acceptance. The private negotiation time is defined as the days from the counteroffer acceptance to final sales. The independent variables of interest are dummies indicating whether the buyer counteroffer price is a round number. The sample used in Panel (a) includes all counteroffers. The sample used in Panels (b) and (c) includes only successful offers. All regressions control for the restricted cubic spline of log list price, housing characteristics, number of competing counteroffers and buyer adjustment. Housing characteristics include the property age, property type, log of square foot, number of bedrooms, and number of bathrooms. We also impose Year × Month, Year × Zipcode, and Buyer Agent fixed effects. Robust standard errors are reported in parentheses.

Figure B22: Effects of Counteroffer Price Format on Outcomes (Single counteroffer without Trivial Adjustment)

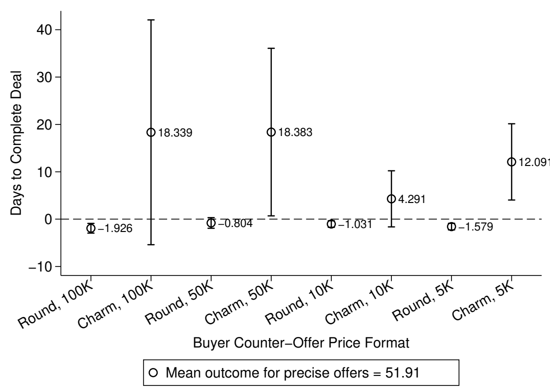
(a) Buyer Success Rate



(b) Log of Sales Price



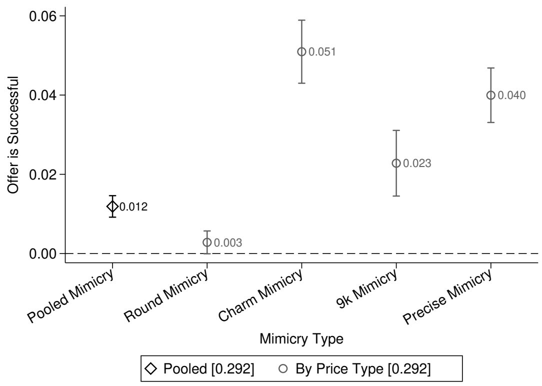
(c) Days to Complete Deal



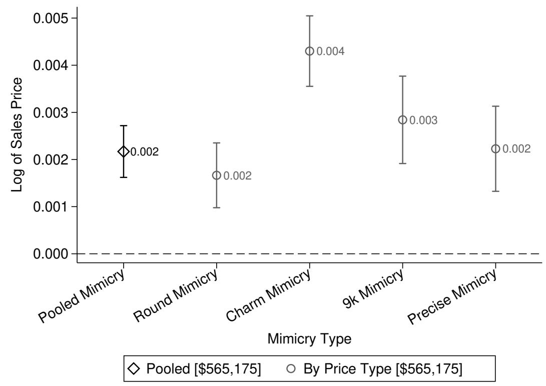
Notes: This set of figures presents the effects of buyer counteroffer format on counteroffer outcomes using the specification shown in Eq. (3), along with 90% CI. The control means are reported in the legends. The sample consists of 91,823 single buyer counteroffers without trivial adjustment using Redfin data across 45 states in the U.S. from January 2012 to December 2022. The dependent variables are a dummy indicating whether the counteroffer is successful in Panel (a), log of the sales price in Panel (b), and days to complete deal Panel (c). Days to complete deal is defined as the sum of acceptance time and private negotiation time. The acceptance time is defined as the days from the counteroffer submission to offer acceptance. The private negotiation time is defined as the days from the counteroffer acceptance to final sales. The independent variables of interest are dummies indicating whether the buyer counteroffer price is a round number. The sample used in Panel (a) includes all counteroffers. The sample used in Panels (b) and (c) includes only successful offers. All regressions control for the restricted cubic spline of log list price, housing characteristics, number of competing counteroffers and buyer adjustment. Housing characteristics include the property age, property type, log of square foot, number of bedrooms, and number of bathrooms. We also impose Year × Month, Year × Zipcode, and Buyer Agent fixed effects. Robust standard errors are reported in parentheses.

Figure B23: Effects of Mimicry Type on Outcomes (Full Sample)

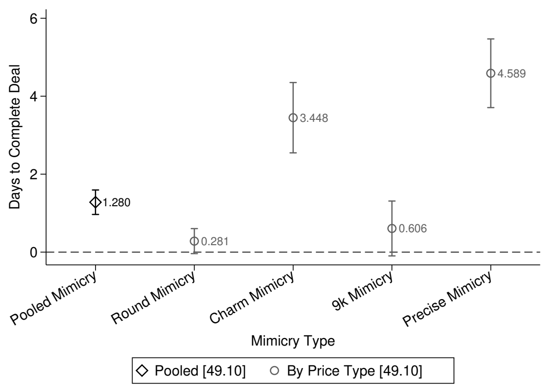
(a) Buyer Success Rate



(b) Log of Sales Price



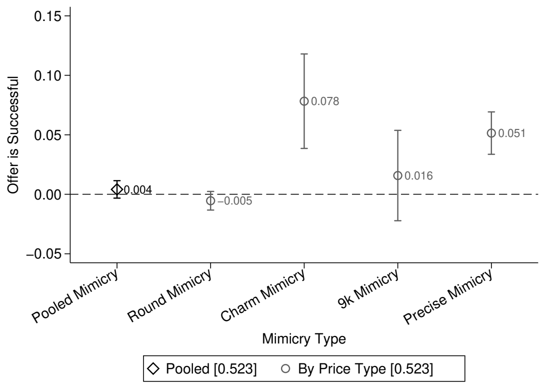
(c) Days to Complete Deal



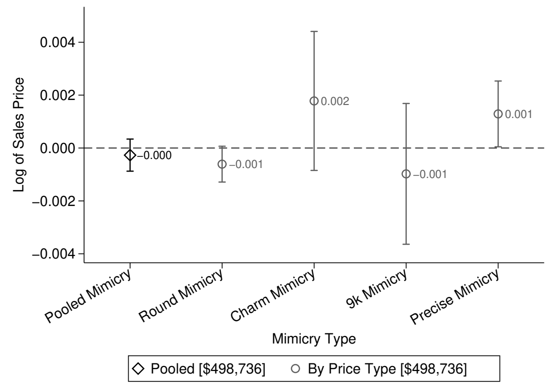
Notes: This set of figures presents the effects of mimicry type on counteroffer outcomes using the specification shown in Eq. (4), along with 90% CI. The control means are reported in the legends. The sample consists of 314,829 buyer counteroffers using Redfin data across 45 states in the U.S. from January 2012 to December 2022. The dependent variables are a dummy indicating whether the counteroffer is successful in Panel (a), log of the sales price in Panel (b), and days to complete deal Panel (c). Days to complete deal is defined as the sum of acceptance time and private negotiation time. The acceptance time is defined as the days from the counteroffer submission to offer acceptance. The private negotiation time is defined as the days from the counteroffer acceptance to final sales. The independent variables round mimicry, 9k mimicry and precise mimicry are dummies indicating whether the list price and the counteroffer price both belong to one of the price types by *Round Price*, *Special 9k Price*, *Charm Price* and *Precise Price*. The independent variable pooled mimicry is a dummy indicating whether list price and the counteroffer price belong to round mimicry, 9k mimicry or precise mimicry. The sample used in Panel (a) includes all offers. The sample used in Panels (b) and (c) includes only successful offers. All regressions control for the restricted cubic spline of log list price, housing characteristics, number of competing counteroffers and buyer adjustment. Housing characteristics include the property age, property type, log of square foot, number of bedrooms, and number of bathrooms. We also impose Year × Month, Year × Zipcode, and Buyer Agent fixed effects. Robust standard errors are reported in parentheses.

Figure B24: Effects of Mimicry Type on Outcomes (Single Offer without Trivial Adjustment)

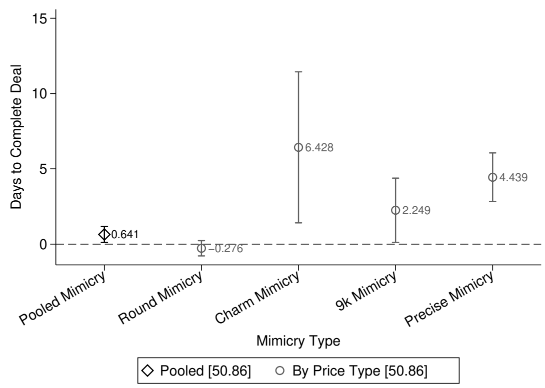
(a) Buyer Success Rate



(b) Log of Sales Price



(c) Days to Complete Deal



Notes: This set of figures presents the effects of mimicry type on offer outcomes using the specification shown in Eq. (4), along with 90% CI. The control means are reported in the legends. The sample consists of 91,823 single buyer counteroffers without trivial adjustment using Redfin data across 45 states in the U.S. from January 2012 to December 2022. The dependent variables are a dummy indicating whether the counteroffer is successful in Panel (a), log of the sales price in Panel (b), and days to complete deal Panel (c). Days to complete deal is defined as the sum of acceptance time and private negotiation time. The acceptance time is defined as the days from the counteroffer submission to offer acceptance. The private negotiation time is defined as the days from the counteroffer acceptance to final sales. The independent variables round mimicry, 9k mimicry and precise mimicry are dummies indicating whether the list price and the counteroffer price both belong to one of the price types by *Round Price*, *Special 9k Price*, *Charm Price* and *Precise Price*. The independent variable pooled mimicry is a dummy indicating whether list price and the counteroffer price belong to round mimicry, 9k mimicry or precise mimicry. The sample used in Panel (a) includes all offers. The sample used in Panels (b) and (c) includes only successful offers. All regressions control for the restricted cubic spline of log list price, housing characteristics, number of competing counteroffers and buyer adjustment. Housing characteristics include the property age, property type, log of square foot, number of bedrooms, and number of bathrooms. We also impose Year × Month, Year × Zipcode, and Buyer Agent fixed effects. Robust standard errors are reported in parentheses.

C Data Construction

C.1 Illustration of Bargaining Events

Panel (a) of Appendix Figure B1 shows an example in which the seller revised the listing price multiple rounds until receiving an offer. The seller initially listed the property at \$399,000 on May 29, 2014. Without receiving an offer, the seller further revised the listing price to \$389,000 on June 16th, 2014, \$379,000 on July 23, 2014, and \$367,000 on August 26, 2014. Shortly thereafter, on August 31, 2014, a buyer proposed a counteroffer of \$365,000. The counteroffer was accepted on September 3, 2014. The buyer and the seller then entered a private negotiation phase, which concluded with the property's sales at the buyer's offer price of \$365,000.

Panel (b) of Appendix Figure B1 illustrates another example in which one seller bargains with multiple buyers. The property was initially listed at \$499,999 on February 1, 2020. Shortly after, on February 5, 2020, a buyer submitted a counteroffer of \$508,000. A subsequent counteroffer of \$515,000 was made by another buyer on February 9, 2020. Despite the higher counteroffer price of the second buyer, the seller accepted the first buyer's counteroffer on February 10, 2020, and ultimately rejected the second buyer's counteroffer. Ultimately, the property was sold to the first buyer for \$508,000 on March 10, 2020.

Panel (c) of Appendix Figure B1 shows an example of sequential bargaining, in which case one seller bargains with one buyer for multiple rounds. The property was initially listed on June 13, 2019, at \$494,000. After two revisions of the listing price, the price was adjusted to \$439,000 on July 16, 2019. Subsequently, on July 19, 2019, a buyer made a counteroffer of \$390,000, which the seller rejected due to the terms presented. In response, the seller adjusted the price to \$424,000 on August 2, 2019. This price adjustment was strategically set above the buyer's counteroffer yet below the prior listing price. The lack of additional buyer interest prompted a further price cut to \$399,999 on August 6, 2019. The same buyer countered with \$360,000, which led to the acceptance of the counteroffer on August 9, 2019.

After the private negotiation, the property was sold to the buyer at $340,000 on August 30, 2019.

C.2 Data Cleaning of MLS Data

We clean the selected MLS data using the following steps:

- **Step 1:** Remove listings lacking a property identifier. We need the property identifier in our repeat-sales model. This identifier is also crucial for eliminating duplicate records in the subsequent step.

- **Step 2**: Eliminate duplicate records. Given that MLS data can contain multiple entries for the same listing event due to its compilation from various local MLS boards, it's possible for the same listing event to appear on multiple boards at the same time. This leads to duplication of records in our sample. Following Garriga and Hedlund (2020) and Guo (2023), we address this by identifying duplicate records using transaction dates. Specifically, we implement specific criteria:

  - For *successful listings*, we consolidate events for properties that have overlapping time on the market, specifically the duration between the initial listing date and the contract date. In cases of overlap, we select the earliest date as the initial listing. This approach is based on the fact that a property, while listed by the same seller, can only be sold once. Appendix Figure B3 shows a few examples of raw listing events and their corresponding refined events.
  - For *failed listings*, our strategy differs due to the absence of a sales date, making the previously used approach for successful listings inapplicable. Instead, we merge events only when they share the same initial listing date. This is primarily because almost all duplicate failed listings have exactly the same listing date and price. In addition, failed listings, which often remain on the market longer until expiration, present a unique challenge. Occasionally, a seller may launch a

new listing with a different price before the previous listing expires. This behavior leads to the imprecise classification of duplicate listings through time overlapping, as the relisted property should be classified as a new listing. Appendix Figure B4 shows a few examples of raw listing events and their corresponding refined events.

- **Step 3**: Trim the prices. To exclude outliers, we trim the initial list price at 1.5 and 99 percentile. Similarly, we trim the sales-to-list price ratio, excluding data below the 0.2 percentile and above the 99.9 percentile.

- **Step 4**: Clean 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 0.2 percentile and above the 99.9 percentile.

For other variables, we winsorize the number of days to close the deal at 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 Appendix Figure B8.

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.