

The Price of Inattention: Evidence from the Swedish Housing Market *

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Abstract

Do behavioral biases affect prices in a high-stakes market? We study the role of left-digit bias in the purchase of an apartment. Left-digit bias is the failure to fully process digits after the first, perceiving prices just below a round number (such as \$3.99) as cheaper than their round counterpart (\$4). Apartments with asking prices just below round millions are sold at a 3-5% higher final price after an auction. This effect appears not to be driven by differences in observables or in real estate agents' behavior. Auctions for apartments listed just below round numbers are more competitive and attract more bidders and bids.

Keywords: Housing market, auctions, inattention, left-digit bias

JEL codes: R31, D44, D83, C78

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1 Introduction

Behavioral economics has challenged rational-agent models, showing that decision makers are prone to mistakes (Simon, 1955; Tversky and Kahneman, 1974). Individuals use heuristics or cognitive shortcuts to process large amounts of information, often leading to sub-optimal decisions. Psychologists and economists have shown a variety of such behavioral biases in laboratory experiments and, more recently, in real market settings, such as the financial market, used car sales, auctions, and supermarket purchases (Lacetera, Pope and Sydnor, 2012; Englmaier, Schmoller and Stowasser, 2017; Malmendier and Lee, 2011; Chetty, Looney and Kroft, 2009, Shlain, 2018). Despite growing evidence, we still have a limited understanding of how these biases affect high-stakes markets.

In this paper, we study a form of inattention known as left-digit bias, which refers to the inability of some buyers to process prices correctly. Left-digit bias is the propensity to focus on the leftmost digit of a number, while partially neglecting the other digits. Sellers exploit these biases by setting prices just below a round number (e.g., \$3.99), which the buyer perceives to be much lower than the round price (\$4). Most of the empirical evidence on the importance of these heuristics comes from settings in which stakes are low. However, in high-stakes markets, rational consumers have strong incentives to avoid heuristics because the potential welfare losses are significant.

We study how left-digit bias affects prices in the Swedish housing market. The housing market offers an ideal setting in which to test the prevalence of heuristics because of its high-stakes and low search costs. First, a home is one of the most important financial assets in a household's portfolio, accounting for as much as two thirds of its total wealth (Iacoviello, 2011).¹ Second, information about units for sale is abundant at a relatively low cost. There are websites that collect and organize information and provide tools to assist buyers in their search.

Most transactions are mediated by a real estate agent, who advertises the dwelling and manages a public ascending price auction. The most salient element in the process is the asking price that appears in the ad and usually serves as the starting price in the auction. The main focus of this paper is to investigate the effect of inattention to the asking price on the final sale price. To this end, we compare the final prices of apartments with asking prices that are very similar but that differ in the first (or second) digit.

We find that the average final price of comparable apartments drops discontinuously by 2.8-5.1% when the first digit of the asking price changes (e.g., from 1,995,000

¹Moreover, the size of the housing market has important implications for the aggregate economy, since the value of this market is larger than the stock market (see Shiller, 2014).

to 2,000,000 SEK). This change in the final price amounts to about \$13,000, equivalent to five months of the disposable income of the median Swedish household. An effect of this magnitude is difficult to reconcile with models of optimal search or rational inattention. Additionally, when studying the second digit, we find that just-below prices yield a slightly smaller premium of 1.1-3.4%, consistent with the existence of both a first- and a second-digit bias.

We have administrative information on about 350,000 apartment sales, collected by Sweden's real estate agents' association, which covers about 90% of all transactions between January 2010 and December 2015. The data contain a rich set of characteristics of each apartment (e.g., size, number of rooms, floor, etc.), exact address, date of transaction, and asking and final prices. Moreover, we merge this dataset with three other sources of information to test mechanisms. Specifically, we collect data to link sales to real estate agents; we download information from the largest real estate firm's web page to obtain the complete history of bids for all of their auctions; and, finally, we survey real estate agents.

Our empirical strategy relies on estimating discontinuous jumps in the final price as a function of the asking price. Because we expect the final price to be a continuous function of the asking price, discontinuities found at each 1 million threshold can be interpreted, in the absence of selection, as evidence of first-digit bias. Similarly, the discontinuities at the 100,000 thresholds suggest the existence of second-digit bias. The richness of the data allows us to control for several observable characteristics and an extensive set of fixed effects, to account for seasonality, common macroeconomic shocks, and unobserved amenities in the neighborhood or building. Our estimates are robust to restricting the sample to different years and regions, to varying the bandwidth, and to alternative estimation methods.

To rule out that our effect is driven by endogenous sorting of apartments around the threshold, we use several strategies. First, to ensure that apartments are comparable, we inspect the averages of each observable characteristic around the thresholds. Observables are balanced around the common threshold obtained by pooling all 1 million marks together. When refining the analysis to each 1 million threshold separately, we observe some differences. In most cases, however, these imbalances suggest that we are underestimating the true effect. We also construct a predicted final price using observables and various sets of fixed effects, and show that it does not exhibit any discontinuity at asking price thresholds.

A second form of sorting arises if apartments on either side of the threshold systematically differ in the ability of the real estate agent – for instance, because more competent agents use just-below prices more often. We rule out this possibility by in-

cluding real estate agent fixed effects, which allow us to compare apartments sold by the same agent, thus controlling for ability and any other unobserved time-invariant characteristic of the agent.

Additionally, we inspect the time on the market, defined as the period between the contract date and the advertisement date. First, the time in the market is roughly constant at around 30 days along the whole distribution of the asking price and does not show any discontinuity, suggesting that agents' incentives are the same across the threshold. This is also indirect evidence against both types of sorting described above and is not consistent with the alternative explanation that our result is driven by impatient sellers choosing to list apartments at round numbers as "cheap talk" to signal a weak bargaining position as in, for example, [Backus, Blake and Tadelis \(2019\)](#).

Finally, we perform a set of robustness checks to confirm our hypothesis. First, we rule out that our effect is due to the design of the search engine by exploiting a change in the web interface of the main web portal for apartment ads, *Hemnet.se*. Previously, users of this website could restrict their search by using a slider. In 2011, the system was replaced by pre-set price brackets that partially coincide with our 1 million thresholds. A simple diff-in-diffs shows that our baseline effect is the same before and after the reform. Second, we implement the bias correction method proposed by [Oster \(2017\)](#) to correct for potential omitted variable bias. While the estimated effect decreases slightly, it remains large and statistically significant for a reasonable range of values of the parameter that governs the degree of bias. Third, we confirm our main result using an alternative estimation method based on [Abadie and Imbens \(2006\)](#) nearest neighbor matching algorithm.

We propose a mechanism to interpret our results in which inattentive buyers, when deciding which apartment to bid on, perceive those with just-below prices as cheaper, inducing them to participate in these auctions. As a consequence, auctions for apartments with just-below prices have more bidders and receive more bids, leading to a higher final price.² Using additional data on over 27,000 completed auctions from Sweden's largest real estate firm, we find that apartments using just-below prices have, on average, 0.72 more bidders and receive 2.7 more bids, in line with our hypothesis. This corresponds to an increase of 25% of the average number of bidders and 30% of the average number of bids per auction, respectively.

Our paper contributes to the behavioral economics literature described by [DellaVigna \(2009\)](#) by documenting that consumers use heuristics even when making important

²The final price in ascending price auctions with independent valuations will be the second-highest willingness to pay, which is an increasing function of the number of bidders ([Krishna, 2009](#)). Moreover, participants in very popular auctions may be affected by herding effects or the "bidder's heat" and bid above their valuations ([Malmendier and Lee, 2011](#); [Schneider, 2016](#)).

decisions, such as buying a home. The closest paper to ours is by [Lacetera, Pope and Sydnor \(2012\)](#) (and its follow-up, [Busse et al. 2013](#)), who document the existence of a first-digit bias in the used car market. In their context, professional dealers have extensive experience from repeatedly participating in the market, but, in general, it is the final consumer who is more likely to suffer from behavioral biases (see, e.g., [List, 2003](#) and [List, 2011](#)). In this respect, we contribute by analyzing the behavior of the final consumer in a high-stakes market in which individuals have limited experience. Moreover, we are able to present evidence on some of the mechanisms.

Our results also relate to the literature on behavioral finance. Dwellings are an example of an asset that is indivisible, illiquid, and heterogeneous ([Campbell, Giglio and Pathak, 2011](#)), whose price can deviate from fundamentals and be affected by behavioral components, such as loss aversion ([Genesove and Mayer, 2001](#)) and herd behavior ([Bayer, Mangum and Roberts, 2016](#)). Our paper relates especially to the literature that studies behavioral biases in processing housing prices, which emphasized their role as anchors, with high asking prices being associated with high final prices ([Northcraft and Neale, 1987](#); [Bucchianeri and Minson, 2013](#)). In our setting, instead, we document a different pattern, with relatively lower asking prices leading to higher final prices.

We also contribute to the behavioral industrial organization literature by documenting an anomaly in the search process. The question of how to search for the best alternative among several choices is a central element in industrial organization (see, e.g., [Weitzman, 1979](#); [Salop and Stiglitz, 1977](#); and [Varian, 1980](#)). When consumers have little or no experience or when they face complicated pricing schemes, they search too little, get confused by the different price schemes, and switch too seldom from past decisions or default options ([Grubb, 2015](#)). Consumers behave in this way because searching and switching are costly, and firms respond by shrouding attributes and hiding information on, for example, add-ons or shipping costs (see, for example, [Gabaix and Laibson, 2006](#), [Brown, Hossain and Morgan, 2010](#)). Our paper contributes to this literature by showing that even when search costs are relatively low, consumers appear to restrict their search sub-optimally.

This paper also contributes to the discussion on the role of the asking price on auction outcomes. The idea that low asking prices may induce a bidding war and yield higher final prices has met with mixed empirical evidence. While [Ku, Galinsky and Murnighan \(2006\)](#) argue that low starting prices can create bidding escalations and increase both the odds of a sale and the price conditional on sale, a recent paper by [Einav et al. \(2015\)](#) that uses eBay auction data shows that this is not always the case. This literature has considered the effect of setting an asking price of a good above or below a reference value, but has not studied how its impact on the final price changes when

crossing a round number. Our results contribute to this line of research by providing evidence that even small differences in the asking price of observationally identical apartments can have a large effect on the final price.

Finally, this paper relates to the marketing and real estate literatures on the effectiveness of just-below pricing strategies (e.g.; [Allen and Dare 2004](#); [Thomas and Morwitz 2005](#); and see [Han and Strange 2015](#) for a review on several economic aspects of the housing market). Most empirical studies from the housing market use data from negotiations and not from auctions. The evidence in these papers is mixed, possibly because of the difficulties in properly controlling for unobserved apartment and seller traits.³ Our paper contributes to this literature by i) being able to control for neighborhood and real estate agent unobservables; ii) providing evidence on mechanisms through analyzing the auction process, and iii) showing the existence of both a first- and second-digit bias.

At a late stage in the writing of this paper, we became aware of a study similar to ours ([Chava and Yao, 2017](#)) who document, using U.S. data, a very small effect of just-below asking prices on the final price (0.1%) and, contrary to our findings, a positive effect on the time on the market. The apparent conflict with our results may stem from the different sale mechanisms in the two markets and by the different role played by the asking price in the two settings. In the U.S., properties are generally sold in private negotiations which, in the vast majority of cases, end below the asking price (see, e.g., [Beracha and Seiler 2013](#)). In this setting, the buyer will try to negotiate the price down from the asking price. Therefore, sellers may choose a high asking price to serve as an anchor (see, for example, [Northcraft and Neale 1987](#)) to limit the scope for significant discounts. In an ascending price auction, instead, the role of the asking price as anchor is arguably weaker and sellers usually set it lower than their reservation value to attract bidders. The presence of behavioral biases in auctions, such as herding ([Simonsohn and Ariely 2008](#)) and endowment effects ([Heyman, Orhun and Ariely 2004](#)) can then drive the price up substantially.

³While, for instance, [Palmon, Smith and Sopranzetti \(2004\)](#) find that just-below asking prices yield lower final prices, [Beracha and Seiler \(2013\)](#) show the opposite result. Recent laboratory evidence suggests that just-below strategies do not generate the highest profits for the seller in bilateral negotiations ([Cardella and Seiler, 2016](#)).

2 Background and data

2.1 The Swedish housing market

The Swedish housing market is competitive and liquid. Anyone is able to buy or sell freely, and prices are set by the interaction of supply and demand.⁴ Due to a relatively strong economy – only marginally affected by the financial crisis – and an intense immigration flow, housing prices almost doubled between 2005 and 2015.

The vast majority of dwellings are sold in auctions organized by real estate agents, who act as intermediaries between sellers and potential buyers. Only licensed agents can operate legally. To be eligible for a government license, prospective agents need to complete a 2-year degree. Differently from other countries, in Sweden there is only one agent involved in the transaction, who is required by law to operate in the best interest of both the seller and the buyer. As of 2015, there were 6,700 registered agents in Sweden. Their remuneration typically consists of a fixed or a variable fee (or a combination of the two) charged to the seller, who pays only if the sale is successful (Österling, 2016).

Agents are in charge of advertising the property, organizing open houses, and setting up the auction process, usually in the form of an anonymous, ascending price auction. The auction is the standard selling mechanism, although private transactions are also possible. Agents advertise the properties through local newspapers, descriptive brochures, and web ads. These ads are then usually posted on the agency's website and on a centralized search engine, *Hemnet.se*, that is collectively owned by the real estate agencies.

This search engine offers several tools for narrowing the search according to the needs of the potential buyer, who can specify the city or neighborhood, the type of dwelling (houses, apartments, etc.), a price interval, and some characteristics, such as the number of rooms, bathrooms, living area and monthly fee.⁵

Each ad describes the property, with pictures and information about characteristics (square meters, year of construction, elevator availability, address, etc.), open houses, and the auction starting date.⁶ Note that the ad shows the asking price, which is an important element of our analysis, as we will describe shortly. To further facilitate the search, *Hemnet.se* also provides information on past sales, which is easily accessible and can be tailored to the buyer's interests. Moreover, several other websites compile statistics and provide historical data that are released to the public free of charge. As

⁴The rental counterpart, however, operates very differently. Prices are regulated by the government and dwellings are assigned on the basis on a queue system.

⁵The monthly fee is a payment, proportional to the size of the apartment, done from the owner to the housing association to cover shared expenses in the building and past mortgages.

⁶For an example of how a typical ad looks, see Figure 9 in the Appendix.

a consequence, potential buyers have access to a large amount of information at an arguably low cost. Before the auction, agents typically show the property once or twice during open houses and register potential bidders. For our purposes, the most relevant characteristic of a property on sale is its asking price, which the owner and the real estate agent decide together.

This asking price, while related to the price that the seller is willing to accept, should not necessarily be interpreted as a reservation price and, rather, serves as a starting point for the auction. In fact, the seller is not obliged to sell, even after receiving offers exceeding the asking price (see [Österling 2016](#) for a more detailed discussion of the role of the asking price in the Swedish market). As a partial commitment device, most contracts with agents prevent sellers from hiring another agent within 3 months after the first attempt at selling the home. Similarly, potential buyers may withdraw a bid and walk away from the auction with no consequences, although this occurs very rarely. There is no fixed auction time, and the bidding continues until the seller accepts an offer, although the majority of auctions ends within a week or two.

After the viewings have finished and the auction has started, bidders interact with the real estate agent using several platforms: SMS, email, phone calls or bids placed directly into the web system. In most cases, the whole auction process is also made public on the agency's website. In an attempt to avoid frauds, agents are required to reveal the identity of the bidders to the buyer and the seller.

2.2 Data

We combine three sources of data to perform our analysis. Our main data source is administrative information on the sales brokered by real estate agents. We complement this dataset with information from three other sources. First, the identity of the real estate agent in charge of each sale was collected from the web page *Hemnet.se*. Second, to obtain information about the auction process, we gathered all the bidding histories of the auctions run by the market-leading real estate firm. Finally, we ran an email survey among real estate agents.

Main Dataset

Our main source is *Mäklarstatistik AB*, a private company that provides transaction data, including sale price, for the housing market in Sweden. According to *Mäklarstatistik*, they cover around 90% of all sales of houses and apartments that are mediated by a broker. The data contain information on the asking price, the final selling price, the date when the ad was posted and the date of the transaction for the period between

2010 and 2015. In addition, we observe a number of characteristics of the dwelling, such as the exact address, the year of construction, living area, number of rooms, number of floors, the presence of an elevator in the building and whether or not the unit has a balcony. For apartments, we also observe a unique housing association identifier and the monthly fee. The housing association, sometimes referred to as the “co-op” is an organization of neighbors that is the formal, legal owner of the apartment block and manages common areas and provide basic services. Associations are small, and they usually include just one or two buildings.

In order to be able to compare units that are as similar as possible, we restrict our analysis to apartments units, hence excluding villas (33.6% of the total), cottages and summer houses (7.4%). The main reason for this choice is that, by comparing apartments within the same housing association, we are able to control for several potential confounders, such as the architectural style, year of construction, proximity to amenities, and quality of the neighborhood. We also exclude from the sample apartments identified as new construction since they are often sold at fixed prices and not in an auction. Finally, we drop apartments with asking prices greater than 5.5 million SEK because such instances are rare (2%) and there is not enough density around thresholds above that number for a discontinuity analysis. Additional details on the construction of the final dataset are available in Appendix A.

The final dataset consists of 346,731 apartments. A limitation of our data is that we do not observe failed sales. This would be a problem for our interpretation of the results as long as unsold apartments are systematically priced just-below (or at) round numbers. However, failed sales are rare in the Swedish context. Using data for a limited sample that only includes Stockholm and Gothenburg for 2007-2014, Österling (2016) shows that i) failed searches are just 4% of the total, and ii) the failed sale variable is essentially unaffected by the asking price.

The first column of Table 1 shows that the average apartment in our sample has an asking price of 1,5 million SEK (about \$165,000) and is sold after the auction at a 10.4% higher price. It is relatively small, with 2.5 rooms (including the living room) and a living area of 66.8 square meters. The monthly fee due to the housing association is, on average, substantial, at 3,600 SEK (corresponding to roughly \$400). Finally, the average time between advertising and sale is slightly above one month.

As Figure B in the Appendix shows, the period covered by our sample is one of expansion. We also observe the substantial seasonal component in both the average asking and sale prices and the large, positive gap between asking and sale price. This gap, amounting to about a 15% increase in 2010, declined substantially to less than 4% in December 2011, when real estate agents committed to set more realistic asking prices.

In recent years, the gap began to increase again and has reached pre-2011 levels.

***Hemnet* subsample**

Given that information on real estate agents is absent from the main dataset, we obtain the history of past sales available on the *Hemnet.se* website. This dataset contains the same type of basic information available in the main dataset and, in addition, information on the identity and affiliation of the real estate agent in charge of each sale. To collect the universe of the data, covering the period between late 2012 and 2015, we used a Python script to download the information directly from the web page.

We are able to merge 97,676 transactions with our main dataset, in order to obtain the full set of characteristics.⁷ We present descriptive statistics in Column 2 of Table 1. On average, the two datasets are comparable with respect to observable characteristics of the dwelling. However, possibly because observations in the second sample are from more recent years, both the asking and the sale price in the latter are higher, on average. In addition, apartments in the subsample appear to be sold slightly faster. In the empirical analysis, we use the identity of the agent to control for all the unobserved traits, such as innate ability, that are time-invariant.

Auctions subsample

Finally, we complement our dataset with a third data source to test mechanisms. We gathered detailed information on completed auctions from the real estate agency *Fastighetsbyrån*, which is the largest broker in Sweden, with a market share of 25%. Again, we use a web script to download the information from the agency's website, which includes several complete auction histories containing bids, their timing and a bidder identifier. However, the coverage at the beginning of our sample period is scarce and increases substantially only in 2014 and 2015. We merge this information with our main dataset to obtain apartment characteristics and geographic identifiers, leading to a final dataset of 26,986 complete auctions. Column 3 of Table 1 shows some descriptive statistics for apartments in this dataset, together with information on the auction outcomes. Apartments in this subsample were sold more recently and were, on average, slightly more expensive than those in the main dataset, but comparable regarding the other observable characteristics. On average, 2.7 bidders participated in the auction, placing about nine bids.

⁷The main reasons for the relatively low merge rate are: i) we do not have unique identifiers in the *Hemnet* subsample, so the merge is performed using asking and final price, date of sale, number of rooms, surface area and monthly fee; and ii) the *Hemnet* dataset essentially has no information at all for the years 2010-2012.

Table 1: Descriptive statistics for the main dataset and the two subsamples

	Main dataset 2010-2015	Hemnet 2013-2015	Auctions 2012-2015	Main dataset 2013-2015
Asking price	1506.1 (1035.8)	1600.4 (1058.6)	1761.6 (1105.1)	1655.5 (1079.3)
Sale price	1647.4 (1124.1)	1783.0 (1162.1)	1967.7 (1208.7)	1813.2 (1169.3)
Sale price (per m2)	27.1 (19.8)	30.0 (21.8)	34.0 (23.2)	30.3 (21.5)
% increase over asking price	10.4 (15.2)	12.9 (15.0)	13.5 (15.0)	10.8 (14.3)
Days on the market	34.1 (79.7)	29.3 (71.6)	24.5 (64.4)	34.6 (89.3)
N. of rooms	2.5 (1.0)	2.5 (1.0)	2.5 (1.0)	2.5 (1.0)
Living area (m2)	66.8 (23.8)	66.1 (23.2)	65.0 (23.0)	66.4 (23.5)
Year of construction	1963.1 (28.1)	1964.8 (27.1)	1964.6 (28.7)	1963.6 (28.4)
Elevator	0.5 (0.5)	0.4 (0.5)	0.5 (0.5)	0.5 (0.5)
Floor	2.4 (1.7)	2.4 (1.7)	2.5 (1.7)	2.4 (1.8)
Monthly fee	3605.2 (1362.7)	3668.1 (1343.0)	3568.9 (1353.4)	3652.6 (1355.4)
N. bids			8.9 (8.7)	
First bid			1782.9 (1126.0)	
N. bidders			2.7 (1.8)	
Bid increment (%)			2.2 (3.0)	
<i>Observations</i>	346,731	97,676	26,986	187,867

Notes: Prices are in thousand SEK, with 1000 SEK corresponding to roughly \$110 as of June 2017. Standard deviations in parentheses. In the first column, the main dataset is used. The second column reports descriptives for the *Hemnet* subsample, for which real estate agent identifiers are available. The third column uses only the subsample for which we also have auction information. Finally, for comparability, the rightmost column uses the main dataset restricted to 2013-2015.

Real estate agents survey

Our final source of information comes from an online survey to real estate agents. In February 2017, we contacted all real estate agents who had at least one sale in the previous year, as recorded in our dataset. We sent out a total of 4,456 e-mail invitations to participate in a survey, of which 301 were returned with a complete answer.⁸ Our main goal was to shed light on whether agents had any belief about the relative advantages of a just-below versus a round-number pricing strategy for the property’s visibility, number of interested buyers and final price. We also asked them how often, and why, the seller intervenes in setting the asking price. Finally, we left room for comments. Results from the survey are reported in Appendix B and throughout the paper.

3 Empirical analysis

3.1 Graphical analysis

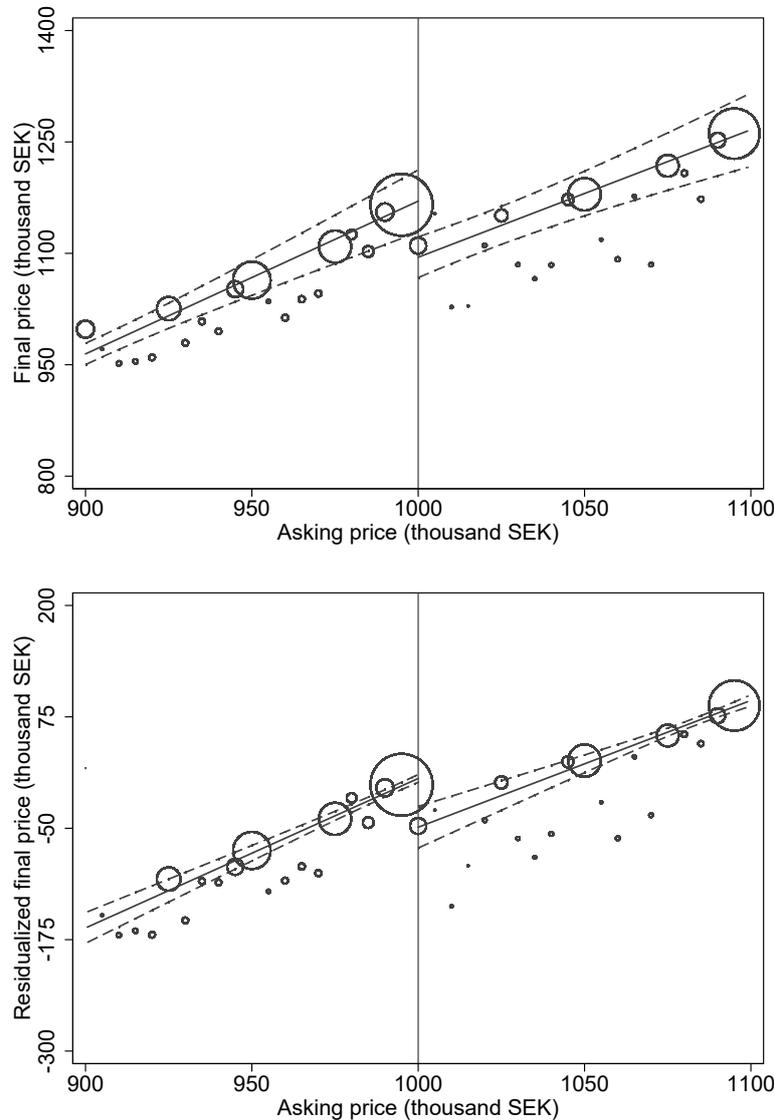
We start by showing that the discontinuities in the final price around 1 million asking price thresholds are visible from the raw data. In the upper panel of Figure 1, we show the average final price for each bin of size 5,000 SEK (about \$550) of the asking price for apartments with an asking price around the 1 million mark. The size of each circle is proportional to the number of apartments in each bin.

We immediately notice that a large number of apartments are listed at a price just below the 1 million threshold. However, there is still a significant number of apartments listed at the threshold or just above. The relationship between asking and final price is positive and approximately linear at both sides of the 1 million threshold. However, when the asking price crosses the threshold, the final price drops sharply, with an estimated discontinuity of 77 thousand SEK (about \$8,500), corresponding to a 7.7% price drop, suggesting that when the first digit of the asking price changes – in this case, from zero to 1 million – the final price is affected negatively. This discontinuity remains large even after controlling for observable characteristics of the apartment, year-month and municipality fixed effects, as shown in the lower panel of figure 1.

This discontinuity is not peculiar to the 1 million threshold. Inspecting all the other thresholds reveals a very similar pattern, as Figure 2 shows. The relationship between asking and final price remains approximately linear, and there are sizable discontinuities in the final price also around the 2, 3, 4 and 5 million marks. While these drops in price

⁸Since some addresses were inactive, it is challenging to assess what the actual response rate was. According to the web platform we used for the survey, 103 addresses were invalid; thus, once we removed these, we were left with a 6.9% response rate.

Figure 1: The discontinuity in final prices around the 1-million asking price threshold

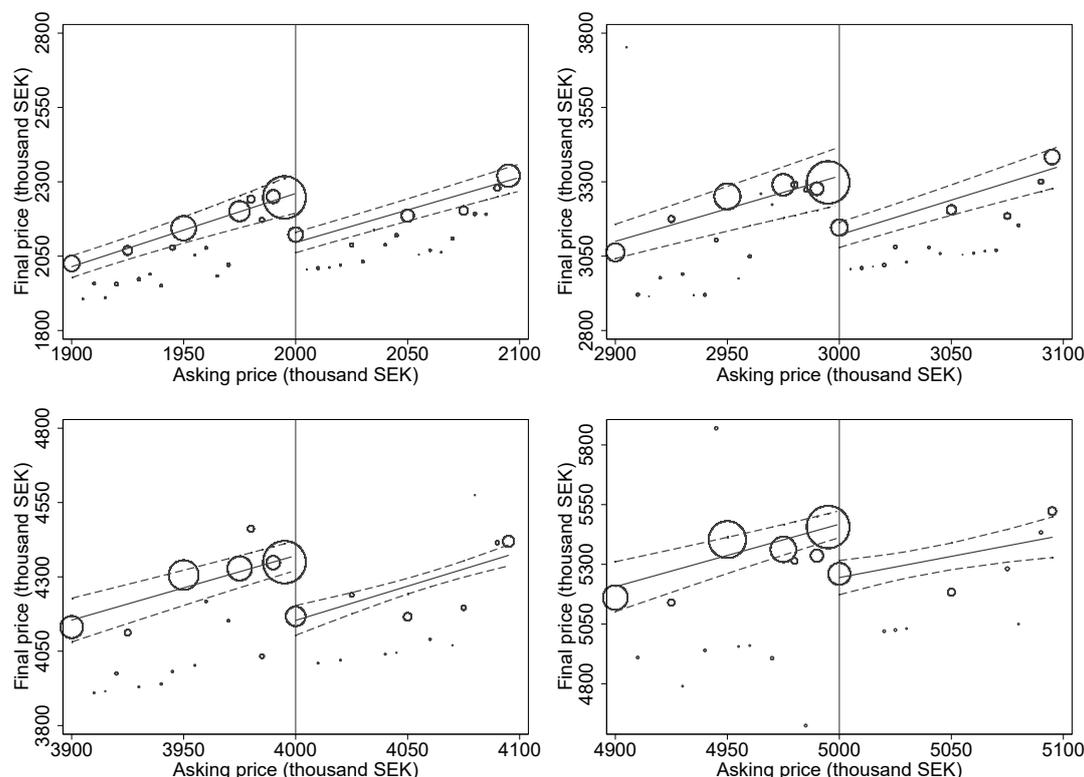


Notes: The figures plot the average final price (upper panel) and the residualized average final price after controlling for observable characteristics, year-month and municipality fixed effects (lower panel), for each bin of size 5,000 SEK of the asking price for apartments with asking price around the 1 million mark. Circles represent averages in 5,000 SEK bins and are centered on the left edge of the interval so, for instance, the circle corresponding to an asking price of 1 million SEK is the average final price for apartments with asking price between 1 million and 1.095 (excluded) million SEK. The circle size is proportional to the number of transactions in each bin. Lines are fitted values from a regression. Dashed lines represent 95% confidence intervals (s.e. clustered at the municipal level).

are even larger in absolute value than the one observed around 1 million, they remain comparable in percentage terms.⁹

⁹A closer inspection of Figures 1 and 2 reveals that apartments with asking price ending in 25,000, 50,000 and 75,000 SEK also sell at a higher final price than those in their immediate proximity. It is possible

Figure 2: The discontinuity in final prices around the other 1-million thresholds

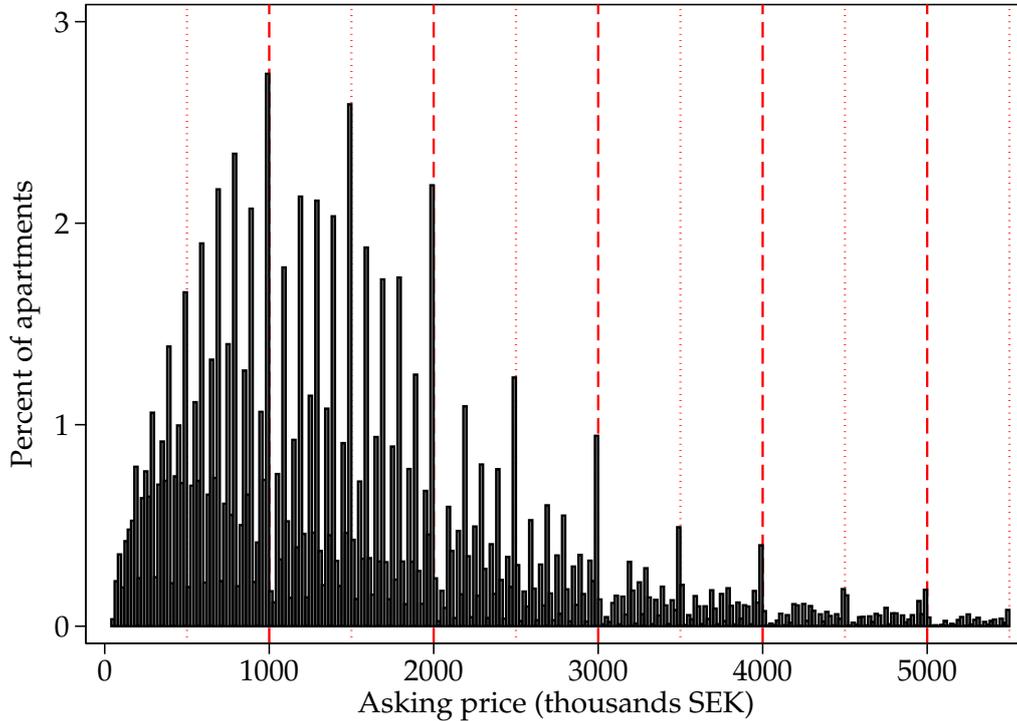


Notes: The figure plots the average final price for each bin of size 5,000 SEK of the asking price for apartments with asking price around the 2, 3, 4 and 5 million marks. Circles represent averages in 5,000 SEK bins and are centered on the left edge of the interval, with size proportional to the number of transactions in each bin. Lines are fitted values from a regression. Dashed lines represent 95% confidence intervals (s.e. clustered at the municipal level).

Taken at face value, these results suggest that it is profitable to choose an asking price just below 1 million marks relative to using round-number pricing or prices just above. Experienced sellers and real estate agents should take this effect into account when choosing the asking price. Hence, we expect to observe bunching just below each of the 1 million marks. Figure 3 presents the distribution of asking prices, showing the percentage of apartments listed at a given asking price in histogram bins of 20,000 SEK width. There is substantial bunching at several points of the asking price distribution. In particular, there is an excessive density just below even millions and a correspond-

that these pricing strategies also yield a premium to sellers. We compare apartments in two groups, one including apartments with asking price ending in 25,000, 50,000 or 75,000 SEK, and another including those listed just below and just above these prices. Apartments in these two groups i) are different in terms of observables, and ii) there is no statistically significant difference in auction outcomes. This evidence suggests that our empirical strategy may not be appropriate to study these prices, and that the mechanism at play here may be very different from the inattention explanation that we pursue in the rest of the paper. For these reasons, we do not follow the analysis of these prices further, as we believe that it lies outside the scope of this paper.

Figure 3: Distribution of asking prices, main dataset, 2010-2015



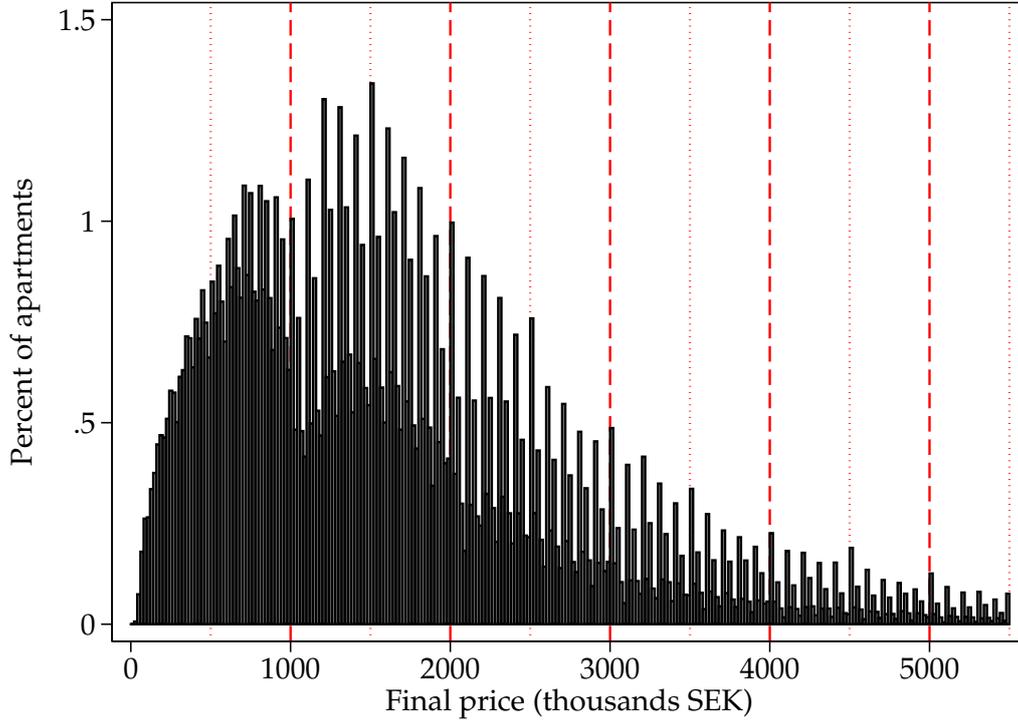
Notes: Distribution of the asking prices in the main dataset. Vertical dashed lines indicate round millions, and vertical dotted lines indicate half millions.

ing “hole” at even millions and just above. Also, bunching occurs around half-millions (dotted lines) and 100,000 SEK round numbers.

When looking, instead, at the distribution of the final prices, the pattern is different. In Figure 4 we show the distribution of the final prices. Contrary to what we observe for asking prices, for final prices, the bunching appears on apartments listed exactly at the threshold or just above (Palmon, Smith and Sopranzetti 2004 have shown this phenomenon using U.S. data). For example, around the 5 million threshold, there are approximately seven times more apartments with a final price between 5 and 5.19 million than between 4.8 and 4.99 million. In the case of negotiations, Pope, Pope and Sydnor (2015) have documented the fact that round numbers serve as focal points. Interestingly, their findings also hold in the presence of ascending-price auctions.

If apartments at either side of 1 million thresholds are equivalent, the final price discontinuities documented above suggest that buyers are behaving sub-optimally by overpaying for apartments to the left of the threshold. One explanation for this phenomenon is that they are subject to left-digit bias; that is, they incorrectly perceive these apartments as cheaper because they tend to ignore, at least partially, the part of the number to the right of the first digit.

Figure 4: Distribution of final prices, main dataset, 2010-2015



Notes: Distribution of the final transaction prices in the main dataset. Vertical dashed lines indicate round millions, and vertical dotted lines indicate half millions.

To interpret our graphical results as evidence of left-digit bias, however, we must be able to reasonably rule out that there are no unobservable characteristics of apartments that are correlated with the decision to list them at either side of the threshold. For example, this issue arises if some sellers (or real estate agents) systematically choose just-below asking prices because they are more knowledgeable about the housing market or have better apartments. In the following, we will consider these selection issues in detail, but first we must introduce a formal empirical model.

3.2 Regression analysis

A natural way of testing for the presence of left-digit bias in our context is to compare final prices of apartments that have an asking price just below to those listed exactly at a 1 million threshold, but that are otherwise equivalent. In the absence of sorting, the average final price should reflect the quality of the apartments and, hence, be a smooth function of the asking price. By contrast, a discontinuity at points where the first digit of the asking price changes could be attributed to the presence of potential buyers suffering from first-digit bias.

Our identification strategy relies on comparing apartments that are similar in terms

of characteristics, location, and the identity of the real estate agent. We test for the presence of sorting based on apartment and agent quality by i) comparing observable characteristics at either side of each round-number threshold, ii) controlling for housing-association fixed effects to control for unobservable neighbourhood amenities, and iii) restricting the comparison to apartments sold by the same agent in the same year. In the absence of evidence on sorting in the previous tests, we interpret a discontinuity in the final price as evidence of buyers suffering from first-digit bias.

Notice that, to have variation in pricing strategies, it has to be the case that some sellers locate at round-number thresholds or above, either because they are not aware or they are unconvinced of the benefits of using just-below prices. Our interpretation of the results as stemming from buyers' inattention relies on the assumption that sellers' characteristics are uncorrelated with their choice of the asking price.

We start by assuming that the discontinuity in the final price is the same around all 1 million thresholds, so that we can pool all thresholds and estimate the following model:

$$p_i = \beta_j + \gamma \cdot \mathbb{1}(a_i \geq c_j) + \theta_j(a_i - c_j) + \phi_j(a_i - c_j) \cdot \mathbb{1}(a_i \geq c_j) + \delta' \mathbf{X}_i + \epsilon_i, \quad (1)$$

where p_i is the logarithm of the final sale price of apartment i , and $a_i - c_j$ is the running variable, defined as the distance between the asking price, a_i , and the j -th relevant threshold, c_j (e.g., 1 million SEK, 2 million, etc.). Because we pool observations around five different thresholds, we include threshold-specific intercepts β_j . The running variable is assumed to have a linear effect on the final price, but the slope can be different at each side of each threshold. Finally, \mathbf{X}_i is a vector of controls and fixed effects, to ensure that we are comparing apartments that are as similar as possible in terms of observable characteristics.

The coefficient of interest is γ , which captures the discontinuity in the final price (in percentage terms) as apartments cross any of the 1-million thresholds. Later, we will relax the assumption of a homogeneous effect, presenting results for each threshold separately. A similar approach will also allow us to test for the presence of a second-digit bias by comparing apartments at either side of the 100,000 SEK thresholds.

Although we are effectively estimating discontinuities, our setup differs from the traditional regression-discontinuity design, in which interpreting the discontinuity as a causal effect relies on the assumption that agents are unable to perfectly manipulate the running variable (Lee and Lemieux, 2010; McCrary, 2008). In our setting, the running variable is perfectly manipulable by the seller, something that appears evident by inspecting Figure 3. This systematic bunching of apartments around thresholds can potentially be a consequence of selection, which can take at least two forms: selection

based on apartment characteristics and selection due to real estate agents. To deal with these issues, we will develop several different strategies in Section 4.

We start by estimating model 1 without any controls or fixed effects, pooling observations from all thresholds and restricting the sample to a bandwidth of 100,000 SEK around the common threshold. Column 1 of Table 2 shows that the average drop in final prices at 1-million thresholds is sizable and equal to about 6.4%, consistent with the graphical evidence presented in Figure 1. Adding controls and month-year fixed effects reduces the point estimate to approximately 5.6%, while including municipality-year fixed effects does not alter the magnitude of the coefficient. In column 4, we go further and compare apartments sold in the same parish – an administrative entity smaller than the municipality – in the same year, and the estimate does not vary significantly. Column 5 is the most demanding, as it requires apartments to be sold in the same year, within the same housing association. Housing associations usually include one or two buildings, generally on the same street and often contiguous. Apartments sold in the sample used in Column 5 belonged to 5,552 different associations. Thus, including association-year fixed effects in addition to controls ensures that we are comparing apartments that are effectively very similar in terms of observable and unobservable characteristics.¹⁰

Although it is standard to assume that the conditional expectation of the final price given the asking price can be approximated by a continuous function, in this case, and despite the fact that the asking price is, in principle, a continuous variable, most asking prices are clustered at multiples of 5,000 SEK. Therefore, the running variable is, in fact, discrete, and we would not observe apartments in a small vicinity of the threshold even if we could increase the sample size indefinitely. One possibility to address the uncertainty generated by a discrete running variable is to cluster the standard errors at each discrete value of the running variable (Lee and Card, 2008). Another natural alternative is to cluster at the municipal level, allowing for correlation in the unobserved component of prices within each municipality of any form. Given that we found that clustering at the municipal level yields standard errors that are three to four times larger, we decided to be conservative and report results for this last specification throughout the paper.

In Figure 5, we explore the sensitivity of our baseline result to different choices of bandwidth by showing point estimates and confidence intervals for bandwidths be-

¹⁰For completeness, we have also estimated our baseline model to study whether a price discontinuity exists when the first (or second) digit of other apartment characteristics changes, such as living surface, monthly fee, and year of construction. We found no evidence of such an effect in any of these characteristics. Our explanation for why we observe a left-digit bias in the asking price but not in these characteristics is that the asking price is the most salient trait of an apartment. Hence, it seems reasonable to assume that individuals might exclude an apartment because of the asking price that sounds too high, but are unlikely to do the same because, for instance, it has a living area of 79 and not 80 square meters.

Table 2: The effect on final prices, pooling all thresholds

	Linear specification & bandwidth = 100k SEK				
	(1)	(2)	(3)	(4)	(5)
Above the threshold	-6.44*** (1.20)	-5.60*** (0.98)	-5.63*** (0.56)	-5.55*** (0.56)	-5.16*** (0.65)
Obs.	57,411	57,245	57,245	56,996	56,937
R^2	0.944	0.952	0.961	0.964	0.990
Controls		✓	✓	✓	✓
Fixed Effects			Year × Municip.	Year × Parish	Year × Assoc.

Notes: Regression estimates of the effect of the asking price on the logarithm of the final transaction price (in thousands SEK) from equation 1, pooling all 1 million thresholds together and using a bandwidth of 100,000 SEK. We use a local linear control function allowing for different slopes at each side of each threshold. Standard errors are clustered at the municipality level. Controls include living area, the number of rooms, monthly fee, and year of construction, plus different sets of fixed effects. Month-year fixed effects are also included in all columns but the first.

* $p < 0.1$, ** $p < 0.05$, *** $p < .01$

tween 100,000 and 0 in steps of 10,000 SEK. We use the most demanding specification used in column 5 of Table 2, which includes housing association-year effects and standard errors clustered at the municipal level. The estimated effect is remarkably stable across various bandwidth choices. In the limiting case – informally displayed as having zero bandwidth in the figure – we use only observations with a value of the running variable of -5 or 0 – that is, apartments sold at a price 5,000 SEK below (about \$550) or exactly at a 1 million threshold. Although the standard errors increase slightly, the point estimate remains virtually unchanged.

3.2.1 Heterogeneity analysis

We now relax the assumption of a common effect and show results from separate regressions for each threshold. Estimates from these specifications show that discontinuities in the final price distribution appear around each 1 million mark. Table 3 shows results for three different samples. Specifically, Panel A reports the estimates for the full sample, while panels B and C split the sample between Stockholm and the rest of Sweden to capture geographical differences. Column 1 presents regression estimates assuming a common effect across thresholds, while columns 2 to 6 show the estimates threshold by threshold. Parish-year, month-year fixed effects and controls are included in all specifications, and clustering is at the municipal level except in Panel B, where we use

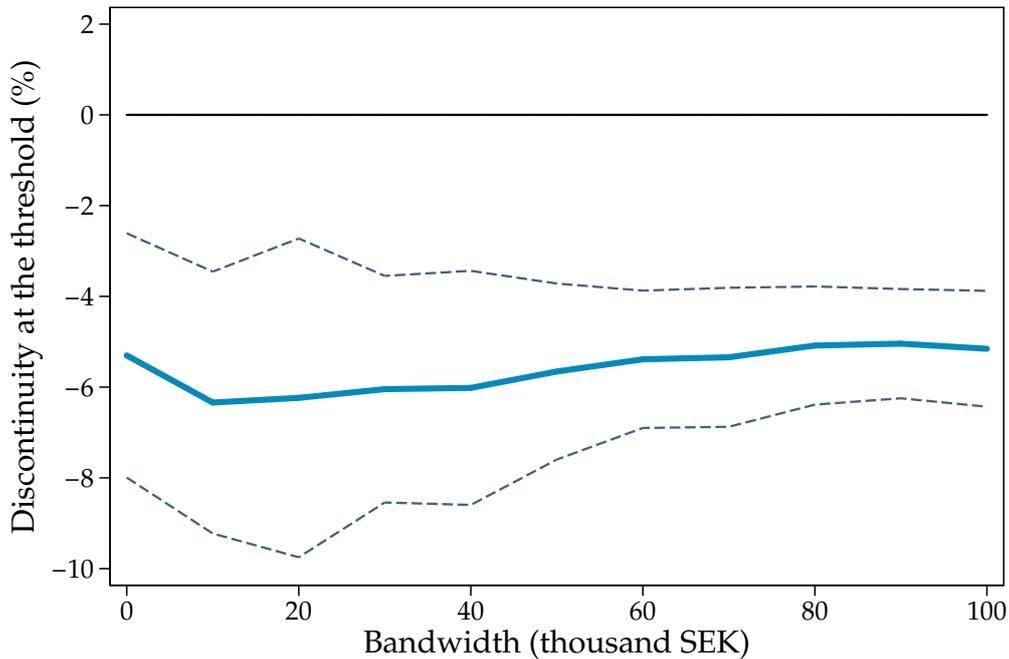


Figure 5: Baseline result for different bandwidth choices

Notes: The figure shows the effect for different bandwidths using a linear control function, including controls and year - housing association fixed effects. The running variable is the distance between the asking price and the closest threshold (defined as the closest million integer). The control function is allowed to have different slopes for each side of each threshold. Standard errors are clustered at the municipal level. Dashed lines represent 95% confidence intervals.

parishes.¹¹

The results for the full sample are entirely consistent with the graphical evidence presented in Figure 2, with the largest discontinuities found, in percentage terms, around the 2 and 3 million thresholds, where they range from 6 to 6.4%. Panel B shows that, in general, the effects for Stockholm – the biggest metropolitan area in the country, accounting for 30% of the sample – tend to be larger. However, Panel C shows that the discrete jump in the final price at round numbers is not peculiar to this market and also appears to be large in the sample of the other municipalities.

Finally, by estimating the model year by year for each threshold, we explore whether the effect varies over time. Table 16 in the Appendix shows that while point estimates vary in magnitude, the effect is negative and significant in all years. Overall, the evidence in this section shows that the effects appear to be pervasive, and are not unique

¹¹Given the reduced sample in some of the specifications in this section, the inclusion of housing association-year fixed effects would be too demanding; hence, we choose to use parish-year effects. Results including association-year effects are, however, qualitatively similar and available upon request.

to a particular threshold, year, or geographical area.

Table 3: The effect on final prices for each threshold, by geographical area.

	Pooled	C=1M	C=2M	C=3M	C=4M	C=5M
	(1)	(2)	(3)	(4)	(5)	(6)
A. Full sample						
Above the threshold	-5.55*** (0.56)	-4.65*** (0.82)	-6.37*** (0.30)	-6.01*** (0.39)	-4.82*** (0.74)	-3.63*** (0.68)
Obs.	56,996	28,686	16,604	6,866	3,184	1,656
R^2	0.964	0.526	0.477	0.445	0.418	0.443
B. Stockholm						
Above the threshold	-6.32*** (0.64)	-8.61*** (1.33)	-6.39*** (0.54)	-5.98*** (0.79)	-4.09*** (0.70)	-3.34** (1.46)
Obs.	16,922	3,239	6,584	3,592	2,222	1,285
R^2	0.96	0.56	0.50	0.44	0.40	0.40
C. Rest of Sweden						
Above the threshold	-4.90*** (0.60)	-4.06*** (0.65)	-6.04*** (0.52)	-5.62*** (1.01)	-7.24*** (1.65)	-7.04 (4.50)
Obs.	40,074	25,447	10,020	3,274	962	371
R^2	0.95	0.49	0.45	0.42	0.50	0.67

Notes: Regression estimates of the effect of the asking price on the logarithm of the final transaction price (in thousands SEK). In column 1, we pool observations from all thresholds, whereas in columns 2 through 6, we estimate the effect around each individual threshold separately. We use a local linear control function allowing for different slopes at each side of each threshold. Controls include living area, the number of rooms, monthly fee, and year of construction, plus month-year and year-parish fixed effects. Standard errors are clustered at the municipality level in panels A and C and at the parish level in panel B.

* $p < 0.1$, ** $p < 0.05$, *** $p < .01$

3.2.2 Second-digit Bias

Having established the existence of a significant discontinuity in the final price when the first digit in the asking price changes, we investigate similar effects for similar asking prices that differ in the second digit, such as multiples of 100,000 SEK. The bunching observed in Figure 3 just before multiples of 100,000 SEK suggests that these numbers might, indeed, be relevant.

Following the methodology described in Section 3.2, we re-estimate the baseline model comparing apartments with asking prices that are similar but have different second digits. For instance, we compare units listed at 1,200,000 with those listed at 1,195,000 SEK, and similarly for all multiples of 100,000. To this end, we redefine the

running variable appropriately as the distance to the closest multiple of 100,000 SEK.¹² Again, the running variable enters linearly, allowing different slopes at either side of each threshold, but we assume that the discontinuity parameter is common to all thresholds.

Table 4: Second digit bias, for each year and for each million.

	Pooled	0-1M	1-2M	2-3M	3-4M	4-5M	5-5.5M
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
A. Full sample							
Above the thresh.	-3.41*** (0.49)	-2.30*** (0.32)	-3.81*** (0.71)	-3.79*** (0.38)	-3.18*** (0.20)	-2.24*** (0.23)	-2.81*** (0.30)
Obs.	305,785	120,693	114,749	45,378	16,451	7,105	1,409
R^2	0.98	0.94	0.80	0.70	0.58	0.52	0.46
B. Stockholm							
Above the thresh.	-4.51*** (0.44)	-6.90*** (1.15)	-5.96*** (0.40)	-4.18*** (0.40)	-3.14*** (0.38)	-2.03*** (0.36)	-2.92** (1.09)
Obs.	65,413	2,232	25,999	20,722	9,973	5,362	1,125
R^2	0.96	0.70	0.76	0.71	0.56	0.51	0.43
C. Rest of Sweden							
Above the thresh.	-2.75*** (0.30)	-2.20*** (0.31)	-2.92*** (0.36)	-3.24*** (0.54)	-2.94*** (0.57)	-2.84*** (0.71)	-3.91 (2.47)
Obs.	240,372	118,461	88,750	24,656	6,478	1,743	284
R^2	0.98	0.94	0.80	0.69	0.61	0.56	0.78

Notes: Regression estimates of the effect of the asking price on the logarithm of the final transaction price (in thousands SEK). In column 1 we pool observations from all 100,000 thresholds, whereas in columns 2 through 7, we estimate the effect for apartments with an asking price between 0 and 1 million, between 1 and 2, and similarly for all millions separately. Controls include living area, the number of rooms, monthly fee, and year of construction, plus month-year and year-parish fixed effects. Standard errors are clustered at the municipality level in panels A and C and at the parish level in panel B.

* $p < 0.1$, ** $p < 0.05$, *** $p < .01$

To avoid overlap, we restrict the sample to a bandwidth of 50 thousand SEK. Also, we discard observations around those thresholds that coincide with the 1 million marks. Table 4 reports estimates including control, month-year, and parish-year fixed effects. Again, in Panel A, we show results for the full sample, while in Panels B and C, we separate Stockholm from the rest of the country. Column 1 shows the effects assuming a common effect around each threshold, while column 2 through 6 show results by grouping apartments by the first digit of the asking price. For example, Column 2 shows the estimated discontinuity obtained by pooling the nine 100,000 thresholds between 0

¹²For example, an apartment with an asking price of 1,203,000 SEK corresponds to a running variable of 3,000, and so on.

and 1 million.

Column 1 in Panel A shows that, on average, apartments listed at 100,000 SEK thresholds are 3.4% cheaper than their counterparts just below. Compared to the first-digit discontinuity estimates, the jump around 100,000 SEK is smaller, at slightly more than half the size. This finding is in line with the inattention model in [DellaVigna \(2009\)](#) and [Lacetera, Pope and Sydnor \(2012\)](#), where, in the presence of inattentive individuals who discount all digits past the first, one expects to see discontinuities at each digit threshold, with smaller discontinuities for smaller thresholds.¹³ Once again, the same conclusions hold for different thresholds and by restricting the analysis to Stockholm or the rest of Sweden, as shown in panels B and C.

4 Sorting around the thresholds

Given that the asking price is essentially a choice variable, it is possible that its choice is systematically related to characteristics of the apartment or the seller. For instance, those who choose a just-below strategy might be sellers with better apartments or more experienced agents. This endogenous sorting of apartments around the threshold is problematic for a causal interpretation of the discontinuity in final prices.

There are two main types of sorting that are relevant in our context. The first is sorting based on apartment characteristics, which arises if sellers with better apartments systematically choose to locate just below a threshold. A second type of sorting stems from sellers or real estate agents choosing different pricing strategies based on their ability or effort. For example, agents listing apartments just-below a round number might be more skilled or experienced than those listing at round numbers. Another possibility is that agents are less motivated by sellers that ignore their recommendations and impose a round number asking price, and hence exert less effort when selling. While entirely ruling out either type of sorting is challenging without conducting a randomized experiment, we can perform several tests that are informative on its importance.

To start, if better apartments are systematically sorted just below a threshold, we should observe a discontinuous jump in observable characteristics when crossing such a threshold. We show that this is not the case in general. In addition, we use apartment characteristics, location, and agent-year fixed effects to predict the final price and show that it does not jump discontinuously at the threshold, further reassuring that apartments are comparable in terms of observables. Ruling out that more skilled sellers (or agents) sort around the threshold is more difficult without having a measure of such

¹³This is true regardless of whether one assumes that individuals are equally inattentive to each digit (so that, for example, they always perceive a digit to be a fraction of what it is) or if individuals are assumed to be progressively more inattentive to digits past the first.

ability. To tackle this issue, we introduce agent fixed effects in estimation, which allows us to control for ability by comparing apartments at and just below a threshold that are sold by the same agent.

4.1 Sorting on apartment characteristics

To explore the importance of sorting by characteristics in our case, we study how each of the apartment’s observed variables differs, on average, at either side of the threshold. Although we are not in an RDD design – so neither continuity of the potential outcomes nor local randomization can be invoked – and our identification relies, instead, on including these variables as controls, it is informative to look at their distribution at the threshold to detect large imbalances that might be a direct consequence of sorting. In particular, we can inspect the conditional expectation of these variables close to the threshold, and test for potential discontinuities. The absence of discontinuities in observable characteristics may indicate that apartments are similar also in terms of unobservables.

In Table 5, we estimate the baseline model (but with no controls or fixed effects), having as the dependent variable each of the covariates that we use as controls in the main specification. Additionally, we use an indicator for the building having an elevator, one for the presence of a balcony, and a variable counting the number of floors.¹⁴ We estimate the model by pooling all thresholds and for each threshold separately. Column 1 shows that, once we pool observations from all thresholds together, none of the seven covariates in our dataset jumps when crossing the threshold, suggesting that, on average, apartments at either side are comparable with respect to all the characteristics we observe.

Columns 2 through 6 show results around each 1 million mark. Out of the 35 possible cases, in 13 we observe a discontinuity, either positive or negative, that is statistically significant at least at the 10% confidence level. Given that our primary concern is that apartments with better characteristics are systematically priced just below the threshold, the problematic cases arise when the imbalance goes in that direction.

Regarding the living area, measured in square meters, we find a negative coefficient around the 2 and 3 million threshold that could, at least partially, explain the discontinuity in the final price. However, the situation is exactly the opposite at the 5 million threshold, where we find a positive discontinuity. However, in both cases, the baseline effect on the final price is negative and statistically significant, suggesting that the discontinuity does not vary with the degree of imbalance. We observe a similar pattern

¹⁴These variables are not used as controls in our baseline specification because they are missing for a significant fraction of the observations.

Table 5: Balance of covariates

	Pooled	C=1M	C=2M	C=3M	C=4M	C=5M
	(1)	(2)	(3)	(4)	(5)	(6)
Squared meters	-0.49 (0.91)	2.33 (1.66)	-2.58* (1.48)	-5.75*** (1.47)	-0.37 (1.63)	5.69** (2.21)
Obs.	57,374	28,852	16,703	6,932	3,213	1,674
Year Constr.	1.19 (1.36)	3.34* (1.99)	-1.63 (2.33)	0.36 (1.95)	1.25 (1.85)	3.48** (1.61)
Obs.	57,411	28,865	16,717	6,940	3,215	1,674
No. Rooms	-0.028 (0.036)	0.077 (0.066)	-0.11 (0.070)	-0.21*** (0.043)	0.018 (0.070)	0.12** (0.049)
Obs.	57,350	28,840	16,693	6,930	3,215	1,672
Monthly fee	-29.2 (42.3)	103.2 (84.7)	-95.5 (76.1)	-231.3*** (66.6)	-153.5** (65.7)	126.6 (85.4)
Obs.	57,297	28,834	16,683	6,913	3,199	1,668
Floor	-0.068 (0.046)	-0.15** (0.060)	-0.078 (0.074)	0.24*** (0.080)	-0.29** (0.14)	0.21* (0.10)
Obs.	47,692	24,441	13,867	5,568	2,514	1,302
Elevator	-0.011 (0.018)	-0.023 (0.019)	-0.0092 (0.026)	-0.021 (0.025)	0.038** (0.017)	0.016 (0.018)
Obs.	50,174	24,558	14,649	6,338	3,024	1,605
Balcony	0.0064 (0.021)	0.0045 (0.031)	-0.016 (0.027)	0.053 (0.053)	0.013 (0.053)	0.036 (0.058)
Obs.	18,645	9,590	5,596	2,140	908	411

Notes: Regression estimates of the effect of the asking price on different apartment characteristics. We report the coefficients of an indicator for the asking price being at the threshold or above. In column one we pool observations from all thresholds, whereas in columns 2 to 6 we estimate the effect around each individual threshold separately. We use a local linear control function allowing for different slopes at each side of each threshold. No controls or fixed effects included. Standard errors are clustered at the municipality level.

* $p < 0.1$, ** $p < 0.05$, *** $p < .01$

with other covariates.

Apartments at the threshold appear to be, on average, slightly older, although in most cases the difference is not significant. The effect of this variable on final prices is, however, ambiguous, as older apartments may be poorly maintained but are often more centrally located. The monthly fee is, in general, balanced, and the negative coefficients at the 3 and 4 million thresholds indicates that apartments at the thresholds

could actually be better than those just below. In this case, the imbalance suggests that our baseline effect is underestimated. The number of rooms is well balanced, on average. Again, we find a negative coefficient at the 3 million threshold and a positive one at the 5 million one. Some imbalances also appear in the floor variable, although the direction of its effect on the final price is also unclear. The elevator variable exhibits only one significantly positive coefficient that again goes against finding our effect, while the balcony indicator is always balanced.¹⁵

If we consider each million threshold independently, results suggest that there is no selection on observable characteristics around the 2 million mark. The 1 and 4 million marks show a small amount of negative sorting that suggest that our baseline estimates might be a lower bound. Finally, thresholds 3 and 5 show significant differences in four characteristics out of seven. For the 3 million mark, two of those four imbalances are potentially worrisome. Apartments just below this threshold are larger than their threshold counterparts. However, they also have a more expensive monthly fee, so the two effects might compensate each other. For the 5 million mark, apartments just below the threshold are smaller and older and are located on a lower floor. Again, these differences would imply an underestimation of the true effect.

In sum, the analysis of the covariates in Table 5 does not suggest a clear sorting in characteristics around the threshold, on average. Reassuringly, as Table 2 shows, we find large and negative discontinuities in the final price around all thresholds, even when the imbalanced covariate would suggest a positive effect. It is also worth remembering that we are controlling for these covariates in the estimation.

As a complement to this analysis, we predict the (logged) final price using our baseline covariates and different sets of fixed effects. Then, we use the fitted values from this regressions as the dependent variable in our baseline model's equation 1.¹⁶ This allows us to investigate whether the predicted final price jumps discontinuously at 1-million thresholds of the asking price. Because their effects are already accounted for in the prediction stage, we do not include any controls of fixed effects in the second stage. Finding a negative and significant effect would be evidence that apartments just below the threshold are systematically better in terms of observable characteristics or geographical location. Reassuringly, Table 6 shows that in all specifications the predicted final price does not significantly differ at either side of the threshold. When including housing association-year fixed effects, in column 4, the point estimate is equal to -0.48%, suggesting that differences in observable characteristics or in attributes controlled by the fixed effects are unable to explain our baseline effect. It is worth noting that real

¹⁵Results around 100,000 SEK thresholds are similar and reported in Table 18 in the Appendix.

¹⁶A similar approach to test for covariate balancing has recently been used by Kirkeboen, Leuven and Mogstad (2016).

Table 6: The effect of the asking price on the predicted final price

	Linear & bw=100				
	(1)	(2)	(3)	(4)	(5)
Above the threshold	-0.86 (0.70)	-0.51 (1.09)	-0.25 (1.17)	-0.48 (1.00)	0.25 (1.17)
Obs.	57,245	57,245	57,245	57,245	16,350
R^2	0.14	0.14	0.10	0.11	0.09
Hedonic regression includes:					
Controls	✓	✓	✓	✓	✓
Fixed Effects	-	Year × Municip.	Year × Parish	Year × Assoc.	Year × Agent

Notes: Estimates from equation 1 using, as dependent variable, the predicted logged final price, pooling all 1 million thresholds together and using a bandwidth of 100,000 SEK. We use a local linear control function allowing for different slopes at each side of each threshold. No controls or fixed effects are included in these specifications. The predicted final prices are obtained as the fitted values from a hedonic regression of the final price on our controls, month-year effects (only for columns 2 through 5), and different sets of fixed effects, as specified in each column. Standard errors are clustered at the municipality level.

* $p < 0.1$, ** $p < 0.05$, *** $p < .01$

estate agents' answers to our survey questions indirectly confirm these results. When asked whether they think that apartments sold at either side of the threshold differ in their market value, most answered negatively (see Table 15).

Of course, given that apartments are complex, multifaceted goods, we would be unable to control for all possible characteristics, regardless of how detailed the data are. For example, even apartments of the same size and floor in the same building might differ because of exposure to sunlight or interior design. Failing to control for these more subtle determinants of price would lead to biased estimates only if those characteristics were systematically related to being located at either side of the threshold. This possibility may arise if, for example, better agents, who understand pricing strategies, systematically get involved in sales of better apartments, or exert more effort. We consider this possibility in the next section.

Another possibility is that sellers that impose their agents to set an asking price at round number are also less likely to keep the apartment in good conditions or failed to renovate it recently. Ruling out this type of selection is difficult in general. However, in Section 4.3 we show that there is no difference in the time on the market at the threshold, which suggests that this possibility appears unlikely.

Table 7: The effect on sale prices, controlling for differences in real estate agents

	Linear & bw=100					
	(1)	(2)	(3)	(4)	(5)	(6)
Above the threshold	-3.18*** (0.83)	-2.96*** (0.75)	-3.83*** (1.29)	-2.90*** (0.74)	-3.00*** (0.76)	-2.82*** (0.90)
Obs.	16,350	16,311	16,325	16,350	16,070	16,070
R ²	0.96	0.97	0.99	0.97	0.97	0.98
Controls	✓	✓	✓	✓	✓	✓
Fixed Effects	Year × Municip.	Year × Parish	Year × Assoc.	Year × Agency	Agent	Year × Agent

Notes: Regression estimates of the effect of the asking price on the logarithm of the final transaction price (in thousands SEK) from equation 1, pooling all 1 million thresholds together and using a bandwidth of 100,000 SEK. We use a local linear control function allowing for different slopes at each side of each threshold. Standard errors are clustered at the municipality level. Controls include living area, the number of rooms, monthly fee, and year of construction, plus different sets of fixed effects. Month-year fixed effects are also included in all columns.

* $p < 0.1$, ** $p < 0.05$, *** $p < .01$

4.2 Selection on real estate agents' characteristics

Even when comparing apartments that are very similar in location and characteristics, a concern arises if real estate agents representing apartments at the threshold or just below differ systematically in their ability or effort. If more sophisticated agents know of the potential higher gains from setting the asking price just below a round number (while naïve ones do not), it is possible that more competent agents will systematically mediate sales of apartments just below the threshold. As a consequence, the discontinuity would capture not only the effect of a round asking price, but also differences in agents' quality.

To rule out this concern, we downloaded all the historical transaction data available in the *Hemnet* website, comprising information on transactions from late 2012 onwards. This dataset contains, for a subsample of transactions, information on the identity of both the real estate firm that managed the sale and of the agent in charge. As Table 1 shows, the subsample compares reasonably well with the main dataset.

Using the *Hemnet* subsample, the first three columns of Table 7 replicate our baseline specifications with municipal-year, parish-year and housing association-year fixed effects that we estimated in columns 3 through 5 of Table 2, respectively. The estimated jump at the threshold for the most demanding specification with association-year fixed effects is -3.8%, which is smaller than the full sample estimate of -5.1% but consistent with the fact that the effect is smaller in more recent years (see Table 16 in the Appendix).

Table 8: The effect around 100,000 SEK thresholds, controlling for differences in real estate agents

	Linear & bw=100					
	(1)	(2)	(3)	(4)	(5)	(6)
Above the threshold	-1.40*** (0.37)	-1.41*** (0.28)	-1.56*** (0.40)	-1.51*** (0.30)	-1.13*** (0.32)	-1.07*** (0.30)
Obs.	86,050	85,891	85,871	86,050	84,649	84,649
R^2	0.98	0.98	0.99	0.98	0.98	0.98
Controls	✓	✓	✓	✓	✓	✓
Fixed Effects	Year × Municip.	Year × Parish	Year × Assoc.	Year × Agency	Agent	Year × Agent

Notes: Regression estimates of the effect of the asking price on the logarithm of the final transaction price (in thousands SEK) from equation 1, pooling all 100,000 SEK thresholds together and using a bandwidth of 50 thousand SEK. We use a local linear control function allowing for different slopes at each side of each threshold. Standard errors are clustered at the municipality level. Controls include living area, the number of rooms, monthly fee, and year of construction, plus different sets of fixed effects. Month-year fixed effects are also included in all columns.

* $p < 0.1$, ** $p < 0.05$, *** $p < .01$

Taking this estimate as our baseline, we proceed to control for the identity of the real estate agency by including agency-year fixed effects. Notice that we need variation in the pricing strategies by the same agency over time to estimate the effects in this specification. Column 4 shows that, when requiring apartments to be sold by the same agency in the same year, we still observe a sizable discontinuity of -2.9%. In column 5, we include identifiers for each real estate agent, hence controlling for all unobserved characteristics of the agent that are fixed over time. Even so, the point estimate remains large and statistically significant at -2.8%. The most demanding specification is the one in column 6, where we include agent-year interactions. Here, estimation relies solely on variation across sales completed by the same agent in the same year; yet the point estimates are essentially unchanged.

In Table 8, we report analogous estimates for the second-digit bias. The point estimates using this subsample are, as in Table 7, smaller than the ones using the full sample. Interestingly, however, we note that the average discontinuity around 100,000 thresholds is between half and one third of the size of the one found around the 1 million marks. After including real estate agent fixed effects, the effect decreases to about -1.1% but remains statistically significant at the 1% level.

The results from Tables 7 and 8 are reassuring for our concerns about selection based on agent quality. First, even when including progressively more demanding sets of fixed effects by controlling for agent-year indicators, the discontinuity estimate preserves its sign and remains statistically significant. Furthermore, its magnitude is essentially un-

changed, suggesting that if agents differ in terms of quality and effort, these differences are not related to sorting around the threshold. A further piece of evidence in this direction is given by column 5 of Table 6, in which we first predict the final price using covariates and real estate agents fixed effects, and then use this predicted price instead of the final price in our baseline model. The estimated discontinuity at round-number thresholds of the asking price is, in fact, positive and very small, suggesting that apartments at either side of the threshold are not different in terms of agents' quality.

Naturally, these approaches can only control for the unobserved characteristics of real estate agents – such as effort and ability – as long as they can be thought of as being roughly fixed over time (or, with agent-year fixed effects, for the same agent over a year). However, it is still possible that the same agency (or their agents) change the pricing strategy depending on the quality of the apartment in a way that changes over time and is correlated with effort. If this were the case, agency fixed effect would not completely control for this unobservable confounding factor.

One last piece of evidence against this concern comes from restricting the sample to apartments sold by a real estate agency that only accepts a fixed fee, hence always giving their agents the same incentives. Point estimates are qualitatively very similar to the ones shown above but are omitted for brevity.

4.3 The time on the market

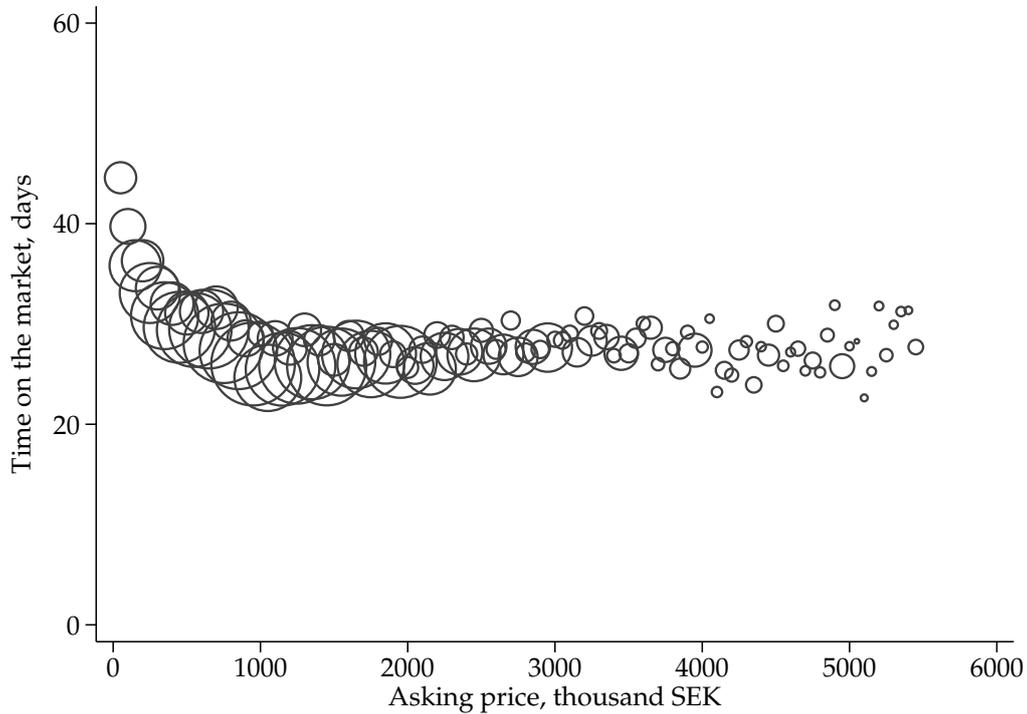
The final price is not the only relevant outcome of the sale. In fact, some sellers could choose the asking price not to maximize profit but to sell as quickly as possible (Levitt and Syverson, 2008). In Figure 6, we plot time on the market – measured as the number of days between the advertising date and the signing of the contract – against the asking price, grouped in 50,000 SEK bins.

Cheaper apartments tend to sell more slowly, but the relationship between time on the market and asking price flattens around 1 million SEK, and stays remarkably stable at around 30 days, even at higher prices. While the graph suggests that the time on the market is essentially unrelated to the asking price, it is interesting to investigate its behavior in more detail around the 1 million marks for the presence of discontinuities.

Figure 7 shows the average time on the market around each threshold using the same procedure described in Section 3.1.¹⁷ There is no appreciable difference at either side of the threshold around each 1 million mark, with the average time on the market being stable around 30 days in all cases. Although the time on the market is an out-

¹⁷To aid visualization, observations exceeding the 99th percentile (equal to 340 days) are excluded from the graphs. Including these observations does not change the conclusions in this section but hinders clarity.

Figure 6: Time on the market and asking price



Notes: Time on the market (measured in days), average in 50,000-SEK bins of the asking price. Main dataset (2010-2015).

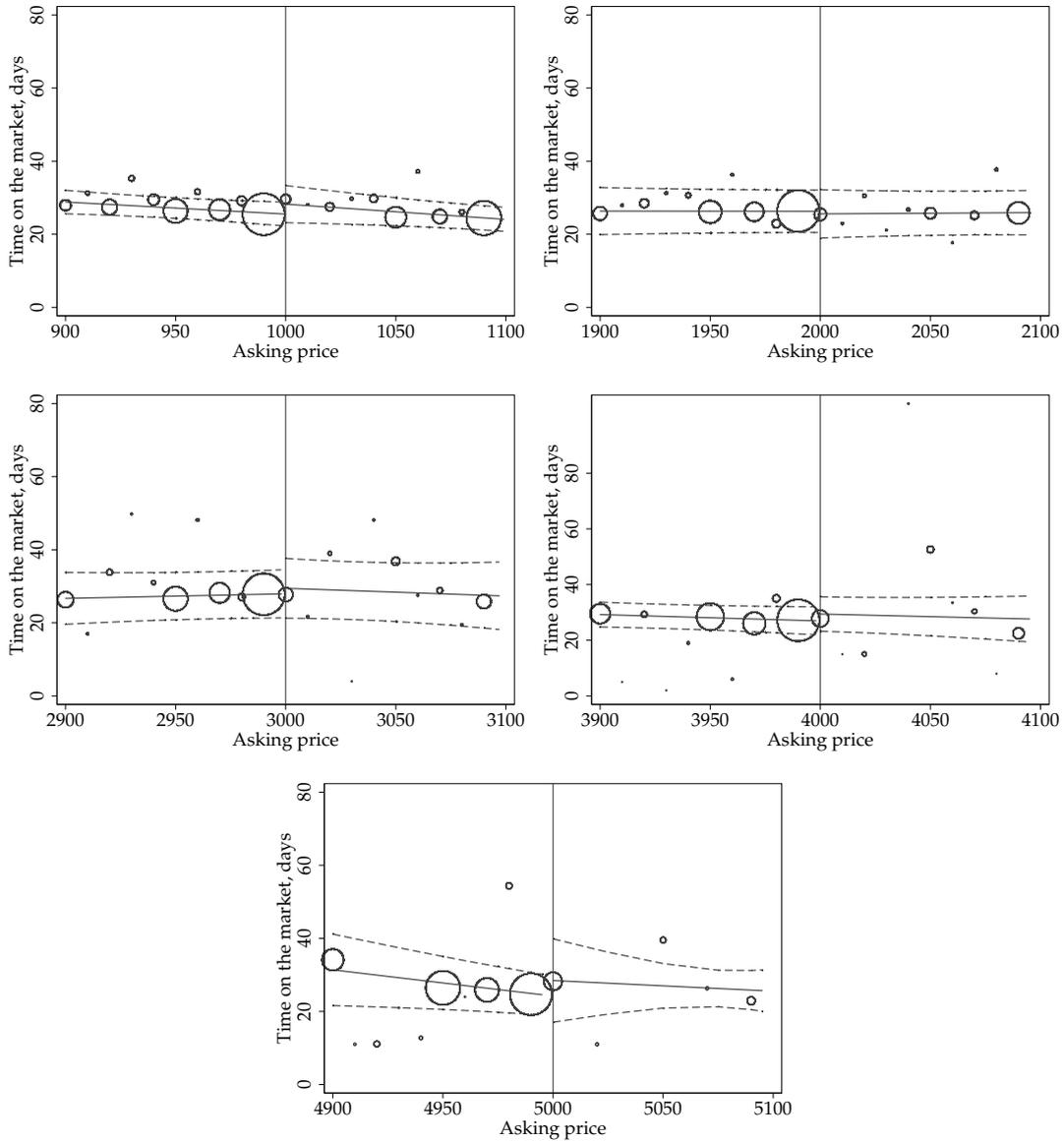
come of the auction process, rather than a characteristic of the apartment, the results in Figure 7 are informative because they show that just-below asking price strategies do not affect how quickly the apartment will be sold, hence indirectly providing additional evidence against both types of sorting detailed earlier. In fact, if apartments just below the threshold had better characteristics, or if their agents were more skilled, we may expect them to sell more quickly, but we do not observe such a pattern in the data.

5 The role of inattention in the housing market

5.1 Left-digit bias and auction outcomes

The evidence in the previous section shows that there are large discontinuities in the final price when the asking price crosses either a 1 million or a 100,000 SEK threshold. In the absence of sorting of the type described in Section 4, these results imply that buyers overpay for apartments with an asking price just below round numbers. One possibility is that they do so because they are partially inattentive to the asking price. Buyers who tend to focus mainly on the leftmost digit of the price may perceive apartments listed just below a round number as being cheaper than those listed exactly at a round number.

Figure 7: Discontinuity estimates in time on the market around each 1 million threshold



Notes: The figure plots the average time on the market (in days) for each 10,000 SEK bin of the asking price for apartments with an asking price around each 1 million mark. Circles represent averages in 10,000 SEK bins and are centered on the left edge of the interval so, for instance, the circle corresponding to an asking price of 1 million SEK is the average time on the market for apartments with asking price between 1 million and 1.099 million SEK. The circle size is proportional to the number of transactions in each bin. The observations above the 99th percentile of the time on the market (equal to 340 days) are excluded from the graph for visualization purposes. Lines are fitted values from a regression. Dashed lines represent 95% confidence intervals (s.e. clustered at the municipal level).

If the asking price is a salient characteristic, sellers can choose it to be just below round numbers to induce inattentive buyers to believe that the apartment is cheaper than the

competition.¹⁸

In principle, given that an auction determines the final price, it is not immediately obvious that inattention to the asking price should have a significant effect on the final price. However, inattentive buyers, when deciding which apartments to view, may disproportionately choose to visit those with an asking price just below the threshold because they appear cheaper. Therefore, more prospective buyers will view these apartments and, as a consequence, more bidders will participate in the auction.

The final price in an ascending price auction corresponds to the second highest willingness to pay which, under reasonable assumptions, is an increasing function of the number of bidders N . As an illustrative example, consider the case in which bidders have independent willingnesses to pay x , distributed uniformly over the interval $[0, \bar{x}]$. The expected final price of the auction, $E[P_N]$, is the second highest order statistic equal to

$$E[P_N] = \frac{N-1}{N} \bar{x}, \quad (2)$$

which is an increasing function of the number of bidders. This simple prediction provides an indirect test for our hypothesis that more buyers participate in auctions for apartments listed just below a round number. Specifically, we should observe that apartments with an asking price just below the 1 million (or 100,000) marks attract more bidders and more bids. To test this hypothesis, we use the subset of the data for which we have full auction information (described in Section 2.2).

In Panel A of Table 9, we start by estimating our baseline model with parish-year fixed effects. As column 1 shows, the estimated discontinuity around 1-million thresholds is -6.12%, slightly larger than what we found using the full sample. Columns 2-3 show that apartments listed just below the threshold attract, on average, 0.72 more bidders and 2.67 more bids than those listed exactly at the threshold, which is consistent with the hypothesis that inattentive buyers disproportionately participate in auctions for apartments listed just below 1 million thresholds. Additionally, these bidders make, on average, 0.57 more bids, again suggesting that the competition for these apartments is fiercer.¹⁹

¹⁸This phenomenon is in line with the theoretical predictions by [Bordalo, Gennaioli and Shleifer \(2016\)](#), where, in the presence of a salient characteristic – that is, one that consumers overvalue in their decisions – sellers compete for buyers’ attention by emphasizing either quality or price.

¹⁹The presence of more bidders may also affect the final price indirectly by triggering other mechanisms that are positively correlated with N , such as herding behavior ([Simonsohn and Ariely, 2008](#)) or “bidder’s heat” ([Malmendier and Lee, 2011](#)). [Ku, Galinsky and Murnighan \(2006\)](#) describe different mechanisms through which a lower asking price can lead to higher final prices, such as the fact that lowering the asking price reduces entry cost, that placing a bid acts as a sunk cost for the bidder, and that bidders entering an auction can update their valuation.

Table 9: Threshold discontinuities in auction outcomes

	Final price	N.bidders	N.bids	Bids per bidder
A. Effect at 1-million SEK thresholds				
Above the threshold	-6.12*** (1.01)	-0.72*** (0.082)	-2.67*** (0.48)	-0.57*** (0.13)
Obs.	4,784	4,784	4,784	4,784
R^2	0.97	0.26	0.25	0.21
B. Effect at 100 thousand SEK thresholds				
Above the threshold	-4.22*** (0.30)	-0.44*** (0.043)	-2.31*** (0.23)	-0.49*** (0.055)
Obs.	23,576	23,576	23,576	23,576
R^2	0.98	0.19	0.17	0.12
Controls	✓	✓	✓	✓
Fixed Effects	Year × Parish	Year × Parish	Year × Parish	Year × Parish

Notes: Panel A shows discontinuity estimates from equation 1 around 1 million SEK thresholds for the logarithm of the final price, the number of bidders and bids, and the number bids per bidder, respectively, using a local linear control function and a bandwidth of 100,000 SEK at each side of each threshold. Panel B reports similar estimates for 100,000 SEK thresholds, using a bandwidth of 50,000 SEK. Standard errors are clustered at the municipality level.

* $p < 0.1$, ** $p < 0.05$, *** $p < .01$

Panel B shows the same result for 100,000 SEK thresholds. Consistent with the evidence in Section 3.2.2, inattention to the second digit also appears to be present – although the magnitude is, as expected, smaller – and apartments listed just below multiples of 100,000 SEK also attract more bidders and bids. While it should be noted that these results might also be consistent with other hypotheses, they suggest that auctions for just-below apartments are more competitive.

Our interpretation that inattentive buyers are disproportionately participating in just-below auctions is also supported by evidence from the real estate agents’ survey. To elicit agents’ beliefs on the effect of the two pricing strategies, we pictured the following hypothetical scenario where there was no selection bias:

“Suppose that two identical objects, A and B, are sold at the same time in the same area. The asking price is 1,995,000 SEK for object A and 2,000,000 SEK for object B.”

Then, we asked which object would perform better in the market in terms of time on the market, web ad clicks, number of bids, open house visitors, and final price (see question 6 in Table 14 in the Appendix). Virtually no agent believed that the apartment listed at exactly 2 million would do better. Instead, roughly a third of agents expected the just-below strategy to yield a faster sale and a higher price, with the rest expecting no difference. As much as two-thirds, however, anticipated an increase in the web ad

views.

Additional evidence from the survey also corroborates our hypothesis of no sorting on apartment characteristics. In question 7 (reported in Table 15), we asked how much they agreed with the statement that apartments listed just below (or exactly at) a round number threshold were artificially under-priced. Interestingly, only 24% agreed or strongly agreed that just-below apartments were under-priced, while 14% suspected it for apartments listed exactly at the threshold.²⁰ Rather, as many agents wrote in the comments to the survey, the reason for just-below pricing lies in the presence of “psychological effects” and the fact that they “sound cheaper”, often drawing the analogy with supermarket pricing schemes such as 99 cent pricing.

A final note is due to discuss potential welfare implications. In order to quantify the impact on aggregate welfare of the presence of inattentive buyers, it is useful to consider the benchmark case in which all buyers are fully attentive. In this case, potential buyers facing identical apartments at either side of the threshold will simply randomize in which auction they participate, hence the final price will be the same in expectation.

In the presence of inattention, some buyers will shift to auctions of just-below apartments, increasing the expected final price. This mechanism will generate a transfer from inattentive consumers to sellers who use just-below prices. Similarly, the reduced number of bidders in apartments listed at the threshold generates a transfer from sellers of these apartments to buyers. Although the aggregate welfare that considers both sellers and buyers is unchanged, the presence of inattention may cause a redistribution of gains and losses between the two groups.²¹

²⁰In general, there was very little difference in the fractions of agents who expressed a particular belief regarding under-pricing (such as strongly agree, agree, etc.) in the two cases. This suggests that, if sorting is present, it is the same above and below the threshold.

²¹As an illustration, consider the cases with two buyers (1 and 2) and two sellers with identical units (A and B) sold in ascending price auctions. Buyers participate sequentially in auctions until the market clears. Inattention causes buyers to start with an auction of a just-below apartment. Assume that apartments have asking prices of s_A and s_B , respectively, and agents have willingness to pay equal to $w_1 > w_2$, both larger than the asking prices. From standard auction theory and eq. 2, we know that the sale price will be either the asking price or the second highest willingness to pay (when more than one bidder participates).

Without inattention, buyers randomize between auctions, and the expected prices will be equal to $E(P_A) = 3/4s_A + 1/4w_2$ for apartment A and $E(P_B) = 3/4s_B + 1/4w_2$ for apartment B. Without loss of generality, assume that apartment A is listed just below a round number, while apartment B is listed at a round number. The presence of inattentive buyers causes an increase in $E(P_A)$ and a decrease in $E(P_B)$. The auction with the lowest asking price attracts all buyers, so $E(P_A) = w_2$ while $E(P_B) = s_B$. For the seller using just-below pricing, the presence of inattention increases profits by $3/4(w_2 - s_A)$, while the profit of the other seller, instead, decreases by $1/4(w_2 - s_B)$. Notice that, in this particular example, the aggregate profits of sellers are always larger in the inattention case.

5.2 Why do round-number asking prices exist?

Given the result described above that just-below asking prices yield higher final prices, one may ask why some agents still choose to list their apartments at a round number. To start, two-thirds of our surveyed agents do not expect that just-below asking prices yield an advantage over round-number prices. This widespread lack of knowledge can explain why we observe both strategies in the data.

We explore whether just-below pricing is correlated with agent experience. Empirically, we divide the sample into quartiles by experience. We define agent experience as the total number of sales they completed in our sample. We then define three mutually exclusive indicators for the asking price strategy used: 1) an indicator for apartments listed just below a round number; 2) an indicator for units listed at round millions or just above; and, finally, 3) an indicator for any other price. About 12% of apartments are listed just below, 1% just above and 87% are listed at any other price.

We find that the probability that an agent chooses a just-below price is monotonically increasing in experience: agents in the first quartile of experience choose a price just below a round million in 11.0% of the cases. This probability grows to 13%, 13.2%, and 13.6% for agents in the second, third and fourth quartile respectively. An individual t-test rejects the null of equality between the top and bottom quartiles at the 1% level. Correspondingly, the probability of listing just above and the probability of any other price decreases monotonically with experience.

A final factor that can also contribute to explaining round number prices is the fact that sellers sometimes go against the agent’s recommendation and choose the asking price directly. As table 13 shows, over 70% of the agents reported some interference in the pricing decision by the seller, who often demands that a higher asking price is set.

6 Robustness checks and alternative explanations

We begin this section by exploring the robustness of our results to controlling for past sale outcomes. Then, we show that our main results hold even when using two alternative estimation methods. We start with a nearest-neighbor matching approach and then implement the bias-corrected estimator suggested by [Oster \(2017\)](#), which attempts to learn about the omitted variable bias by analyzing how the coefficient estimate changes when adding controls.

In the second part of the section, we investigate and rule out two alternative explanations for our results. First, we consider the possibility that a design feature of the market – the interface of the search engine on *Hemnet.se* – explains the observed discontinuity in the final price. Then, we look for support in our data for the alternative “cheap talk”

hypothesis, according to which impatient sellers use round numbers to signal a weak bargaining position.

6.1 Robustness checks

Controlling for past sale outcomes

Our dataset contains 21,892 apartments sold more than once (6.3% of the total), 3,616 of which are within the bandwidth. Although this subsample of repeated sales amounts to just 1% of the full sample, analyzing it may be informative about selection issues.

In Table 19 in the Appendix, we perform balancing checks on several observable characteristics using this subsample only. Apartments that today are listed at a round number or just above are significantly different from those listed just below. Specifically, they are 2.6 square meters smaller and have 0.12 fewer rooms. Both these differences have a negative effect on the final price. Instead, there are no significant differences in terms of monthly fee and year of construction.

When looking at the time since last sale (measured in days), we notice that apartments listed at the threshold were sold previously 74 days earlier, on average, potentially because their quality is lower. This intuition is corroborated by the last two columns of Table 19, which show that both the lagged (log) asking price (that is, the asking price of the previous sale) and the lagged (log) final price are about 5% lower than their just-below counterpart.

Finding these difference in the lagged asking and final prices could potentially be problematic insofar as they arise as the consequence of selection around the threshold, so that apartments listed at the threshold or just above are systematically worse. However, the failure of the balancing checks in Table 19 raises doubts about whether we can draw such a conclusion.

The most important issue is whether these discontinuities in lagged outcomes are the result of some selection induced by restricting the sample to repeated sales or are due to more substantial differences in apartment quality. The latter explanation would imply that our left-digit bias estimates are biased upwards. To rule out this possibility, in Table 20 in the Appendix, we start by estimating our baseline effect on the final price using the repeated sale sample only and including municipality-year fixed effects (the same specification used in Table 2, column 3 above).

As column 1 shows, the baseline effect remains negative and statistically significant and grows in magnitude with respect to our baseline estimates using the full sample. In column 2, we add both the lagged sale price and the time since previous sale as controls, in order to capture characteristics of the apartment that we cannot observe but that

should be reflected, at least in part, in the previous sale price. The point estimates remain largely unaffected. Finally, in the rightmost column, we estimate our model including apartment fixed effect. This specification proves to be too demanding for the data, as instances of repeated sales in which the apartment is listed, at some point, at either side of the threshold are extremely rare. Reassuringly, however, although the sample uncertainty is very large, the point estimate remains negative.

To conclude, the evidence from the analysis of repeated sales shows some differences in terms of outcomes of the previous sale when crossing the round million asking price threshold. Although these differences may be indicative that apartments with asking price at round numbers are of lower quality, the inclusion of both the lagged price and the time since previous sale in our baseline specification gives a similar point estimate to those reported in the paper, which reassures us about the validity of our main analysis.

Nearest-neighbor matching

One concern arises from the fact that the linear specification in equation 1 may be too restrictive and may fail to control for nonlinear effects of the covariates on the final price. This issue is well known in the treatment effects literature, in which practitioners often worry about OLS results when treatment and control groups differ too much regarding observables. One common solution to this issue is to use matching methods instead. These methods estimate the effect of being at the threshold by first finding, for each apartment just below the threshold, another apartment that is as similar as possible in observable characteristics but that has an asking price exactly *at* the threshold. Then, the treatment effect is estimated as the difference in average price between treated and matched control groups; therefore, it does not rely on linearity to control for observable characteristics.

Table 10 shows results from several variations of the nearest-neighbor matching method developed by [Abadie and Imbens \(2006\)](#). To have a clear distinction between treated and non-treated observations, we restrict the sample to apartments with an asking price just below or exactly at the common threshold. Apartments listed at round millions are, therefore, “treated”, while those listed up to 5,000 SEK below are not. In column 1, we report, as a reference, the OLS coefficient obtained by estimating the discontinuity in equation 1 on the sample restricted as before and including parish-year fixed effects.

The nearest neighbor-matching algorithm finds the closest neighbor in terms of surface area, number of rooms, monthly fee and year of construction. Following [Abadie and Imbens \(2006\)](#), we also use these variables to implement the bias correction. The

Table 10: The effect on sale prices, estimates from nearest-neighbor matching

	OLS		Nearest-neighbour matching		
	(1)	(2)	(3)	(4)	(5)
Above the cutoff	-4.92*** (0.48)	-4.92*** (0.33)	-6.33*** (0.88)	-5.48*** (1.02)	-3.67*** (1.26)
Obs.	21,769	21,874	20,964	17,011	12,012
R^2	0.97				
Controls	✓	-	-	-	-
Fixed Effects	Year × Parish	-	-	-	-
Exact match on:	-	-	Mun.	Year & Mun.	Year & Parish

Notes: In all columns, the sample is restricted to apartments with a listing price just below or exactly at the threshold (i.e., with running variable equal to -5,000 SEK or 0). In the first column, we report OLS estimates including year-parish and year-month effects. Columns 2-5 use a different specification of [Abadie and Imbens \(2006\)](#) nearest-neighbor matching with bias-correction using all the covariates used for matching. In column 2, we match on square meters, the number of rooms, monthly fee and year of construction. In addition, in column 3, we require observations to match exactly on municipality; in columns 4 and 5, instead, we require exact matching on year and municipality, and on year and parish, respectively. Standard errors are clustered at the municipality level in column 1 and are heteroskedasticity-robust in the remaining ones.

* $p < 0.1$, ** $p < 0.05$, *** $p < .01$

matching results show that the coefficient drops slightly, but remains significant.²² To make the comparisons more stringent, in column 3, we require apartments to match exactly on the municipality, and the coefficient remains negative and significant and even increases slightly in magnitude. When we require apartments to match exactly on municipality and year (column 4), the estimated coefficient decreases but remains larger in absolute value than the OLS estimate. In the most demanding specification of column 5, when we require an exact match on parish and year, the point estimate decreases to about -3.7. The drop in the number of observations is due to the fact that the algorithm needs at least two observations in each cell. We cannot go further than year-parish cells by, for instance, requiring exact matching on housing association and year because the number of observations drops to a prohibitively low level. The results from the specification in column 5, which uses comparisons within parish-year, are roughly of the same magnitude as those obtained by controlling for agent-year fixed effects in Table 7, suggesting a conservative estimate of the effect of about 2.8-3.7% of the final sale price.

Coefficient stability when adding controls

[Oster \(2017\)](#) shows that, if observables (W_1) and unobservables (W_2) are related in the

²²Standard errors in columns 2-5 are heteroskedasticity-robust and not clustered because the option is not available in the STATA command *teffects*.

same way to the treatment variable X , in the sense that the regression coefficient of each on X yield the same result (up, at most, to a proportionality factor δ), then the following is a consistent estimator of the effect of X on Y :

$$\beta^* \approx \tilde{\beta} - \delta[\hat{\beta} - \tilde{\beta}] \frac{R_{max} - \tilde{R}}{\tilde{R} - \hat{R}}, \quad (3)$$

where $\tilde{\beta}$ is the OLS estimator from regressing Y on X and W_1 , while $\hat{\beta}$ is the estimator from regressing Y on X . Clearly, δ – the relative degree of selection on observed and unobserved variables – and R_{max} – the R^2 of the regression that also includes W_2 – are not estimable and are chosen by the researcher for sensitivity analysis.

Inspection of the baseline results in Table 2 reveals that, in our, case, the more controls we add, the less negative our estimates become – hence, $\hat{\beta} < \tilde{\beta}$. If we assume that the unobservables and the observables are related in the same way to X (a plausible assumption here), then $\delta > 0$, so that the true effect is less negative than our estimate, $\tilde{\beta}$. The size of this bias also depends on our assumption on R_{max} . Given that the value of R^2 in our estimates is very close to 1, it seems natural to set R_{max} at its most conservative level – that is, 1.

According to equation 3, the bias correction that we need to implement in this case is larger i) the greater the change in the slope when we include controls; and ii) the greater the corresponding change in the R^2 are. Given that, in our case, both changes are small, the bias correction is minimal. Looking at Table 2, we see that when we move from the specification without controls (column 1) to the one with controls and association-year fixed effects, the coefficient changes from $\hat{\beta} = -6.44$ to $\tilde{\beta} = -5.15$, while the R^2 increases from 0.944 to 0.990. Assuming that $\delta = 1$, we can calculate an upper bound using equation 3 with $R_{max} = 1$, $\delta = 1$ and the above values as $\beta^* \approx -5.15 + 1.29 \times 0.046 = -5.21$.

Equation 3 is derived under some restrictive assumptions, so it should be used only to have a first approximation to the size of the bias correction. The more general version of the estimator does not, in general, have a simple formula like 3; thus, to implement it we use STATA 15.1 and the user-written command *psacalc* made available by the author. To implement the estimator correctly, we first residualize the dependent variable and the covariates by regressing them on the running variables and the group indicators, each equal to one if the observation is close to one of the five 1 million thresholds (following the advice in Section 3.3.3 of Oster 2017). Our uncontrolled baseline effect $\hat{\beta}$ is then obtained by regressing the residualized log price on the threshold dummy, as reported in the first column of Table 11.

The controlled effect, and its corresponding R^2 , are obtained by including the full

Table 11: Robustness of the main effect to selection on unobservables

	Baseline eff.	Controlled eff.	Bias adjusted		
			$\delta = 0.75$	$\delta = 1$	$\delta = 1.25$
Above the threshold	-6.42*** (0.22)	-5.67*** (0.85)	-4.96*** (0.73)	-4.47*** (1.18)	-3.60 (2.29)
Observations	57,095	56,936	56,936	56,936	56,936
R^2	0.014	0.805			

Notes: Bias-corrected OLS estimates for the effect of the asking price on the logarithm of the final transaction price (in thousands SEK). We use a local linear control function and a bandwidth of 100,000 SEK at each side of each threshold. Estimation is performed in STATA 15.1 with the *psacalc* command by Oster (2017) using different values of δ and setting $R^{max} = 1$. Standard errors are bootstrapped by resampling at the municipality level (500 replications).

set of year-month and association-year fixed effects used in our most demanding baseline specification and reported in the second column. In the rightmost part of Table 11, we estimate the bias-corrected discontinuity in the final price around the round million thresholds for different values of δ and assuming $R^{max} = 1$. Standard errors are bootstrapped using municipalities as clusters and 500 replications. The residualization that we performed at the beginning causes the R^2 of the uncontrolled regression to be very small. The increment in R^2 due to the inclusion of the fixed effects is so dramatic (from 0.014 to 0.8) that, in principle, the bias-corrected estimator could be very different from the uncontrolled one. However, as we can see in column 3, for a value of $\delta = 0.75$, the point estimate decreases only slightly to -4.9. When setting this parameter to the suggested value of 1, the estimated discontinuity is reduced to -4.47 but is still statistically significant. It is only when imposing that δ be 1.25 that significance is lost, although the sign and, partially, the magnitude – of the coefficient are preserved. The estimated value of δ for which the effect eventually is zero is 1.59, a number that appears rather extreme compared to the recommended value of 1.

6.2 Alternative explanations

Institutional features of the market

Given that the vast majority of apartments on sale are also listed on *Hemnet*, it is possible that, if its interface makes apartments listed just below more visible than those listed at a round number, our results could be driven by a feature of the interface and not by inattention by the buyers. Indeed, the *Hemnet* search engine allows us to restrict the search results to apartments with prices within some predetermined brackets (each usually 250,000-500,000 SEK apart; see Figure 11 in the Appendix).

Figure 8: The *Hemnet* interface in 2011

In large cities like Stockholm, it is almost unavoidable to restrict the search results in some way because of a large number of units for sale. Simply enlarging the search by including one more bracket increases the number of results by hundreds, and the cost of processing those additional results may become too burdensome for potential buyers.

Although reasonable in principle, the hypothesis that these brackets are driving the result is unlikely because apartments listed exactly at the ends of a bracket are always shown in the search results (for instance, an apartment listed at 2 million SEK appears both in a 0-2 million search and in a 2-4 million search). This fact means that apartments listed at round numbers are, if anything, *more* visible than those listed just below. Even with this in mind, we can test this hypothesis formally by taking advantage of the fact that the search engine in *Hemnet* was changed on March 12, 2011 (as a quick investigation using the Internet archives reveals, see <https://archive.org/web/>). Before that date, *Hemnet* did not have price brackets but a slider with 100,000-SEK increments, as Figure 8 shows.

We can use this change in the interface to estimate whether the price discontinuity at round numbers was different before and after using a diff-in-diffs strategy. To this end, we augment our baseline model described in Section 3.2 by including an indicator *Post* for transactions of apartment advertised after the date of the interface change, as well as its interaction with our threshold indicator.²³ In Table 21 in the Appendix, we see that the discontinuity was present even before the introduction of the brackets. The result is the same even when using observations from 2011 only (Panel A), suggesting that this particular feature of the search engine does not have an effect on final prices.²⁴

²³Given that the slider's increments were multiples of 100,000 SEK, this exercise is only informative about our estimates around 1 million thresholds, where the first digit of the asking price changes.

²⁴Notice that the *Post* indicator is not collinear with the year-month fixed effects because it is defined as being 1 for apartments listed after March 12, 2011 and, hence, it varies within a month.

Cheap talk

An alternative explanation for the effect that we document is that using round asking prices is one of the two optimal strategies that arise in a separating equilibrium. In such a model, some sellers are impatient, in the sense that they are willing to forgo a higher final price in exchange for a quicker sale. To signal their weak bargaining position to buyers, they use round numbers as a distinctive pricing strategy. In this framework, sellers are behaving rationally and behavioral biases play no role.

This is the approach followed by [Backus, Blake and Tadelis \(2019\)](#), who argue, using a large dataset of eBay negotiations, that patient sellers use round number for their asking price to signal that they are willing to accept a lower price in exchange for a quicker transaction. Items listed at multiples of \$100 receive offers that are 8-12% lower but they are 15-25% more likely to sell than items listed at any other number. They also complement their evidence with data on apartment sales in the U.S., showing that apartments listed at round numbers are sold more at a lower price (although they have no information on the time on the market before sale).

It might be the case that a similar mechanism drives our result, and that round numbers are used as “cheap-talk” signaling to let potential buyers know of a weak bargaining position. However, in our case, the evidence goes against this hypothesis. In fact, even if round-million priced apartments are sold at a 3.5-5% lower price than apartments listed just below a round million, they do not differ in the amount of time they stay on the market, as shown in Figures 6 and 7. This result violates the incentive-compatibility constraint because round-number pricing appears to be a dominated strategy, as it yields lower prices without a faster sale.²⁵

Given the number of apartments that are sold at round numbers, one might ask why sellers choose to incur such a large loss by picking this price. One possibility is that, as [DellaVigna \(2009\)](#) points out, behavioral biases are likely to be large in markets where players have little experience, as it happens for most buyers in the housing market and even for some sellers, especially when not guided by a real estate agent. In fact, although agents are often experienced professionals, the apartment owners ultimately decide the listing price. As the survey evidence reported in Tables 13, 14, and 15 shows, over 70% of the agents reported some interference by the seller in the choice of the final price, and 9.2% of them even reported that the sellers decided the price in all of their last five sales.

Furthermore, when asked why someone would pick an asking price of 2 million SEK,

²⁵One important difference between [Backus, Blake and Tadelis \(2019\)](#)’s case and ours is that they study descending price negotiations and not ascending price auctions. In negotiations, the role of the asking price might be different because, for example, it is often set much above the reservation value and used as an anchor.

65.7% of agents declared that this was the price the seller required, although only 3% of agents said that they believed it would yield the highest sale price. When asked the same question regarding a 1.95 million price instead, only 6.4% declared that the seller would have chosen this amount. The vast majority believed that just-below pricing will generate the highest final price. This suggests that, while agents know that the best strategy is to price just below round numbers, sellers often disagree, possibly because of their lack of experience in the market.

Reciprocity

Another alternative explanation for our results is that buyers of just-below apartments bid more in order to reciprocate the gesture of the seller of setting a slightly discounted price (see, e.g., [Fehr and Gächter 2000](#)). If this were the case, the observed effect of just-below asking prices would not be due to inattention but rather to a conscious choice of buyers to thank the seller for asking for a little less than the rounded-up price.

While this mechanism is certainly plausible, we believe it is unlikely to be driving the results. To start, the magnitude of our effect vastly exceeds the discount: for example, comparing apartments with asking prices just below 1 million SEK with those listed at 995,000 SEK (a difference of 0.5%), we observe that the difference in the final price is 4.65% (see column 2, Table 3). If the buyer intends to reciprocate, the magnitude of this effect should be roughly of the same size of the discount, but we observe that the final price difference is almost ten times as large.

Another reason that goes against the reciprocity explanation is that the auction process is intentionally designed and implemented in an impersonal way. The apartment owner is virtually never present at the open house, and the real estate agents typically employ decorators and professional photographers to make the apartment look new and cozy. These measure, and the decision to use an agent as intermediary, are all aimed to help the buyer imagine the apartment as her own. As such, it appears unlikely that buyers would want to reciprocate a gesture made by someone who they do not know. The presence of several bidders at the same time also complicates this potential effort to reciprocate, as early bids are typically quickly surpassed.

A final piece of evidence in this regard can be drawn from Figure 1 above. In presence of reciprocity, we should expect buyers to reciprocate more when the apartment is listed, e.g., 10,000 SEK below a round number than when it is listed 5,000 SEK below. This idea would translate in having the two points closest to the threshold from the left placed roughly on a horizontal line, or at least. Instead, they lie on the fitted line, suggesting that the magnitude of the price increase is about the same for both apartment types, in line with the inattention mechanism.

7 Discussion and comparison to the U.S. case

While auctions are not uncommon and are also used in other countries such as, e.g., Norway, Denmark and Australia, in most markets, including the U.S., sales usually take place after a direct negotiation with the seller. [Han and Strange \(2015\)](#) notice that, although negotiations are prevalent in the U.S., in boom periods as many as 15% of properties end up being sold in a “bidding war”, an auction-like transaction where multiple buyers compete against each other. Similarly, in our data, 15% of the properties are sold at a price lower than the asking price, so that, in practice, the two sale mechanisms often coexist.

Our results suggest that, in an ascending price auction setting, inattention to the left-digit of the asking price has a significant and pervasive effect on sale prices. The evidence on the effect of left-digit bias on negotiation outcomes is scarce and points to much smaller effects. [Chava and Yao \(2017\)](#) show that, in U.S. data where most transactions are the outcome of a negotiation, just-below asking prices yield a 0.1% higher final price and a faster sale. Differently from us, Chava and Yao define just-below prices as those ending with 900 and compare these with apartments with asking price ending with 1,000. Hence, they estimate a pooled effect of the first-digit bias and the effect of other lower digits. Although the two approaches are distinct, comparing their results to ours begs the question of whether the sale mechanism plays a role.

One important difference between auctions and negotiations is the role of the asking price. In ascending auctions the asking price is, in general, set below the seller’s reservation value and serves as a starting point for the subsequent bidding process. On the contrary, in negotiations, the asking price is generally chosen above the seller’s reservation value to leave room for negotiating.

In negotiations, there is a large body of evidence showing that the anchoring effect is substantial, so that sellers and agents often choose high asking prices in order to tie buyers’ offers to a high anchor (see, e.g. [Galinsky, Ku and Mussweiler 2009](#)). As noted by [Northcraft and Neale \(1987\)](#), this mechanism is especially relevant in markets when the value of the good is not objectively determinable, such as the housing market. In contrast, this behavior is different from what we usually observe in auctions, where the asking price is often set lower than the reservation value in order to attract more bidders.²⁶

In the presence of both anchoring effects and left-digit bias, the effect of just-below pricing on the final price is, at least in theory, ambiguous. For instance, just-below asking prices could lead to lower final prices because they act as lower anchors for the

²⁶For a review of the role of the asking price in housing markets see [Han and Strange \(2016\)](#).

subsequent auction. Alternatively, one could also argue that since in most cases the final prices go well above the closest round number, setting the asking price just-below or at the threshold should have no effect at all. Although certainly plausible, we do not find evidence for either of these mechanisms. Instead, apartment listed just-below round numbers attract more attention from potential buyers.

In the auction, the presence of well-known biases, such as herding ([Simonsohn and Ariely, 2008](#)), quasi-endowment effects ([Heyman, Orhun and Ariely, 2004](#)), and bidder's heat [Malmendier and Lee \(2011\)](#) can then drive the price up substantially.²⁷ The fact that different behavioral biases can be at play in negotiations and auctions might explain why [Chava and Yao \(2017\)](#) find much smaller effects in the U.S. setting, where negotiation are prevalent. Even if left-digit bias affects buyers in both settings, its consequences might be amplified by the other behavioral biases that have been shown to play an important role in auctions but are less likely to matter in negotiations.

8 Conclusions

The tendency to use cognitive heuristics is deep-rooted in the human nature and is amply documented in laboratory experiments and, to some extent, in the field. In this paper, using a large and detailed dataset of transactions, we investigate the effect of partial inattention to the asking price of an apartment on the final sale price. We find that apartments with an asking price just below a 1 million threshold are sold at a 3-5% premium compared to similar apartments listed exactly at the threshold. A similar, but smaller, effect is found around 100,000 thresholds. Our estimates are robust to several specification checks and sample restrictions, suggesting that the effect is ubiquitous. To ensure that this result is not driven by sorting around the threshold, we control for a large set of covariates and increasingly more demanding fixed effects, restricting the comparison to apartments sold in the same building or by the same agent in the same year.

Turning to mechanisms, the effect appears to be caused by potential buyers who are inattentive to the asking price. Consistent with this hypothesis, apartments with just-below asking prices receive more attention, and their auctions have more bidders and more bids. Overall, the size of the effect, equivalent to roughly to five months of disposable income, appears to be hard to reconcile with predictions from an optimal search model, in which individuals stop searching when the marginal cost of searching

²⁷The idea that auction could amplify behavioral biases in the housing market is not new. For instance, [Ashenfelter and Genesove \(1992\)](#) show that, using data from a unique pooled auction, apartments sold in auctions yielded a 13% price than identical ones sold through bargaining.

is equal to the marginal benefit ([Weitzman, 1979](#)). Rather, buyers appear to pay a large price for their inattention.

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A Appendix - Data and sample restrictions

Main dataset

Data from Mäklarstatistik for all sales brokered by their agents (covering 90% of brokered sales in Sweden), 2010-2015. The original dataset was provided by Ina Blind, Matz Dahlberg, and Gustav Engström. The dataset has some inconsistencies and errors that we fix, as follows:

- Drop 51 duplicate transactions.
- Fix some unreasonable years of construction when possible.
- Drop transactions with a missing, unreasonable or unclear year of construction.
- Drop 35,467 new constructions and units constructed and sold in the same year, as they are generally not sold in auctions.
- Keep only apartments.
- Drop apartments with zero or missing asking or final sale price.
- Drop apartments with asking price larger than 5.5M SEK (very few) and smaller than 50,000 SEK.
- Drop apartments with inconsistent characteristics: e.g., zero rooms/square meters, floor higher than 30, or with missing municipal ID.

Outliers: Given that the housing association fee and the surface area have very few large outliers in both tails, we drop apartments for which the value of one of these two variables is either larger than the 0.995 or lower than the 0.005 quintiles. We use the same trimming for the price increase, dropping apartments sold at a final price that far exceeds the asking price or sold at a fraction of the asking price. We also drop apartments with a number of rooms exceeding the 0.995 quintile (equal to 12 rooms), dropping 1,057 outliers in total, and apartments with a negative time on the market. The final dataset comprises 346,731 transactions, with some missing values in some of the variables.

In Table 12 we estimate our baseline model with year-housing association fixed effects, using indicators for each of the main covariate being missing as dependent variables. Variables with no missing values are, of course, excluded. None of indicators jumps at the threshold, suggesting that the likelihood that a particular covariate is missing does not correlate with whether the apartment is listed just below or at the threshold.

Table 12: Analysis of attrition for the main covariates

	Sq. met.	Rooms	Fee	Floor	Elev.	Balc.
	(1)	(2)	(3)	(4)	(5)	(6)
Above the threshold	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.005 (0.007)	0.006 (0.007)	-0.002 (0.019)
Mean of dep. var.	0.999	0.999	0.998	0.832	0.874	0.326
R-sq	0.64	0.73	0.88	0.78	0.73	0.74
Obs.	57096	57096	57096	57096	57096	57096

Notes: Regression estimates of the effect of the asking price on an indicator for each apartment characteristic to be missing or not around 1-million thresholds. We report the coefficients of an indicator for the asking price being to or above a threshold. We use a local linear control function allowing for different slopes at each side of each threshold. Year-housing association and month-year fixed effects are included. Standard errors are clustered at the municipality level.

* $p < 0.1$, ** $p < 0.05$, *** $p < .01$

***Hemnet* subsample**

This dataset was downloaded from the *Hemnet.se* web page with the help of a Python script. We obtained information on the real estate firm and agent with every transaction that was available on 25/4/2016. The coverage of this dataset is small in 2010-2012 and becomes satisfactory only for 2013-2015, where the overlap with our primary dataset ranges from 40 to 57%.

Due to the absence of a unique identifier, the merge with the main dataset is based on asking and final price, sale date, rooms, surface area, and monthly fee. For this reason, we had to drop transactions that are indistinguishable from one another (for example, because they are apartments sold in the same building on the same date but on different floors). Also, possibly because the coverage differs in the two datasets, we were unable to merge all the *Hemnet* transactions to our main dataset. However, for the years 2013-2015, we could match about 52% of them (97,676).

Auctions subsample

The largest real estate agency in Sweden (with about 20% market share), *Fastighetsbyrån*, publishes several auction results on its web page. Although the coverage is not perfect and some items are missing, the vast majority of auctions managed by *Fastighetsbyrån* can be obtained directly from the website with a script. We clean the dataset by dropping auctions for apartments sold abroad (in Euros), and auctions in which one or more bids lack the bidder identifier. We also drop 400 bids below 10,000 SEK and above 200 million SEK. In addition, we exclude a few auctions (0.14%) in which there is at least one bid that exceeds the previous one by more than 100% or is less than half of it, or for which there is a bid that is 1 million SEK lower than the previous one, as those are usually coding errors. We drop 90 cases in which the auction lasted more than 90 days.

We drop transactions that are observationally equivalent to be able to merge them – based on geographical coordinates, price, and date of the auction – to the main dataset. We can match 26,986 apartments of the main dataset to the bidding information. Finally, we identify auctions in which a participant bids below the first bid. These cases can happen in reality when the first bidder leaves the auction, and the auction remains open, sometimes for months, until a new bidder arrives. These are not dropped but are identified by an indicator variable named “tag_lower_bid.”

B Appendix - Survey results

Table 13: Survey results - I

1) Which are the main arguments you would say there are in favor of choosing an asking price of 1,995,000 SEK? It is possible to select multiple answers.		
	Fraction	Frequency
a. It generates the highest sales price.	0.23	70
b. It is the asking price that is usually used.	0.34	102
c. It attracts the most people during the open days.	0.35	104
d. Such a starting price is essentially when the seller insists on.	0.07	22
e. It generates the highest number of views on Hemnet	0.44	130
f. Other reason (please specify)	0.32	95
Answers		298
No answer		2

2) Which are the main arguments you would say there are in favor of choosing an asking price of 2,000,000 SEK? It is possible to select multiple answers.		
	Fraction	Frequency
a. It generates the highest sales price.	0.04	10
b. It is the asking price that is usually used.	0.09	26
c. It attracts the most people during the open days.	0.01	2
d. Such a starting price is essentially when the seller insists on.	0.66	190
e. It generates the highest number of views on Hemnet	0.02	7
f. Other reason (please specify)	0.31	90
Answers		289
No answer		12

3) If you think of your five most recent sales, in how many of these it was the owner who essentially decided the asking price?

	Fraction	Frequency
None	0.30	87
1	0.28	82
2	0.17	49
3	0.11	33
4	0.06	17
5	0.09	27
Answers		295
No answer		6

Table 14: Survey results - II

4) In situations where the seller insists on a different asking price than the one the broker suggests, would you say it is more often lower or higher than the broker's suggestion?

	Fraction	Frequency
a. More often lower	0.14	41
b. More often higher	0.86	249
Answers		290
No answer		11

5) What would you say are common reasons for the seller to insist on a different asking price than the one the broker suggests? It is possible to select multiple answers.

	Fraction	Frequency
a. The seller wants the asking price to be the same he/she originally bought the item for.	0.03	10
b. The seller believes to know which strategy gives the highest sales price	0.60	181
c. The seller wants it to be the lowest price at which he/she is willing to sell the item for.	0.29	86
d. Other reason (please specify)	0.33	100
Answers		299
No answer		2

6) Suppose that two identical objects, A and B, are sold at the same time in the same area. The asking price is 1,995,000 SEK for object A and 2,000,000 SEK for object B.

	Object A	Object B	No difference
a. Which item will sell faster?	0.34	0.01	0.65
b. Which item will get the most views on Hemnet?	0.65	0.02	0.33
c. Which item will get more visitors in the open days?	0.47	0.02	0.52
d. Which item will get the most bids in the auction?	0.45	0.02	0.53
e. Which item will sell at the highest price?	0.39	0.05	0.56
Answers			299
No answer			2

Table 15: Survey results - III

7) There has been extensive discussion about asking prices set far below market value. To what extent do you agree with the following two statements?					
	Fully disagree		Indifferent		Fully agree
a. An object with an asking price of 1,995,000 SEK is likely to have an asking price much lower than market value	0.42	0.15	0.19	0.12	0.12
b. An object with an asking price of 2,000,000 SEK is likely to have an asking price much lower than market value	0.45	0.21	0.21	0.06	0.08
Answers					290
No answer					11

8) How many years of experience do you have as a real estate agent?		
	Fraction	Frequency
Less than 1 year	0.04	12
Between 1 and 3 years	0.14	42
Between 3 and 6 years	0.16	47
Between 6 and 10 years	0.23	70
More than 10	0.43	130
Answers	299	
No answer	2	

Appendix - Additional figures and tables

Figure 9: Hemnet main interface and an example of an ad

The screenshot displays the Hemnet website's main interface for rental searches in Södermalm, Stockholm. At the top, there is a search bar with the text "search for a place to live" and navigation links for "Inspiration", "Find brokers", "Build & Renovate", "housing Statistics", and "if". Below the search bar, the current search is "Your search for rental - Södermalm" with 2385 results. A map shows the search area with numerous purple pins indicating available properties. To the right of the map is a sidebar with filters for "Area" (Södermalm, Stockholm), "Property" (All types, Villa, Town hall, Tenant, Vacation, Plot, Farm/Forestry, Other), "Room" (1 room, 3 rooms), "Living area" (30 m², 55 m²), "Charge" (My, Max), "Price" (2 000 000 S, 4 million SE), and "Keyword" (Balkong, kakelugn, etc.). Below the map, a "broker tip" highlights a "Top Refurbished dream 3rd!" for 4.65 million SEK in Hammarby Sjöstad. A list of results is shown below, with the first entry for "Hornstull" at Högalidsgatan 52 A, 2tr, priced at 2 250 000 SEK. The detailed view of this property shows a modern interior with colorful curtains, a dining table, and a television. The text below the photos provides details: "Högalidsgatan 52 A, 2tr", "Hornstull, Stockholm", "2 250 000 SEK", "1662 SEK / month", "30 m²", "1 room", "75 000 kr / m²", "1310 / year", and "Operating cost 1911". A "Bidding in progress" badge is visible next to the price.

Notes: The top picture shows the main search engine in Hemnet. It shows the results for a search in central Stockholm. The map shows the different units available, which are also listed to the end (partially visible in the picture). The search can be narrowed down to different criteria listed on the right of the picture. The bottom picture shows the page that appears by clicking on an ad, showing the relevant characteristics of the unit, pictures, real estate information, etc.

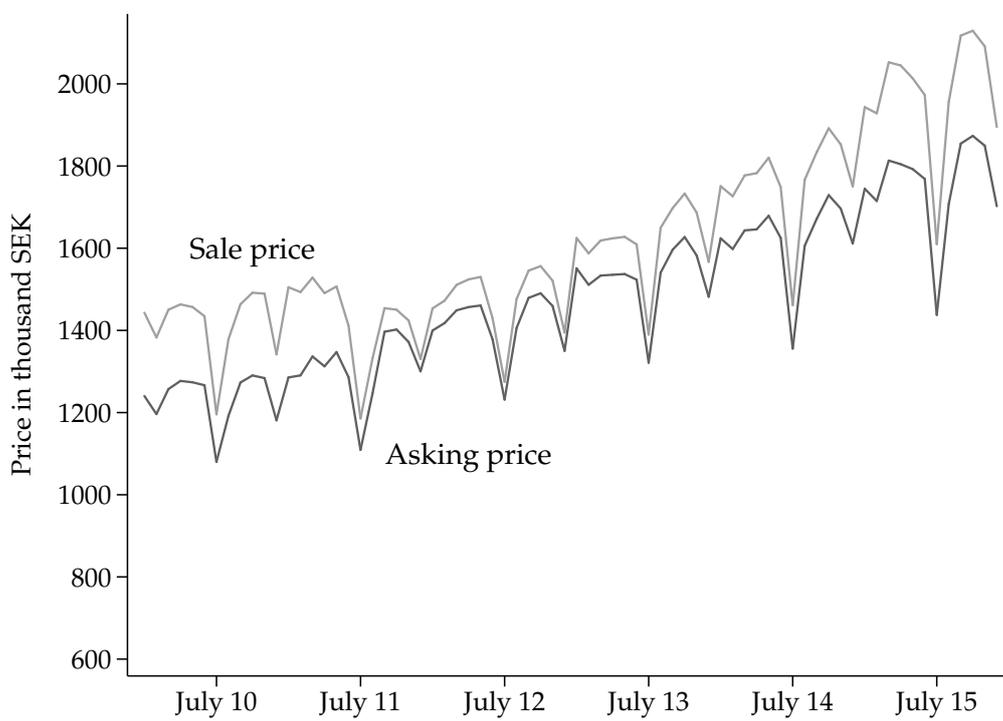


Figure 10: Evolution of average asking and sale prices for apartments sold in the whole of Sweden, 2010-2015.

Figure 11: The Hemnet.se interface

The screenshot displays the Hemnet.se website interface. At the top right, there are links for "Sign in" and "Create Account". Below these is a navigation bar with buttons for "search for a place to live", "Inspiration", "Find brokers", "Build house", "housing Statistics", and "If". The main heading is "Homes for sale in Sweden". Below this, there are two buttons: "For Sale" with a count of 27 139 and "Results" with a count of 298 030. A "Watch / save search" button is also present. The central part of the interface is a map of Sweden and surrounding regions, showing numerous property listings marked with colored dots. The map includes labels for "Norwegian Sea", "Baltic Sea", "North Sea", and various countries like Norway, Finland, Estonia, Latvia, Lithuania, Poland, Belarus, Ukraine, Germany, Czech Rep, Slovakia, Austria, and the United Kingdom. The map also shows major cities like London, Paris, Berlin, Prague, Vienna, and Moscow. The bottom of the map has a "Google" logo and "Map data © 2016, Google, INEGI, ORION-ME" text. On the right side, there is a search filter panel. It has a section for "Area" with a list of price ranges in SEK: My, SEK 100 000, SEK 200 000, SEK 300 000, 400 000, 500 000, SEK 750 000, SEK 1 000 000, 1.25 million SEK, 1 500 000 (highlighted), 1 750 000 SEK, 2 000 000 SEK, 2 250 000 SEK, 2 500 000 SEK, 3 000 000 SEK, 3.5 million SEK, 4 million SEK, 4.5 million SEK, 5 million SEK, and 5 500 000 SEK. There are also dropdown menus for "Max" and "Other". Below the "Area" section is a "Keyword" field with the text "Balkong, kakelugn, etc." and a "Search again" button. At the bottom of the filter panel, there is a link for "more search-options".

Table 16: The effect on sale prices for each year and at each million.

	Pooled	C=1M	C=2M	C=3M	C=4M	C=5M
	(1)	(2)	(3)	(4)	(5)	(6)
A. Year 2010						
Above the threshold	-7.69*** (2.23)	-5.57*** (1.86)	-11.6*** (2.89)	-8.45*** (1.03)	-8.89*** (2.32)	-5.38** (2.02)
Obs.	8,804	5,986	1,694	677	295	152
R^2	0.94	0.54	0.44	0.40	0.35	0.56
B. Year 2011						
Above the threshold	-6.63*** (1.13)	-6.00*** (1.82)	-7.49*** (0.72)	-5.66*** (1.72)	-4.69*** (1.11)	-4.13* (2.23)
Obs.	8,030	4,869	1,852	812	323	174
R^2	0.96	0.53	0.48	0.52	0.54	0.52
C. Year 2012						
Above the threshold	-2.72*** (0.88)	-3.79*** (0.70)	-2.06* (1.04)	-1.49 (1.12)	-2.58 (3.01)	-0.97*** (0.26)
Obs.	8,485	4,633	2,360	861	417	214
R^2	0.97	0.46	0.34	0.32	0.21	0.40
D. Year 2013						
Above the threshold	-3.66*** (0.51)	-4.64*** (0.77)	-3.68*** (0.47)	-2.80*** (0.50)	-2.12*** (0.75)	0.71 (0.45)
Obs.	9,262	4,377	2,942	1,098	577	268
R^2	0.97	0.46	0.35	0.30	0.30	0.36
E. Year 2014						
Above the threshold	-5.42*** (0.56)	-4.88*** (0.96)	-6.70*** (0.96)	-5.86*** (0.46)	-3.70*** (0.30)	-2.29*** (0.65)
Obs.	10,195	4,408	3,313	1,411	733	330
R^2	0.97	0.51	0.38	0.36	0.27	0.34
F. Year 2015						
Above the cutoff	-6.91*** (1.11)	-2.18 (1.39)	-8.46*** (0.73)	-8.78*** (0.74)	-7.26*** (0.84)	-8.24*** (2.07)
Obs.	12,220	4,413	4,443	2,007	839	518
R^2	0.96	0.49	0.44	0.38	0.34	0.29

Notes: Regression estimates of the effect of the asking price on the logarithm of the final transaction price (in thousands SEK), using a bandwidth of 100,000 SEK around the threshold. In column 1, we pool observations from all thresholds, whereas in columns 2 through 6, we estimate the effect around each individual threshold separately. We use a local linear control function allowing for different slopes at each side of each threshold. Controls include living area, the number of rooms, monthly fee, and year of construction, plus month-year and year-parish fixed effects.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 17: The effect on sale prices at 100,000 SEK cutoffs, for each year and for each million.

	Pooled	0-1M	1-2M	2-3M	3-4M	4-5M
	(1)	(2)	(3)	(4)	(5)	(6)
A. Year 2010						
Above the thresh.	-5.62*** (1.61)	-3.21*** (0.62)	-6.99*** (2.29)	-6.94*** (1.61)	-5.55*** (0.77)	-2.17 (1.54)
Obs.	47,440	23,432	17,314	4,486	1,512	573
R^2	0.98	0.95	0.75	0.64	0.52	0.53
B. Year 2011						
Above the thresh.	-4.74*** (1.24)	-1.83*** (0.57)	-6.38*** (1.65)	-4.75*** (0.62)	-3.01*** (0.34)	-3.21*** (0.64)
Obs.	45,216	21,175	16,667	4,798	1,749	684
R^2	0.98	0.95	0.77	0.68	0.58	0.58
C. Year 2012						
Above the thresh.	-1.24*** (0.38)	-1.43** (0.57)	-1.41*** (0.39)	-0.90* (0.47)	-0.78 (0.74)	-0.60** (0.22)
Obs.	49,064	20,615	18,388	6,493	2,400	978
R^2	0.98	0.95	0.84	0.74	0.52	0.59
D. Year 2013						
Above the thresh.	-1.88*** (0.23)	-2.49*** (0.58)	-2.00*** (0.27)	-1.57*** (0.40)	-1.11*** (0.23)	-1.09*** (0.29)
Obs.	51,621	19,391	19,949	7,842	2,927	1,269
R^2	0.98	0.95	0.83	0.73	0.66	0.49
E. Year 2014						
Above the thresh.	-2.87*** (0.33)	-2.07*** (0.51)	-2.96*** (0.51)	-3.70*** (0.35)	-2.30*** (0.25)	-2.22*** (0.17)
Obs.	53,706	18,199	20,880	9,425	3,346	1,592
R^2	0.98	0.94	0.81	0.70	0.58	0.38
F. Year 2015						
Above the thresh.	-4.46*** (0.51)	-2.75*** (0.69)	-3.97*** (0.62)	-5.38*** (0.61)	-5.94*** (0.63)	-3.42*** (0.62)
Obs.	58,738	17,881	21,551	12,334	4,517	2,009
R^2	0.98	0.93	0.79	0.66	0.54	0.47

Notes: Second-digit bias regression estimates of the effect of the asking price on the logarithm of the final transaction price (in thousands SEK), using a bandwidth of 50,000 SEK around the threshold. In column 1, we pool observations from all 100,000 SEK thresholds, whereas in columns 2 through 7, we estimate the effect only for apartments with an asking price between 0 and 1 million SEK, between 1 and 2, and similarly for all millions separately. We use a local linear control function allowing for different slopes at each side of each threshold. Controls include living area, the number of rooms, monthly fee, and year of construction, plus month-year and year-parish fixed effects. Standard errors are clustered at the municipality level.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 18: Balance of covariates - around 100,000 SEK thresholds

	Pooled	0-1M	1-2M	2-3M	3-4M	4-5M	5-5.5M
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Squared meters	-0.012 (1.05)	2.48*** (0.78)	0.048 (1.56)	-1.64 (1.47)	-3.35** (1.50)	1.00 (2.01)	1.04 (3.87)
Obs.	307,662	121,342	115,403	45,716	16,600	7,178	1,423
R^2	0.05	0.00	0.00	0.01	0.01	0.01	0.01
Year Constr.	-0.11 (1.56)	2.36*** (0.87)	1.16 (2.11)	-1.37 (1.32)	-6.44*** (1.61)	-4.23** (1.67)	-5.85** (2.74)
Obs.	307,896	121,441	115,495	45,750	16,607	7,180	1,423
No. Rooms	0.0021 (0.047)	0.095*** (0.031)	0.019 (0.069)	-0.062 (0.054)	-0.16*** (0.047)	0.019 (0.047)	-0.043 (0.098)
Obs.	307,501	121,257	115,354	45,699	16,594	7,176	1,421
Monthly fee	-11.6 (59.7)	121.5** (48.0)	20.2 (76.1)	-99.5 (76.2)	-221.3*** (77.4)	-123.3 (82.4)	-80.1 (177.2)
Obs.	307,398	121,330	115,276	45,649	16,570	7,156	1,417
Floor	-0.075 (0.055)	-0.094* (0.052)	-0.077 (0.062)	-0.064 (0.061)	-0.041 (0.13)	-0.065 (0.053)	-0.12 (0.21)
Obs.	256,780	102,692	96,882	37,451	13,035	5,608	1,112
Elevator	-0.0089 (0.021)	-0.012 (0.013)	-0.0029 (0.023)	-0.013 (0.042)	-0.017 (0.033)	-0.0099 (0.013)	0.011 (0.015)
Obs.	265,027	101,149	99,130	41,131	15,415	6,839	1,363
Balcony	0.0030 (0.016)	-0.0019 (0.020)	0.0032 (0.017)	0.013 (0.024)	0.0096 (0.036)	-0.053 (0.035)	0.042 (0.046)
Obs.	98,907	36,366	40,670	14,796	4,842	1,892	341

Notes: Regression estimates of the effect of the asking price on different apartment characteristics around 100,000 SEK thresholds. We report the coefficients of an indicator for the asking price being at the threshold or just above. In column 1 we pool observations from all 100,000 SEK thresholds, whereas in columns 2 through 7, we estimate the effect only for apartments with an asking price between 0 and 1 million SEK, between 1 and 2, and similarly for all millions separately. We use a local linear control function allowing for different slopes at each side of each threshold. No controls or fixed effects included. Standard errors are clustered at the municipality level.

* $p < 0.1$, ** $p < 0.05$, *** $p < .01$

Table 19: Balance of covariates for the sample of repeated sales

	Living area	N.rooms	M.fee	Year constr.	Time since last sale	Lag ask price	Lag price
Above thr.	-2.61* (1.47)	-0.12** (0.059)	-155.0 (93.7)	-2.00 (2.18)	-74.3* (41.7)	-4.83*** (1.66)	-5.47*** (1.36)
Obs.	3,615	3,613	3,613	3,616	3,603	3,616	3,616
R^2	0.076	0.057	0.022	0.033	0.008	0.854	0.883

Notes: Regression estimates of the effect of the asking price on different apartment characteristics. We report the coefficients of an indicator for the asking price being equal or above the threshold. The sample is restricted to apartments sold more than once after at least 2 months. We use a local linear control function allowing for different slopes at each side of each threshold. No controls or fixed effects included. Observable characteristics are lagged, that is, they refer to the previous sale. Time since last sale is measured as days since the previous sale. Lag ask price is the logged asking price of the previous sale. Lag price is the logged final sale price of the previous sale. Standard errors are clustered at the municipality level.

* $p < 0.1$, ** $p < 0.05$, *** $p < .001$

Table 20: Baseline results for the sample of repeated sales

	Repeated sales sample	Adding controls	Apartment FE
Above thr.	-6.94*** (1.24)	-6.39*** (1.39)	-3.28 (4.11)
Lag price		0.094*** (0.031)	
Time since last sale		0.0028*** (0.00071)	
Obs.	7,159	3,596	7,159
R^2	0.959	0.970	0.997

Notes: Regression estimates of the effect of the asking price on the logarithm of the final transaction price (in thousands SEK). The sample is restricted to apartments sold more than once after at least 2 months. In the first column, we estimate our baseline first-digit bias effect of the asking price on the final price using the restricted sample only. In the second column, we add the price of the previous sale (in logs and multiplied by 100) and the time since last sale (in days) as controls. In the last column, we estimate the baseline effect including apartment fixed effects. All specifications include controls such as living area, the number of rooms, monthly fee, and year of construction, plus month-year fixed effects. Columns 1 and 2 also include year-municipality fixed effects, while in column 3 we only include apartment fixed effects. Standard errors are clustered at the municipality level. The bandwidth is 100 thousand SEK at either side.

* $p < 0.1$, ** $p < 0.05$, *** $p < .001$

Table 21: The effect of the introduction of price brackets on *Hemnet.se*

	(1)	(2)	(3)	(4)
A. Using observations for 2011 only				
Above the threshold	-6.30*** (1.89)	-6.39*** (1.85)	-6.79*** (1.31)	-6.76*** (1.39)
Above the threshold*Post	-0.20 (0.75)	-0.14 (0.70)	-0.0092 (0.72)	0.14 (0.73)
Post	-4.85*** (1.15)	3.87*** (0.79)	2.96*** (0.68)	2.72*** (0.71)
Obs.	8,083	8,061	8,061	8,030
R^2	0.93	0.94	0.95	0.96
B. Using all sample, 2011-2015				
Above the threshold	-5.60*** (1.35)	-5.58*** (1.32)	-5.72*** (0.91)	-5.85*** (0.94)
Above the threshold*Post	-0.029 (0.52)	-0.072 (0.48)	0.11 (0.47)	0.37 (0.53)
Post	0.61 (0.80)	1.11* (0.58)	0.33 (0.36)	-0.26 (0.41)
Obs.	57,411	57,245	57,245	56,996
R^2	0.95	0.95	0.96	0.96
Controls		✓	✓	✓
Fixed Effects			Year × Municip.	Year × Parish

Notes: Regression estimates of the effect of the asking price on the logarithm of the final transaction price (in thousands SEK) from equation 1, pooling all 1 million thresholds together and using a bandwidth of 100,000 SEK. We use a local linear control function allowing for different slopes at each side of each threshold. Standard errors are clustered at the municipality level. Controls include living area, the number of rooms, monthly fee, and year of construction, plus different sets of fixed effects. Month-year fixed effects are also included in all columns but the first. *Post* is one for apartments sold after the change in the *Hemnet.se* interface on March 12, 2011 (see Section 6 in the text for details).

* $p < 0.1$, ** $p < 0.05$, *** $p < .01$