Cognitive Reference Points, the Left-Digit Effect, and Clustering in Housing Markets

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Abstract

Using a quasi-experimental setting of two similar properties listed only $100 apart, but with a different left digit, we document that properties listed with smaller left digits are 3.8% more likely to sell, stay 5% fewer days on market, and sell for 0.1% more. Additionally, buyers of these homes are more likely to have a lower credit score, lower income, higher leverage and pay a higher interest rate on their mortgage, resell for a lower rate of return, and are more sluggish in refinancing their mortgages. Our results highlight how behavioral biases can affect even high-value purchases such as housing.

Keywords: Left-digit effects, Real estate, Financial sophistication

JEL Classification: D4, D12, G10, L1, L8, R2, R3, R20

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I. Introduction

Do behavioral biases affect even large household decisions like housing transactions? It is well documented that people use cognitive reference points, that is, standard benchmarks against which other stimuli are judged (Rosch, 1975). The left-digit effect manifests when the left digit dictates how a consumer's brain works and a change in the left-digit of a price causes people to move from one cognitive reference point to another. For example, $3.99 is perceived to be significantly less than $4.00, not just one cent less, due to the left digit effect. Hence, retail prices are often set to end in a 9 (e.g., $3.99 instead of $4.00).[1] But, housing purchases are much more consequential than retail purchases and given housing is the dominant asset of a typical U.S. household, any systemic mistake in housing decisions is of significant economic importance and may have major policy implications. In this paper, we analyze whether households exhibit behavioral biases in housing transactions. Specifically, we analyze whether the left digit of the listing price has a significant impact on the sales transaction and whether these buyers make other mistakes in their housing and mortgage decisions.

We first examine the clustering patterns in list and contract prices using single-family listing and sale records from 1990 to 2014 from multiple listing services (MLSs) for the 14 largest and most diverse metropolitan statistical areas (MSAs) in the United States. We document significant clustering around listing prices with the rightmost digits of 900 or 1,000. A total of 85% of the rightmost digits of all listing prices are either 900 (e.g., $329,900) or 1,000 (e.g., $330,000), with 40% and 45%, respectively. We also analyze sales contract prices and find similar clustering around prices with the rightmost digits of $1,000.

We next examine the determinants of these two listing strategies: listings with prices ending with 900 versus those ending with 1,000. There is an overall negative relation between the likelihood of listing houses at prices with smaller left digits and lower property values. The choice of a left-digit strategy has a significant relation with the listing price level rounded down to the nearest $10,000. Also, the listing agent's past performance has a very significant and positive effect on choosing the smaller left-digit strategy – one extra successful sale in the past year increases the likelihood of a smaller left digit listing by 2.1%. We also find that in tighter housing markets with shorter average

[1] Stiving and Winer (1997) attribute the effectiveness of the strategy to two effects. One is the level effects as a cognitive process that causes the buyer to underestimate the perception of a price. The other is image effects that cause the consumer to believe that the product has higher quality and the store has set the price at the lowest possible amount, given prevailing market conditions.

time on the market, wherein the seller has potentially more bargaining power, sellers are more likely to adopt a smaller left-digit strategy and vice versa.

Do home buyers perceive listings with prices ending with 900 versus those ending with 1,000 to have a much greater difference in their price than \$100? Based on the aforementioned evidence of clustering in listing prices, our identification strategy focuses only on listing prices ending with either 900 or 1,000. We thereby create a quasi-experimental setting that exploits the sale outcomes of two properties that have identical property attributes, list date, and location, but with a \$100 difference in their prices and a different left-digit.

Our baseline results with MLS data indicate that properties listed at prices with smaller left digits, compared to very similar properties that are listed for \$100 more but potentially perceived as being much more, are 3.8% more likely to be sold. Their time on the market is 3.5 days less and they are sold at a 0.1% higher price, or \$431. The gain represents a net fourfold return on the initial \$100 investment. The 3.5-day savings of time on the market alone is roughly 5% of the average listing time.[2] In addition, there are significant benefits for sellers when their property spends less time on the market, such as avoiding prolonged uncertainty. The estimated gains from the sale price are very robust across most home values. The magnitude of the gains generally increase with home value, ranging from \$149 for less expensive homes to \$5,098 for luxury homes.

We next explore the importance of the relative bargaining power of the buyer and seller, as well as market demographics. To do so, we divide the sample into terciles for these dimensions and compare the coefficients of the smaller left-digit listings between the lowest and highest terciles. We find much stronger effects when buyers have potentially more bargaining power (in soft housing markets with high DOM) and where there are many less sophisticated buyers.

We run a number of tests to explore possible explanations of the estimated effects on sale outcomes besides buyers' behavioral bias. One alternate explanation for the left-digit effects that we document is that buyers may be using filters at or below round numbers to limit the search results. Since we do not observe the number of offers to different listing prices, we take an alternative approach by focusing on properties listed at exact multiples of \$100,000 that are commonly used as the minimum

[2] Assuming the realtor expects to collect a standard 3% commission rate when the property is sold and an annual discount rate of 20%, that is the equivalent of \$300 extra value for the average sales contract price.

and maximum search values. We do not find any evidence that supports more favorable outcomes for properties listed at these round numbers. Moreover, to the extent that the search is set with a maximum value that includes listings with cutoffs at round numbers of $1,000, our results are likely to be downward biased.

We also address potential measurement errors in the sales contract price, since the seller could provide incentives to the buyer in other pricing terms, such as assistance with closing costs and mortgage rates that are not captured in the contract price, which would distort the measured left-digits in the final sales price. Our results suggest that there is little difference in the effect on the sales price between new and relatively new properties.

Realtors, especially the agent who helps the seller set the initial listing price, are important players in a housing transaction. We find that when listing agent fixed effects are included, the effect of a smaller left digit on the sale's likelihood, DOM, and the sales price are still statistically significant, with greater magnitude. With the interaction with top-performing agents included, we find that, on top of the base effects, properties listed by top-performing realtors increase the sale likel ihood by 0.6% (or 60% increase), shorten time on the market by another 3.4 days (or 50% increase), and increase the sale price by 0.4% and $361. These results suggest that seller's agents, especially top-performing ones, play a significant role in achieving better listing outcomes from a left-digit strategy.

Next, we adopt conforming loan limits (CLL) as an exogenous instrument that would stipulate prospective buyers' home purchase decisions and add four interactions of a smaller left-digit dummy with indicators for borrowers borrowing at different amounts relative to CLLs in a given year[3]. Because interest rates are often higher for jumbo loans, some borrowers with a loan demand near the CLL may borrow less than they would otherwise to take advantage of the lower rate. As borrowing approaches the loan limit, there should be more demand for home purchases. Our results indicate that as buyers borrow near the CLL, the left-digit effects significantly increase with the sales price, both as the percentage and the dollar amount, and decrease with DOM. All else being equal, a greater credit supply at the conforming loan limits significantly shortens the time on the market and

[3] Researchers have considered the role of the credit supply induced by government policies at the level of asset prices and the development of bubbles (Hubbard and Mayer 2009; Loutskina and Strahan 2009; Di Maggio et al. 2015; Favara and Imbs 2015). Adelino, Schoar, and Severino (2012) and An and Yao (2016) provide evidence that changes in conforming loan limits have a positive causal effect on home purchases.

increases sale prices.

In the final part of the analysis, we use a matched mortgage sample to further explore the characteristics of the buyers and their performance in subsequent mortgage outcomes. We run a linear probability model containing a full array of borrower and mortgage attributes using a sample of the borrowers who purchased left-digit listed houses. These buyers are more likely to have a lower credit score and lower income and to be more leveraged on their household balance sheets than those in the control group. The results are consistent with studies of the financial mistakes made by households (Calvet, Campbell, and Sodini, 2009; Agarwal, et al 2016).

If the the left-digit effects that we document are driven by a behavioral bias of buyers, then they are also more likely to make future housing decision mistakes. Our findings indicate that buyers of left-digit listed properties tend to pay a 17 bps higher interest rate. In addition, when these buyers sell the property, they tend to achieve a 4.2% lower return over a five-year holding period. Controlling for home price as well as interest rate changes, there is no significant difference in default outcome between buyers who bought properties listed with smaller left digits and the others. However, in response to a mortgage interest rate drop of 1% relative to their original mortgage rate, buyers who purchased left-digit listed properties in the past have a 16% lower probability of refinancing, which is about 2% less than the other buyers. These results are consistent with borrower inattentiveness, suggesting that these homeowners are not actively managing their finances and do not make optimal financial decisions.

Our paper is closely related to Pope, Pope and Sydnor (2015), who document a sharp increase in the distribution of house sale prices at multiples of $50,000 using a sample of national housing transactions during 1998 and 1999. Our results while consistent with their results, also focus on the clustering pattern in listing prices as the seller's competitive listing strategy to exploit gains from prospective buyers and the ex-post outcomes for the buyers. Allen and Dare (2004) use the term "charm price" to characterize houses with prices ending in 500, 900 and 1,000 in Broward County, Florida and find positive transaction price effects associated with most charm listing prices. We conduct more in–depth analysis on a more representative national sample and attempt to rule out alternative explanations. We highlight the role of top-performing listing agent in the use of the left-digit strategy. Most importantly, our analysis of the buyers of left-digit listed homes shows that these buyers are more likely to make other mistakes in their future housing decisions is an additional contribution to this literature.

Our paper contributes to the extensive literature on heuristic thinking in behavioral economics and behavioral finance. Brenner and Brenner (1982) present a theoretical model where people only remember a limited amount of the prices of thousands of goods. The authors note that the economic value of remembering the first digit is much greater than that of remembering the second, and so on. A number of studies provide evidences of left-digit effects in banks' deposit rates, consumer goods, used cars, and stock markets.[4] We examine such evidence in the context of housing markets, one of the most consequential decisions made by households in the U.S.

Our analysis also broadly contributes to the literature that documents mistakes in household financial decision making in general (See Campbell (2006), Campbell, et al. (2011), Agarwal, et al. (2014), and Agarwal, et al. (2015)). Relatedly, DellaVigna and Malmendier (2006) show that gym members underutilize their gym memberships. Akin to the current study, these gym members overstate the benefits from the contracts offered and pick the wrong one. Examples of other mistakes made by households include individuals leaving money on the table in their 401(K) decisions (Choi, Laibson, and Madrian, 2011), borrowers taking out payday loans with astronomical annual percentage rates when other, cheaper forms of credit are available (Bertrand and Morse, 2011), and consumers with multiple credit card offers failing to optimally choose the right one (Agarwal, et al. 2015).[5] People who buy left-digit listed properties are another example of these types of behavior biases in household financial decision making.

The remainder of the paper is structured as follows. We describe the data in Section II and document the clustering in list and contract prices based on MLS data in Section III. Our identification strategy and main left-digit results are presented in Section IV. Section V explores alternate explanations for the left-digit effects. We analyze the buyer attributes and mortgage performance of

[4]See Ahn, et al. 2005; Christie and Schultz 1994; Harris 1991; Kahn, Pennacchi, and Sopranzetti 1999; Kavajecz and Odders-White 2004; Knoteck (2011); Bhattacharya and Holden (2012); Lacetera, Pope, and Sydnor 2012; Manning and Sprott 2009; Pope , Pope, and Sydnor 2015; Thomas and Morwitz 2005.

[5]More broadly, it is puzzling that less than 30% of U.S. households participate directly in equity markets (Li, 2014) and, among those who do hold stocks, many have highly concentrated portfolios and trade excessively (Korniotis and Kumar, 2011, 2013). Stango and Zinman (2009) find that U.S. borrowers regularly underestimate the annual percentage rate of a loan if they are given only the loan principal and repayment stream. Bertrand and Morse (2011) find that payday loan borrowers who are shown information on the aggregate cost of their loan or the time to repayment frequently borrow significantly less per pay cycle.

left-digit buyers in Section VI. We conclude in Section VII.

II. Data

In this section, we describe our data sources and the construction of the variables in our empirical analysis and present descriptive statistics of the data.

A. Data Sources

Our primary data source is the listing and sales records from the 14 largest and most diverse MSAs in the United States. All of these MLSs are covered in the Case–Shiller 20-City Home Price Indexes and represent more than half of all housing transactions in the country, with good data coverage since 1990. These MLSs act as the clearinghouses through which the realtors in each market advertise properties for sale. Although many platforms provide the listing information (e.g., Realtor, Redfin, and Zillow), each independent MLS board remains the primary data source for all of them. There are many advantages to using the MLS data. First, they cover virtually every house for sale in a local market, regardless of whether the house eventually sold. Therefore, there is no selection bias. Second, the data contain detailed information about properties on the market, such as the exact location, detailed housing characteristics, the initial listing price, the listing date, and the date when the house went under contract, as well as the contract price. From this information, we can define several variables to measure the listing outcomes from the perspectives of listing agents and sellersthe variable $SOLD$ equals one when the property is sold, the number of days on the market (DOM), and $Price$ is the sales price. The sales price can also be measured as a ratio to the initial listing price that measures whether the house sold at a premium or a discount. Third, each listing is associated with a hired realtor or real estate agent with a unique ID. We can thus track the performance of individual realtors. Fourth, since the address is geocoded, we can track the sales history of individual properties to explore the resale returns of the buyers, even though we do not link the MLS data to public records.

The MLS data have, however, some important limitations. For example, because the information is entered into the databases by the realtors themselves, there is no independent check of the accuracy of the property descriptions, especially when compared to other sources, such as public information used by tax assessors or collected by appraisers in the field. As pointed out in other studies, some variables are missing substantial data, such as property age, which is one of the most important characteristics of a property's condition and market value. Other data, such as the lot size, lack uniform standards regarding units (e.g., square feet vs. acres) or precision (e.g., exact numbers vs. a range). Therefore, we exclude any record with invalid data values for prices, zip codes, and property characteristics. All listings with a listing price above $1 million or below $49,900 are excluded from the sample. We supplement the MLS data with decennial census information at the county level. We use the percentage of people with a higher education to delineate the demographics of the individual markets. To supplement buyer information, we use mortgage data that captures mortgages obtained by buyers to finance their home purchases. We also employ a nationally representative loan-level mortgage sample from one of the largest mortgage insurers in the country. The data contain detailed information on mortgage origination, as well as dynamic performance tracked monthly. Our sample covers mortgage origination information from 2001 to 2013, with performance updated through 2014. The information at origination includes the borrower's credit score (FICO), loan-to-value (LTV) ratio, and debt-to-income ratio; the loan purpose; the occupancy status (e.g., owner-occupied vs. investment); the property type (e.g., single-family house, condominium); the level of documentation (low vs. full); the loan amount; the interest rate type (fixed vs. adjustable); and so forth. We restrict our sample to fully documented, fully amortized 30-year fixed-rate mortgages, which account for the vast majority of prime conforming loans, to focus on a more consistent and pristine mortgage profile. To obtain listing information from the MLSs, we match the mortgage data with MLS data using MSA data, the date, and the sales price in thousands of dollars. The final sample contains 240,261 matched loans. Each loan is tracked in dynamic files until the borrower defaults or prepays the loan. Default is defined as the borrower missing at least three consecutive payments, so-called serious delinquency. The borrower may prepay the loan for the purpose of moving or refinancing.

B. Summary Statistics

Table I, Panel *A*, reports statistics based on the overall sample. Our sample contains about 7.33 million listings from 1990 to 2014 in the 14 largest MSAs. Among them, about half, or 3.53 million, of the listings sold. The average listing price is $281,665, while the average contract price is $234,627. The average number of days on the market is 68 days. The average ratio of sale to listing price is 97%, suggesting that most properties sell below the initial listing price. Among all the properties sold, 16%, 15%, and 69% sold above, exactly at, and below the listing price, respectively. The average house living area is 1,796 square feet, with a lot size of 0.52 acres and a property age of around 29.5 years. The average percentage of residents with a bachelor's degree or higher education at the county level is 28.5%, based on county census data. We also use the average number of days on the market in the previous three months in a given zip code to measure real-time market conditions, which averages out to be two months. A low number of days on the market value indicates a potentially overheating market with more demand than supply, while a high one indicates a slow market that takes longer to clear.

Panel B of Table I reports the overall summary statistics of variables contained in the loan-level sample matched with the MLS sample, where we observe information on the borrowers who bought properties listed at smaller or greater left digits. There are 240,261 loans in our sample that are restricted to listing prices with rightmost digits of either 900 or 1,000. These mortgages are conventional conforming loans (not government insured) made to prime borrowers. Conforming mortgages meet the government-sponsored enterprise (GSE) conforming loan limit, which has been $417,000 since 2006 for single-family one-unit properties in most of the United States. The average mortgage note rate is 6.0%. The average FICO score of all borrowers is high, at 724, since they are all prime conforming loans, and 6% of borrowers have a FICO score below 620. The average LTV ratio is 81.0, with 26% of loans having an LTV ratio at and above 90. Borrowers, on average, are aged 41 years, with 40% younger than 35. The average monthly income is $7,523 and we define the lowest 25% of mortgagors as low-income borrowers. A total of 7% of the loans in the sample are for investment purposes, as opposed to those for a primary residence; 52% of the loans are originated by brokers, as opposed to retail banks. The average backend debt-to-income ratio that includes monthly mortgage payments is 38%. The average loan amount borrowed is $194,394. From the LTV ratio and loan amount, we also derive the final purchase price, in addition to the initial listing price and the sales price under contract from the MLS data, which average $246,679, $254,547, and $246,562, respectively. Differences between the contract prices and final sale prices can be attributed to origination fees, closing costs, and points that are capitalized in the mortgage. In our sample, 32% of borrowers are first-time homebuyers, who may lack experience managing their mortgage accounts, and 29% are non-white minorities, who are often underrepresented in the credit market.

Loans can terminate due to refinancing to a new loan for the purpose of rate savings, default caused by adverse events such as unemployment or divorce, or resale in order to move. In our sample, 69% of the loans were refinanced by the end of 2014, which includes both true refinances and moves; 11% of loans defaulted and the others were still active. From the public records, we were able to match the resale deeds for some movers, who represent 28% of the sample. Of these, the average resale appreciation (or return) is 7.3% over the holding period. The average loan duration is 59 months.

III. Evidence of Clustering

In this section, we explore possible clustering patterns in both the listing and contract prices in housing transactions. There is much evidence that the prices of convenience goods as well as financial products are set at levels that either simplify transactions or attract more demand (e.g., Kotek 2011; Bhattacharya and Holden 2012).

Consider a standard two-party Nash bargaining model with a buyer and a seller, both risk neutral. A house on the market has an investment value of P_s from the seller's perspective and an investment value of P_b from the buyer's perspective. The listing agent/realtor also provides a best estimate of the most probable selling price based on current market conditions, since, with a fixed commission rate, typically 3%, the listing agent's primary objective is to sell the house in the shortest amount of time. The potential buyer also hires a realtor. The respective investment values of the buyer and seller are influenced by the realtor's opinions (knowledge and experience), depending on the realtor's search efforts and market conditions. When sellers have strong bargaining power, the influence of realtors should be minimal. Market conditions also determine the bargaining power of the buyer and seller. The listing price in the MLS data is captured by the variable P_s. Once a house is put on the market, it can be sold only if the contract price, P_m, is at or above P_s and at or below P_b. The difference between P_s and P_b is the maximal negotiable price or the gains for either the buyer or the seller. We have $P_m = W_s$ x P_s + (1 - W_s) x P_b, where W_s defines the seller's bargaining power and 1 - W_s is the buyer's bargaining power.

A. Listing Price

Compared to the contract price, the initial listing price is the seller's asking price, P_s. Yavas and Yang (1995) explore the role of the original listing price in marketing real estate and find that the seller's choice of listing price depends on the seller's valuation of the property and relative bargaining power, the seller's agent's incentives, and the seller's strategic consideration of signaling to the market. Genesove and Mayer (1997) provide evidence that the seller's motivation to sell, measured by the seller's equity position, operates primarily through the original listing price and its variation reflects most of the variation in the seller's reservation price.

We first plot the distribution of the last three rightmost digits in the listing price in Figure 1(a). The listing prices are clearly clustered around those with rightmost digits 900 and 1,000; 85% of the right digits are either 900 or 1,000, 40% and 45%, respectively. This suggests it is most popular to list the property for sale at a price ending with either 900 or 1,000. Another 6.6% of the listing prices end up with the right digits 500. These three sets of rightmost digits combined account for 91% of all listing prices. It is possible that the pattern of clustering in listing prices is concentrated at certain price levels. In Figure 1(b), we plot the percentage of listings with clustered prices, defined as those with listing prices with the rightmost digits 900 or 1,000, by listing price rounded down to the nearest $10,000. The results show that the percentage of listings with clustered prices is well above 85% and has a direct relation with the price level. More than 90% of the properties valued above $500,000 listed with rightmost digits of 900 or 1,000, this percentage peaking at 94% for luxury homes near and above $1 million.

To explore differences in the two most commonly adopted rightmost digits in listing prices, 900 and 1,000, we also plot the percentages of these two types of price listings in Figure 1(c). The chart shows striking differences in the patterns of the listings. The percentage of listings with prices ending with 1,000 has a direct relation to price levels, while the share of listings with prices ending with 900 has the opposite, inverse relation. The difference is not very significant for homes worth less than $300,000, each group accounting for 40% of all homes on the market. Homes worth more are more likely to list at prices ending with 1,000 and less likely to list at prices ending with 900. The percentage of listings with prices ending with 1,000 steadily increases to above 60% once the price reaches $500,000, while the share of listings with prices ending with 900 drops to below 20%. Figure

1(c) shows a significant temporal increase or decrease in both series at certain price intervals. In Figure 1(d), we provide an alternative way to visualize the clustering of listing prices at key price intervals. We plot residuals from a regression of the percentage of homes listed at prices ending with 900 in a higher-order (fourth-order) polynomial of the listing price. By using the residuals, we eliminate the smooth home price trend component and focus on the unexplained components. We find sizable levels of unexplained mass in certain bins. For example, there are significantly more homes with listing prices ending with 900 than expected when the rounded listing prices end with 40,000, for example \$340,000, \$440,000, \$540,000, and \$640,000, and so forth. There are fewer homes with listing prices ending with 900 than expected when the rounded listing prices end with 0 or 50,000, for example \$300,000, \$350,000, \$400,000, and \$500,000, and so forth. As expected, the positive and negative residuals in the share of listings with prices ending with 900 complement the negative and positive residuals of the share of listings with prices ending with 1,000.

B. Contract Price

Once the buyer and seller agree on pricing terms and sign a contract, the house will proceed to close, pending on the appraisal, house inspection, and the buyer's mortgage approval. Therefore, the contract price, P_m, reflects both parties' values, as well as their relative bargaining power. Pope, Pope, and Sydnor (2015) document sharp increases in the distribution of house prices under contract at exact multiples of \$50,000. They attribute the observed clustering pattern as evidence of focal points in the buyer–seller negotiations.

In Figure 2(a), we plot the distribution of the last three rightmost digits in the listing prices. The contract prices are clustered around the rightmost digits of 1,000, this cluster accounting for 70% of all sold properties. Listings with the rightmost digits 900 and 500 account for 9% and 11% of the listings, respectively. In Figure 2(b), we plot the percentage of prices ending in 1,000 among all contract prices rounded down to the nearest \$5,000. The percentage also has a direct relation with price levels, at approximately 40% for extremely inexpensive homes, increasing to above 70% for homes worth more than \$200,000 and increasing further to above 80% for homes worth more than \$400,000. Among sold homes costing more than \$600,000, those sold at round number prices (prices ending in 1,000) account for nearly 90% of all sales. These findings are all consistent with those of Pope, Pope, and Sydnor (2015), since $50,000 is also a multiple of 1,000.

C. *Differences between the Two Listing Strategies*

We next test whether home buyers perceive two nearby and similar listings with only a difference in their prices' rightmost digits—900 versus 1,000—to have a much greater difference in their prices' left digits. These tests parallel the penny-wise and dollar-foolish experiments in marketing research. We now define the listings with prices ending with 900 as having smaller left digits and those with prices ending with 1,000 as having larger left digits. We consider listings with prices with smaller left digits as following left-digit list strategies and those with prices with larger left digits as following an alternative strategy. We focus only on listings with prices ending with 900 and 1,000, which account for the vast majority of all listings.

We first explore differences in observables in summary statistics to understand why the seller and the seller's agent choose to list at prices with smaller rightmost digits, as well as the resulting smaller left digits. The overall listing prices are split exactly 50/50 between those with smaller left digits and those with larger ones. In Panel C of Table I, we compare the characteristics between the two respective left-digit subsamples. The average listing price for the smaller left-digit subsample is $230,655, only 71% of that for the greater left-digit subsample. This indicates that less expensive properties are more likely to be listed at prices with smaller left digits, a difference in composition. The likelihood of listings at prices with smaller left digits being sold is 51.8%, five and half points higher than those with larger left digits. The average time on the market is 66.7 months, three months shorter than otherwise. Consistent with lower listing prices, the contract prices for the smaller left-digit subsample are also lower, with a 0.3% higher sale to list price ratio. The percentage of properties sold above the listing price is 2% higher for those listed at prices with smaller left digits, while the percentage of properties sold at exactly the listing price is 7% lower for those listed at prices with smaller left digits. All the other variables, including house characteristics and county-level education level, as well as prior DOM values in the same zip code, are very similar between the two subsamples, suggesting these have comparable properties.

We also compare the mortgage characteristics for the two left-digit subsamples in Panel D of Table I. Compared to buyers of properties with prices with greater left digits, those who buy properties with prices with smaller left digits have lower FICO scores (by seven points), a higher LTV (by two points), are younger (by one year), earn less (by 15%), have a higher backend debt ratio, and are equally likely to be first-time homebuyers. Regarding their loan outcomes, their average note rate is 30 basis points higher, reflecting their relatively poor quality. This subsample has a much higher default rate, 12% versus 10% for the other subsample. It also involves more refinancing, 71% versus 67%. In terms of resale outcomes, this subsample's movers' resale appreciation is much lower, 5.7% versus 9.4% for the other subsample. The other characteristics are similar across the two subsamples.

Next we examine the seller's choice of a smaller left-digit list strategy on information as of the listing date. In the regression, the right-sided variables include property characteristics, the listing agent's past history, local housing market conditions, the percentage of residents with a bachelor's degree or higher at the county level, the time, the location, and price levels. In addition to controlling for the listing price and its square, the regression for the results in Figure 1(d) also includes indicators for whether prices are near round multiples of $10,000 to capture sizable levels of unexplained mass. The seller's agent's past history is defined as the listing agent's number of successful sales in the prior year. We use the average DOM value in a given zip code in the prior three months to measure local housing market conditions. A higher DOM value indicates a soft market, where the buyer has more bargaining power than the seller. A lower DOM value indicates a tight market, where the seller has more bargaining power than the buyer or the seller's agent. The percentage of residents with a bachelor degree or higher provides a good view of the sophistication level of the local buyers and sellers.

Table II reports the results of a linear probability model. We control for the county-level percentage of those with a bachelor's degree or higher instead of MSA fixed effects and report the results in column (1). We next control for the local DOM at the zip code level instead of zip code fixed effects and report the results in column (2). We then control for zip code fixed effects and report the results in column (3). We find an overall negative relation between the likelihood of listing at a price with smaller left digits and property value, measured as a positive coefficient for the logged listing price and a negative coefficient for the squared log price. As in Figure 1(d), the choice of a left-digit strategy has a significant relation with the listing price rounded down to the nearest $10,000. Among all the bins defined on the four rightmost digits, the seller is much less likely to adopt a left-digit listing strategy if the price is near a multiple of $100,000 (e.g., $400,000–$409,999, $700,000–$709,999) and much more likely to do so if the price is near a multiple of $50,000 (e.g., $450,000–$459,999, $750,000–$759,999), as well as ending in $40,000 and $60,000. Property age matters in the choice of listing strategy, that is, older homes are less likely to be listed with a left-digit strategy. The listing agent's past performance has a very significant and positive effect on choosing the smaller left-digit strategy. One extra successful sale by the listing agent in the past year increases the likelihood of using the smaller left-digit strategy by 2.1%. In column (2), when MSA fixed effects are controlled for, we find local housing market conditions to also be important. In a tighter market with a shorter DOM value, where the seller has more bargaining power, sellers are more likely to adopt a smaller left-digit listing strategy and vice versa. According to the results in column (1), a smaller left-digit listing strategy is more common when buyers and sellers are more educated.

IV. Left-Digit Effects

In this section, we explore the possible outcome effects of a listing price with smaller left digits. We first design a plausible identification strategy to evaluate differences in listing outcomes resulting from the two different listing strategies. Following our baseline analysis, we test for alternate explanations for the estimated left-digit effects.

A. Identification Strategy

Based on the observed clustering pattern above, our identification strategy for analyzing left-digit effects focuses only on listing prices ending with either 00 or ,000. Comparing two similar listing prices, such as $329,900 versus $330,000, while the actual difference between the rightmost digits 00 and ,000 is only 00, we find that the implied left digits of these two right digits can be perceived to differ by a much greater ,000. The setting is very similar to the penny-wise and pound-foolish experiments where researchers compare consumers' perceptions and purchase attitudes of two products: Although $100 is 10,000 times one cent, it accounts for 1% of $100,000, which is similar to one cent relative to a dollar. We thus explore the possible differences in listing outcomes resulting from the buyer's perception of a much larger left-digit effect with a very negligible dollar difference.

Because our data contain a large number of listings, we use a regression discontinuity design between the two sets of listing prices or pairs that are only $100 apart and compare the listing outcomes within each of the price pairs. By controlling for MSAs, list date fixed effects, and an array of property attributes, we create a quasi-experiment that contains two sets of comparable properties that are listed at the same time and in the same market and that could have been listed at the same price and had similar listing outcomes. However, the one that is listed at $100 lower appears to have much greater left digits, by ,000, potentially leading to different listing outcomes. More formally, to analyze the effect of the left digits on listing outcomes, we run linear regressions of the following form:

$$
\begin{aligned}
Y_{i,t} = \beta_i * H_i + \beta_2 * \text{Zip Code}_i + \beta_3 * \text{Time}_t + \beta_4 * \text{Price Pair}_i \\
+ \beta_5 * \text{Price Pair}_i * \text{Smaller Left Digit}_i + \epsilon_{i,t} \qquad (1)
\end{aligned}
$$

where Y_i, t is the listing outcome of property i at time t; H_i is the property's characteristics that determine the value of the property, such as the square footage of the living area, the lot size, and the age of the property; $Zip - Code_i$ is the MSA's location's fixed effects; and $Time_i$ is the list year and quarter fixed effects to capture the local market conditions. The term $PricePair_i$ is a large number of fixed effects for every pair of listing prices that are only $100 apart. For example, a house listed at $329,900 and another listed at $330,000 are defined as being part of the same pair; a house listed for $330,900 and another listed for $331,000 are defined as the same pair. The interaction term of $PricePair_i$ and $SmallerLeftDigit_i$ denotes the properties listed at prices with smaller left digits, that is, those listed with the right digits of 900 relative to those listed with the right digits of 1,000. Thus, while $PricePair_i$ captures the common attributes at a very fine price level, the interaction term captures the incremental differences of those that are listed at $100 less that exhibits a possible left-digit effect.

B. Baseline Effects on Home Sales

We first run equation (1) on the entire sample to test if listing prices with smaller left digits affect the outcomes. The baseline regression results are reported in Table III. Columns (1) to (5) present the regression results of the three different listing outcomes on property characteristics, the listing year and quarter fixed effects, and zip code fixed effects, but without the price pair fixed effects. Since the price pairs are not included, the coefficient for the smaller left digits captures both the difference between smaller left-digit listings and their counterparts, as well as the difference between low and high listing prices. The listing price pair fixed effects are included in columns (6) to (10). By including listing price pair fixed effects, we can test the incremental effects due to the perceived left digits. Since days on the market and the listing price are two simultaneous outcomes from successful sales, we control for days on the market in regressions on the sales price to account for extra gains from more time on the market. Levitt and Syverson (2008) find that sellers can achieve higher sales prices when selling their own homes, compared to selling their customers' homes, which remain on the market longer.

In columns (1) to (5) of Table III, the listing of properties with prices with smaller left digits has consistent and significant positive effects, since such properties are more likely to sell and spend less time on the market. However, the effect on higher sales prices becomes significantly positive when we include the price pair fixed effects, due to listing prices with smaller left digits being more concentrated among lower-valued properties. The magnitudes from the full specification controlling for location and listing price are much greater. When properties are listed with smaller left digits, although just \$100 less, they are 5.2% more likely to be sold, their time on the market is 3.7 days less, and the sales price is actually 0.068% higher than it would be otherwise. The higher sales price is equivalent to \$328, on average, based on the results in column (9). The gain represents a net threefold return, even after we adjust the sales price to account for the initial \$100 investment. Relative to the initial list price, the final sale price of homes listed with smaller left digits is 0.085% higher than similar homes listed with greater left digits.

In columns (11) to (15) of Table III, we report regression results based on a matched sample using the propensity score matching (PSM) method. This helps to circumvent potential mismatches of homes listed with smaller left digits in one market (or time) to similar homes listed with greater left digits in another market (or time) and thus presents a cleaner experiment. The PSM model used is similar to those reported in column (3) of Table II, where the zip code and listing time are controlled for, along with other attributes. We keep all the homes listed with smaller left digits and those listed with greater left digits, but only those closely matched according to the PSM predictions. Compared to the results in columns (6) to (10), the magnitude of the effects on sale likelihood on DOM is slightly smaller, but that of the effects on price measures is much greater. When properties are listed with smaller left digits, they are 3.8% more likely to be sold and their time on the market is 3.5 days less. The sales price is 0.10% higher as a percentage, $431 higher in dollars, and 0.12% higher as measured in sale list ratio.

The 3.5-day savings of time on the market is roughly 5% of the average listing time, assuming the realtor expects to collect a standard commission of 3% rate when the property is sold and an annual discount rate of 20% (consistent with Genesove and Mayer 2007; Levitt and Syverson 2008), that is, the equivalent of 0.15% of the contract price, or approximately $300 for the average contract price. In addition, there are significant benefits that we cannot monetize to not having to wait longer for the final contract and avoiding prolonged uncertainty for homeowners. In the absence of seller constraints, such as for the equity-constrained sellers studied by Genesove and Mayer (2007), both the seller and the listing agent should be more incentivized to list at prices with smaller left digits.

C. Nonlinear Effects by Home Value

We also examine different listing price bins to explore possible nonlinear effects on the sales price. It is likely that a $100 difference in listing price may only matter in low-end housing markets and left-digit effects manifest only with budget buyers. We split the PSM-matched sample into 10 price bins and regress the baseline specifications by these subsamples. The estimated coefficients are plotted in Figure 3.

In Figure 3(a), the effect of smaller left digits on sale likelihood declines in home value, regardless of the significant positive overall effect. The positive effect on sale likelihood only exists for inexpensive homes, while the estimated effect is significant and negative for homes exceeding $400,000. The negative effect on time on the market is universal along the full price spectrum, as shown in Figure 3(b). However, although all the point estimates of the effect are around 3.5 days shorter, they are not statistically significant for the highest price bins, possibly due to insufficient observations of listings at smaller left digits in these subsamples, as shown in Figure 1(c).

The effects on three price measures by price bins, shown in 3(c)–3(e) are consistent among them.

Except for inexpensive homes valued under \$100,000 and luxury homes worth between \$700,900 and \$800,000, which account for less than 14% of all listings, there is a significant positive effect on the sales price of the vast majority of the market and the magnitude of the gains on the sale price generally increases with price. For homes worth between \$100,001 and \$200,000, the average net gain on the sales price is about \$149 after accounting for the initial \$100 difference, 0.14% as a percentage, or 0.17% in the ratio-to-list price. Net gains increase to \$463 and 0.21% for homes valued \$200,001 to \$300,000, to \$906 and 0.29% for homes valued \$300,001 to \$400,000, to \$1,388 and 0.29% for homes valued \$500,001 to \$600,000, to \$1,801 and 0.33% for homes valued \$600,001 to \$700,000, and to \$5,098 and 0.60% for homes valued more than \$900,000. The results suggest that the estimated gains on the sales prices are very robust across different price levels.

D. *Heterogeneity across Market Conditions*

In Table II, we find that the left-digit strategy is more likely to be used by sellers in tight markets when they have more bargaining power. In this subsection, we explore different effects in a seller's market versus a buyer's market. We use the average DOM value in each zip code in the prior three months to divide the entire sample into terciles and define tight markets, or seller markets, as the lowest third tercile and soft markets, or buyer markets, as the highest tercile. We run the baseline specification for these terciles and report the results in Table IV.

Panel A of Table IV shows much stronger effects of using the smaller left-digit listing strategy in buyer's markets. The left-digit effect makes a sale 5.5% more likely in a buyer's market, compared to 4.8% in a seller's market. There are greater differences in effects on DOM and the sales price. The left-digit effect on DOM translates to 4.0 days less in a buyer's market, but only 3.3 days less in a seller's market. The effects on the sales price are 0.09% and \$378 higher in a buyer's market, but only 0.01% and \$215 in a seller's market. The results suggest that sellers reap more gains when buyers have more bargaining power in the negotiations.

E. *Different Market Education Level*

We explore the effects of the level of education of the buyers and sellers in different markets. We use the percentage of residents with a bachelor's degree or higher at the county level to split the entire sample into terciles and define markets with a population with the lowest level of education as the lowest tercile and markets with a population with the highest level of education as the highest tercile. We run the baseline specification for these subsamples and report the results in Table V.

The results in Panel B of Table IV show much stronger effects of a smaller left-digit listing strategy on time on the market and the sales price in markets where people have less education. The left-digit effects are such that properties with listing prices with smaller left digits are 5.3% more likely to be sold in markets where people have less education, similar to the 5.8% in markets where people have more education. There are much greater differences in the effects on time on the market and the sales price. The left-digit effect on DOM is such that properties remain 4.7 fewer days on markets where people have less education but only 2.2 fewer days on markets where people have more education. The effects on the sale price are 0.1% and $476 higher in markets where people have less education, while the effects are insignificant in markets where people have a higher education level. The results suggest that sellers can only reap significant gains on the price when there are many less educated buyers.

V. Possible Explanations

In this section, we explore possible explanations for the left-digit effects estimated on listing outcomes on both the seller and buyer sides.

A. Role of Seller's Agents

In the previous subsection, P_s and P_b can be affected by the professional opinions of both the sellers' and buyers' agents due to the imperfect nature of real estate markets. To list a property on the market, an individual has to register with the local MLS board and pay annual dues of approximately $2,000. The high entry cost and specific marketing skills required for selling a home, such as professional photography, staging services, and 360-degree visual tours, explain why the vast majority of homes are listed for sale by realtors, not homeowners.

Table V displays the results of two different specifications to test for the role of the seller's agent as it applies to the left-digit effects. First, we include listing agent fixed effects as an additional control in the baseline regression, with the results given in columns (5) to (8). Because we would lose the majority of the sample when we include the realtor, MSA, and zip code fixed effects, we rerun the baseline specification based on the same subsample. The results reported in columns (1) to (4) show the incremental impacts of including realtor fixed effects in the regression. Second, instead of listing agent fixed effects, we interact the smaller left-digit dummy with an indicator of whether the property is listed by a top-performing realtor, with the results reported in columns (9) to (12). We define top performers as those who successfully closed more sales than the median of the market in the prior year.

When listing agent fixed effects are included, the effects of smaller left digits on the sale likelihood, the number of days on the market, and the sales price are still statistically significant and the magnitudes are much greater in columns (5) to (8), compared to the results in columns (1) to (4). Among listings by the same agent, properties listed with smaller left digits are 1.3% more likely to sell. The time on the market is 5.5 days shorter. The effect on the sales price is 0.3%, or $360, higher. These results suggest the left-digit effects are very significant, even within the listings of the same realtors.

When the interaction term for top-performing realtors is included in the regression, we find additional gains on listing outcomes. The coefficients for smaller left digits capture the average effect for properties listed by average realtors. Their properties listed with smaller left digits are 1.0% more likely to sell, the time on the market is 3.8 days shorter, and the sales price is 0.1% and $173 higher. In addition to these base effects, properties listed by top-performing realtors increase the likelihood of a sale by another 0.6% (a 60% increase), shorten time on the market by another 3.4 days (a 50% increase), and increase the sales price by 0.4% (or three times more), or another $361 (or twice more). This finding suggests that good realtors play a significant role in achieving better sales outcomes using a left-digit listing strategy. They are responsible for most of the gains on the sales price and half of the decrease in the time on the market.

Compared to the seller's agent, the buyer's agent's role is a little limited. With houses on the market readily available through websites such as Redfin, Zillow, and Realtor.com, buyers' agents' traditional role of locating suitable homes for sale has diminished. They face strong competition from new partial-service models that offer cash rebates or other incentives to homebuyers (Pancak

2010). Since the left-digit listing strategy is commonly adopted by realtors, one would anticipate the buyer's agent to recognize this and advise buyers of its potential impact. However, the distribution of sales contract prices in Figure 2 shows little counterplay of the left-digit strategy from the buyer's side in the final contract. Our data do not contain information that would allow us to test for the effect of buyers' agents, such as that of the seller's agent in Table IV.

B. Search

How does the smaller left-digit listing strategy affect buyers and the negotiation process? One possibility is that smaller left-digit listing prices attract more visits to the listing page and more traffic to open houses. So, when listing prices conform to a prospective buyer's search criteria, we would expect spikes in transaction volumes. Our data indicate sharp increases in the distribution of house prices at multiples of $10,000 and we can consider this evidence of focal points in buyer–seller negotiations. However, we do not observe the number of offers on or visits to properties at different listing prices to perform a straightforward test. We take an alternative approach to test for search effects by focusing on properties listed at multiples of $100,000, since these numbers are common in defining the minimum and maximum search values. In this section, we include the interaction terms of a smaller left-digit dummy with indicators for properties listed at multiples of $100,000 to test if there are additional favorable listing outcomes from prices close to the search criteria.

In Table VI, our results do not support more favorable outcomes for properties listed at prices in round numbers. On the contrary, the effects on sales likelihood have the most significant interaction terms, but they are negative. The effects on DOM are either significantly positive or insignificant, suggesting it takes a longer or an equal amount of time to sell these properties, compared to similar properties not listed at multiples of $100,000. The effects on the sales price are either significantly negative or insignificant, suggesting that no price premium is associated with these properties when they are sold.

C. Seller Concessions

Another explanation for the left-digit effects from the baseline analysis is related to our measure of sale outcomes. In addition to time on the market and the sales price, it is possible that the seller offers incentives to buyers. For example, they can offer concessions in the form of assistance with closing costs, interest rate points, and origination fees, as well as other non-monetary compensations. This is relatively rare for existing home sales but may be more common for new constructions. We thus test for the effect of seller concessions by adding an interaction term of smaller left digits with an indicator term for new construction, meaning the property was built within two years of the listing date, to the baseline specification. We restrict the sample to properties built within five years of the listing date to obtain a close comparison.

The results reported in column (1) in Table VII, Panel *A*, show little evidence of the different effects for new homes (zero to two years old) compared with those for homes that are (two to five years) older. The coefficient of the interaction term with the dummy for new homes is not statistically significant. Since the sample is restricted to relatively new homes and only buyers of new homes are more likely to be offered non-price concessions, the results suggest no evidence of non-price factors having any impact on the estimated left-digit effect on the sales price.

We also test the matched mortgage samples, where we observe the sales price, which includes closing costs, origination fees, and points costs that buyers can include in the loan amount. The sales price is derived from the loan amount and the LTV. Columns (2) and (3) of Table VII show the baseline regression results based on the contract price and the sales price from the matched mortgage sample. First, we find very similar effects on the sales price, \$404 and \$388, between columns (1) and (2), which are based on the sales price from the MLSs and matched mortgage data samples, respectively. This result confirms that our matching algorithm is robust. Second, in column (3) we find a significant and positive effect on the sales price derived from the LTV and the loan amount. On average, listing prices with smaller left digits sell for \$272 more in the final sale. The difference between the two prices from the matched mortgage sample, \$116, likely suggests that non-pricing terms contribute to the reduced left-digit effects on the sales price. However, the effect on the sales price is still statistically and economically significant.

D. Buyer Access to Credit

If the estimated left-digit effects reflect buyers' behavioral bias, factors that affect buyers' home purchase decisions should manifest or magnify the left-digit effects. A number of researchers debate the role of the credit supply induced by government policies at the level of asset prices and the development of bubbles (Hubbard and Mayer 2009; Di Maggio, Kermani, and Korgaonkar 2015; Favara and Imbs 2015). Adelino, Schoar, and Severino (2012) and An and Yao (2016) provide evidence that changes in CLL have a positive causal effect on home purchases. We adopt the CLL as an exogenous instrument that stipulates prospective buyers' home purchase decisions. We add to the baseline specification four interactions of the smaller left-digit dummy with indicator terms for borrowers borrowing different amounts relative to CLL in a given year. Loutskina and Strahan (2009) and An and Yao (2016) explore the discontinuity at CLL and show that, since interest rates are higher for jumbo loans, some borrowers with loan demand near the CLL may borrow less than they otherwise would to take advantage of the lower rate. As borrowing nears the loan limit, there should be more home-buying activities.

The results in Table VII Panel *B* show that an increase in the credit supply of prospective buyers has a positive effect on sale outcomes. For buyers borrowing near the CLL, the left-digit effects significantly increase with the sales price, as both a percentage and a dollar amount, and decrease with DOM. All else being equal, greater credit supply at the limits shortens the time on the market by 2.4 days (from -5.0 to -2.6 days), compared to those borrowing at 70–79% of the limits. The sales price increases from 0.6% to 1.5% and from $1,403 to $5,872 when borrowing increases from 70–79% to 100%. These results indicate that the credit supply, as a factor affecting buyers' purchase decisions, has a significant effect on the sale outcomes of a left-digit listing strategy.

E. Summary of Results

The results indicate that the top-performing agents exploit significant gains from buyers. Left-digit effects are the most significant in markets where buyers have more bargaining power and there are fewer educated buyers. We also show that the buyers are more exposed to left-digit effects when they have a greater credit supply. The combined results suggest that left-digit effects reflect more of buyers' behavioral bias than search efforts or measurement errors.

VI. Analysis of Buyers

In this section, we identify the characteristics of buyers who are more attracted to the left-digit listings. Then we evaluate these buyers' performance in mortgages above and beyond standard risk attributes.

A. Buyer Characteristics

Given our findings that the buyers of properties listed with smaller left digits have shown behavioral bias, it is important, from a policy standpoint, to explore who they are. In our mortgage data, we have demographic information about the buyers at the time of their loan applications, including their income, age, and race/ethnicity. One possibility is that they lack financial sophistication. For example, they may want to lower the purchase price; however, they do not properly weigh the benefits against the costs involved. A second possibility is an unexpected demand for homes. When many buyers prefer smaller left-digit listing prices, they end up bidding against one another and driving up the final contract price. The third possibility is that these buyers are liquidity constrained and greatly value the $100 difference.

We examine the characteristics of people who buy properties at listing prices with smaller left digits. The dependent variable in our analysis is an indicator of whether a buyer bought a house that had a listing price with smaller left digits. The explanatory variables are mortgage and borrower characteristics at the time of origination, as well as loan application.

The results are presented in Table VIII. The results show that the most important predictor of buying properties listed with smaller left digits is the backend debt-to-income ratio, with higher values capturing those who do not have enough income to meet the mortgage and other debt obligations. Borrowers with a low credit score as well as low-income homebuyers are also more likely to prefer listing prices with smaller left digits. They generally lack experience managing their finances. Minorities are also more exposed to buying properties listed with smaller left digits. These findings are consistent with the studies examining the financial mistakes of households (Calvet, Campbell, and Sodini 2009; Agarwal, Rosen, and Yao 2016).

B. Ex Post Mortgage Outcomes

The significant left-digit listing price effects suggest net gains for sellers and listing agents. Does this result also suggest that buyers of properties priced with smaller left digits are subject to consistent behavioral bias? We study this by examining the ex post performance of buyers based on other mortgage outcomes: the interest rate they pay on the mortgage, the resale appreciation when they sell their home, post-purchase refinancing, and default outcomes. The second outcome is a direct test of buyer performance related to price: If the buyers cannot sell for a higher return from resales to compensate for the higher prices they paid, then they incur a loss on home purchases. The tests on refinancing are used to explore whether buyers of properties listed with smaller left digits are inattentive to their finances. Specifically, we test whether buyers of smaller left-digit listed properties fail to refinance their mortgages when interest rates drop.

Borrowers refinance their mortgages to lower their interest rate or monthly payments.[6] To examine buyer performance based on other mortgage outcomes, we adopt specifications similar to those in equation (1); they include additional controls for a full array of borrower and mortgage characteristics, including FICO scores, the LTV ratio, investment properties, broker-originated loans, and the backend debt ratio. For default and refinance outcomes, we control for the mark-to-market combined LTV, as well as interest rate changes from the origination date to the last performance date, which indicate important put and call option values for mortgage termination decisions. While regressions of mortgage rate and resale returns are estimated using loan-level data, default and refinance outcomes are based on a loan–quarter panel using a the standard Cox hazard model. For those buyers who resold their properties by 2014, we also control for sale date year and quarter fixed effects so that the holding period returns are comparable.

In Table IX, we find that, across different performance measures, buyers who favor listing prices with smaller left digits tend to show consistent behavioral bias. Column (1) reports the results of the regression of the origination note rate on left digits, controlling for buyer and mortgage characteristics. Buyers of properties listed with smaller left digits pay 17-basis-point higher interest rates on their mortgages. Assuming they hold on to their mortgages for five years, on average, that implies $1,244 extra financing costs for an average mortgage.

[6] An extensive literature estimates the optimal time for a borrower to refinance (Dunn and McConnell 1981; Hendershott and van Order 1987; Keys, Pope, and Pope 2014; Agarwal, Rosen, and Yao 2016).

In addition, when buyers sell a property, they tend to have a negative return relative to similar house sales in the same market that are bought as well as sold at the same time. The return is 4.2% lower for an average holding period of five years, the equivalent of a loss of $1,420. These results indicate that buyers of properties listed with smaller left digits consistently underperform outcomes compared to other buyers.

The sample we use for the default and refinance analysis is a panel data set of all mortgage–quarters. We use Cox hazard model regressions in which the dependent variables are indicators of whether the borrower refinances by the end of the performance period. The results reported in columns (3) and (4) of Table IX address the hazard rates of default and refinancing. Controlling for the home price as well as interest rate changes, there is no significant difference in default outcomes between buyers of listings with smaller and greater left digits. We then interact the potential savings with the left-digit indicator and find a strong interaction effect in column (4). Buyers of properties priced with smaller left digits react more slowly to interest rate savings. Refinancing a mortgage to a lower interest rate means more savings.

To see the effects of rate savings on the hazard of refinancing, consider the following example. Compare two borrowers who can save 1% relative to their original mortgage rates by refinancing. The borrower with larger left digits increases the hazard of refinancing by 18% (= exp(-2.93 * -0.01) - 1). In contrast, the borrower with smaller left digits has a lower hazard of refinancing: 16% (= exp(0.195 + (-2.93 * -0.01) + (0.294 * -0.01)) - 1). The difference is 2% less. These results are consistent with the inattentiveness of borrowers, suggesting that these homeowners do not actively manage their finances and do not make optimal financial decisions.

Although different outcomes require different sets of knowledge and expertise to manage, the same group of buyers makes suboptimal decisions in housing transactions, as well as mortgage obligations. As the results in Table VIII show, buyers exposed to property listings with smaller left digits have low creditworthiness and low income and are generally financially stressed. It is not surprising that they are attracted to the smaller left-digit listings, especially those listed by top-performing agents. Such buyers are exploited more when they have more bargaining power and where buyers have similar education levels. They are also exploited more when they have access to more credit at an affordable rate, such as with conforming loans.

VII. Conclusion

We use this clustering in listing prices as a quasi-experimental setting in which two similar properties are identical in property attributes, listing date, and location but are listed \$100 apart. We find that listing prices with smaller left digits, compared to similar properties listed at \$100 more, are 3.8% more likely to sell, stay on the market 3.5 days less, and are sold at prices \$431 higher. We then explore alternative explanations of the estimated effects on sale outcomes and find that top-performing realtors play a significant role in achieving better outcomes from a left-digit listing strategy. We also address potential measurement errors in the contract price, since the seller can provide incentives, such as assistance with closing costs, and mortgage rates that are not captured in the contract price. We find that, although the effect on the contract price and the sales price differs by only \$116, it is still statistically and economically significant. We also explore the buyer's decision making and find that, all else being equal, a greater credit supply at the CLL significantly shortens the time on the market and increases the sales price.

Finally, using a matched mortgage sample of buyers, we find that buyers who are exposed to a left-digit listing strategy are more likely to have a low credit score and low income and to be more leveraged with their household finances. In line with their purchase price decisions, we find that these buyers pay higher interest rates on their mortgages, resell their homes at a lower rate of return, and are more sluggish about refinancing their mortgages. Our results highlight how behavioral biases can affect even significant and high-value purchases such as housing. It appears that, even in significant and large-value transactions such as housing, buyers can make unfortunate mistakes.

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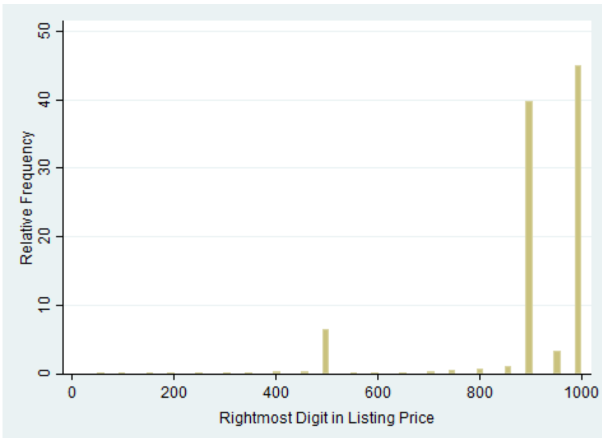
Figure 1 Rightmost Digits in Listing Prices

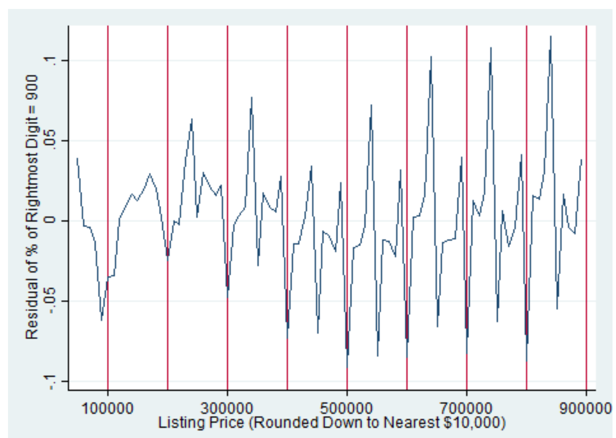
(a) Distribution of Rightmost Digits



(b) Pct. of Clustered Rightmost Digits

(c) Pct. of Two Rightmost Digits

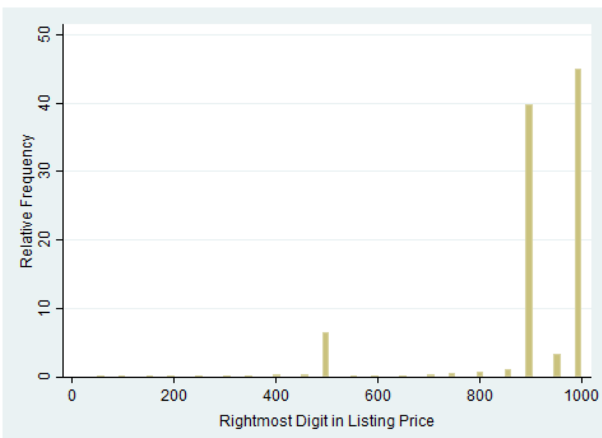
(d) Residual Pct. of the Rightmost Digits at 900



In 1(a), we plot the relative frequencies of the rightmost digits in listing prices to determine evidence of clustering. The rightmost digits are obtained by dividing the listing price by 1,000. The Y axis is the relative frequency. The chart shows significant clustering in listing prices with endings with 900 and 1,000. In 1(b), We plot the relative frequencies of listings with the rightmost digits of 900 and 1,000 in the listing price. The Y axis is the percentage of listings with these two clustered rightmost digits. The X axis is the listing price rounded down to the nearest 10,000. In 1(c), we plot the relative frequencies of listings with the rightmost digits of 900 and 1,000, respectively, in the listing price. The Y axis is the percentage of listings with each of the two clustered rightmost digits. The X axis is the listing price rounded down to the nearest 10,000. In 1(d), we plot the residual percentages of listings with the rightmost digit of 900 in the listing price. The residuals are obtained from a regression of the percentage of listings with the rightmost digits of 900 in the listing price on a higher-order (fourth-order) polynomial of the listing price. The X axis is the listing price rounded down to the nearest 10,000.

Figure 2 Rightmost Digits in the Contract Price

(a) Distribution of Rightmost Digits

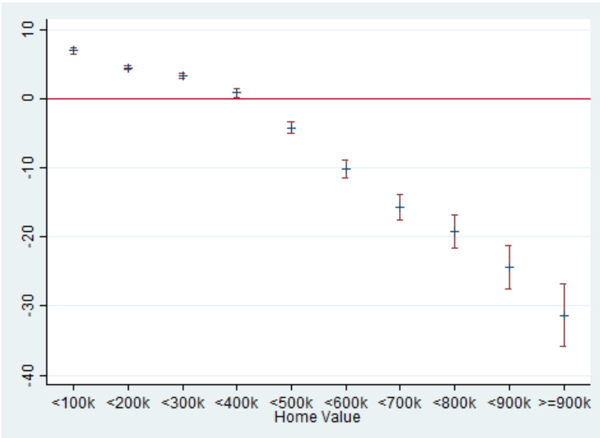


(b) Pct. of Clustered Rightmost Digits

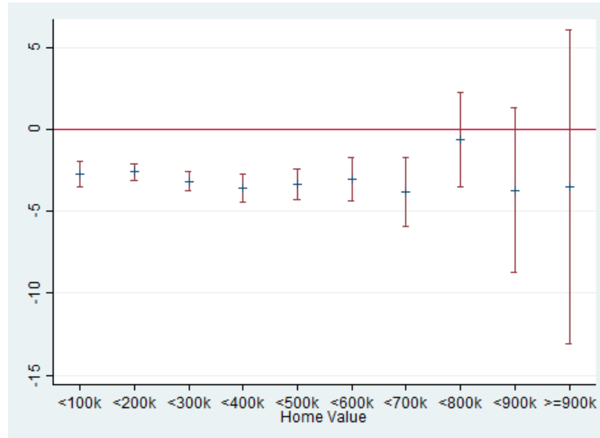
In 2(a), we plot the relative frequencies of the rightmost digits in the contract price to identify evidence of clustering. The rightmost digits are obtained by dividing the contract price by 1,000. The Y axis is the relative frequency. The chart shows significant clustering in contract prices that are multiples of 1,000. In 2(b), We plot the relative frequencies of listings with the rightmost digit of 1,000 in the contract price. The Y axis is the percentage of sold properties with these two clustered rightmost digits. The X axis is the contract price rounded down to the nearest 5,000.

Figure 3 Nonlinear Effects of Smaller Left Digit on Listing Outcomes

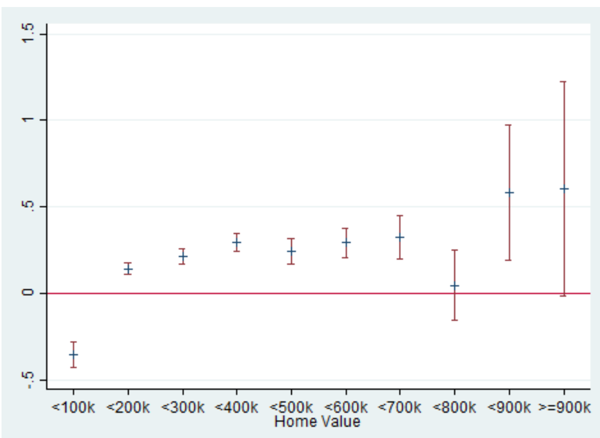
(a) Effect on $SOLD$



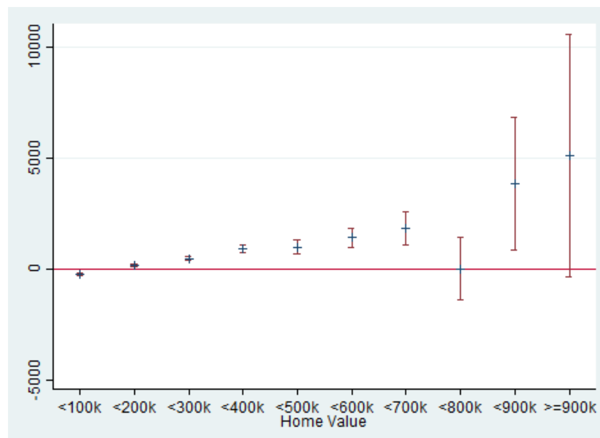
(b) Effect on DOM



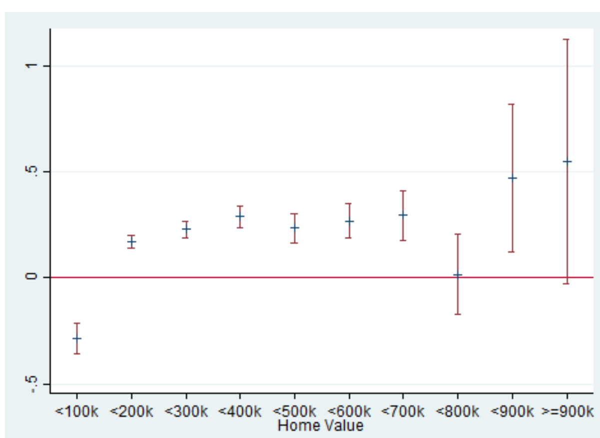
(c) Effect on $Log(Price)$



(d) Effect on $Price$



(e) Effect on $SALE/LIST$



This table reports the coefficient on smaller left-digit on listing outcomes by subsamples defined by listing price ranges. The specifications are the same as baseline results reported in Table III. All the regressions are OLS regressions with standard errors are clustered around Zip Codes. $SOLD$, $Log(Price)$ and $SALE/LIST$ are multiplied by 100. $Price$ are contract price of the listing. DOM and $Price$ are available for sold listings. Right-hand variables include listing price pair fixed effects, left-digit dummy, property age, living area, lot size, zip-code fixed effects, and year and quarter fixed effect effects. The purpose of the regression is explore whether there is any effect of left-digits on listing outcomes. Data is the listings with rightmost digits at 900 and 1,000 from MLS data in the 14 largest MSAs in the country. t–statistics are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table I Summary Statistics

Panel A: Overall MLS Sample

Variable	N	mean	sd	min	p25	p50	p75	max
List Price	7,330,588	$281,665	$188,446	$49,900	$143,900	$228,000	$369,900	$999,000
SOLD	7,330,588	48	50	0	0	0	100	100
DOM	3,456,277	63	65	0	15	43	89	365
Contract Price	3,456,277	$261,322	$172,058	$49,000	$136,000	$210,600	$340,000	$1,355,000
SALE/LIST	3,456,277	98	5.3	50	96	98	100	150
Square Foot	7,330,588	7.4	0.43	0	7.1	7.4	7.7	9.9
Lot Size	7,330,588	9.4	0.94	0	8.8	9.2	10	14
Property Age	7,330,588	3.1	0.96	0	2.5	3.3	3.8	4.4
Pct of Bachelor+ Degree	7,330,588	28	7.7	9	25	28	34	52
DOM in Prior 3 Months	7,256,041	67	31	0	45	64	83	674
Smaller Left Digit	7,330,588	0.47	0.5	0	0	0	1	1

Panel B: Matched Mortgage Sample

Variable	N	mean	sd	min	p25	p50	p75	max
Note Rate	240,261	6	1.1	0.087	5.4	6.1	6.8	13
FICO	240,261	724	60	377	684	735	774	899
FICO <= 620 Dummy	240,261	0.059	0.24	0	0	0	0	1
LTV	240,261	81	14	6	79	80	94	103
LTV >= 90 Dummy	240,261	0.26	0.44	0	0	0	1	1
Borrower Age	240,261	41	12	18	31	38	48	99
Age <= 35 Dummy	240,261	0.4	0.49	0	0	0	1	1
Monthly Income	240,261	$7,523	$6,599	$408	$4,309	$6,287	$9,070	$692,100
Low Income Dummy	240,261	0.25	0.43	0	0	0	0	1
Investor Dummy	240,,261	0.066	0.25	0	0	0	0	1
Broker Dummy	240,261	0.52	0.5	0	0	1	1	1
Backend Ratio	240,261	0.38	0.13	0.0001	0.29	0.37	0.45	1
Loan Amount	240,261	$194,394	$93,161	$10,000	$125,000	$17,7510	$250,000	$729,000
First-Time Buyer	240,261	0.32	0.47	0	0	0	1	1
Minority	211,289	0.29	0.45	0	0	0	1	1
Refinance	240,261	0.69	0.46	0	0	1	1	1
Default	240,261	0.11	0.31	0	0	0	0	1
Duration (months)	240,261	52	37	0	23	43	74	179
Resale Appreciation	66,453	7.3	45	-98	-15	4.3	26	1983
Resale Duration	66,453	59	37	1	30	53	84	168
Smaller Left Digit	240,261	0.55	0.5	0	0	1	1	1

Panel C: Comparison of MLS Subsamples

	Larger Left Digit		Smaller Left Digit		
Variable	**mean**	**sd**	**mean**	**sd**	**Δ**
Listing Price	326,665	209,589	231,137	145,725	-95,528***
SOLD	45	50	52	50	6.43***
DOM	71	92	67	77	-3.25***
Contract Price	308,215	194,416	213,666	132,544	-94,549***
SALE/LIST	97	8	98	8	0.18***
Square Foot	1,856	934	1,729	833	-127.15***
Lot Size	23,423	58,792	21,272	53,293	-2,151***
Property Age	30	20	29	20	-1.44***
Pct of Bachelor+ Degree	28	7	28	8	0.06***
DOM in Prior 3 Months	66	33	68	30	1.87***
N		3,877,353		3,453,235	

Panel D: Comparison of Mortgage Subsamples

	Larger Left Digit		Smaller Left Digit		
Variable	**mean**	**sd**	**mean**	**sd**	Δ
Note Rate	5.8	1.1	6.1	1	0.30***
FICO	728	59	721	61	-7.00***
FICO <= 620 Dummy	0.052	0.22	0.066	0.25	0.014***
LTV	80	14	82	14	2.00***
LTV >= 90 Dummy	0.23	0.42	0.29	0.45	0.06***
Borrower Age	41	12	40	13	-1.00***
Age <= 35 Dummy	0.39	0.49	0.42	0.49	0.03***
Monthly Income	$8,122	6825	$7,040	6371	-$1,082***
Low Income Dummy	0.21	0.41	0.28	0.45	0.07***
Investor Dummy	0.065	0.25	0.067	0.25	0.002
Broker Dummy	0.51	0.5	0.52	0.5	0.01***
Backend Ratio	0.37	0.13	0.38	0.13	0.01***
Loan Amount	$212,702	101,482	$179,647	82,987	-$33,055***
First-Time Buyer	0.32	0.47	0.32	0.47	0
Minority	0.29	0.46	0.28	0.45	-0.01***
Refinance	0.67	0.47	0.71	0.45	0.04***
Default	0.1	0.3	0.12	0.32	0.02***
Duration (months)	51	36	54	38	3.00***
Resale Appreciation	9.4	46	5.7	43	-3.70***
Resale Duration	57	37	61	37	4.00***
N		107,191		133,070	

In Panel (A, we report the summary statistics based on the overall MLS sample. Data are the complete listings in 1990-2014 from MLS data in the 14 largest MSAs in the country. In Panel B, we report the summary statistics based on a nationally representative loan-level sample matched with MLS data in order to obtain initial listing information. The sample includes mortgages used to finance home purchases in 1990-2014. Mortgage data are restricted to fully documented and fully amortized 30-year mortgages. Home purchases are restricted to those with listing prices ending with $900 and $1,000. In Panel C, we report the summary statistics based on overall MLS sample by smaller and larger left digits. Smaller left digits are the listings with listing price ending with 900 and larger left digits are those with listing price ending with 1,000. In Panel D, we report the summary statistics of the matched mortgage sample by smaller and larger left digits. Smaller left digits are the listings with listing price ending with 900 and larger left digits are those with listing price ending with 1,000.

Table II Determinants of Left-Digit Listing Strategy

	(1)	(2)	(3)
	Smaller Left Digit x 100		
Log(List Price)	231.274***	182.766***	151.056***
	(242.19)	(195.88)	(42.89)
Log(List Price) Sq	-10.290***	-7.996***	-6.650***
	(-265.94)	(-210.96)	(-46.85)
Rightmost Digit = 20,000	1.453***	1.329***	1.414***
	(16.83)	(15.83)	(13.12)
Rightmost Digit = 30,000	3.646***	3.574***	3.621***
	(40.32)	(40.66)	(32.48)
Rightmost Digit = 40,000	3.539***	3.304***	3.533***
	(41.70)	(40.06)	(28.64)
Rightmost Digit = 50,000	4.124***	4.292***	4.388***
	(45.41)	(48.62)	(34.67)
Rightmost Digit = 60,000	3.744***	3.798***	3.969***
	(41.89)	(43.70)	(33.81)
Rightmost Digit = 70,000	1.829***	1.833***	2.061***
	(21.24)	(21.88)	(17.71)
Rightmost Digit = 80,000	2.183***	2.230***	2.444***
	(24.52)	(25.76)	(21.18)
Rightmost Digit = 90,000	2.206***	1.897***	2.329***
	(26.50)	(23.44)	(21.25)
Rightmost Digit = 100,000	-4.443***	-4.143***	-4.109***
	(-44.22)	(-42.42)	(-35.23)
PropGLA	10.853***	3.620***	1.826***
	(190.83)	(55.22)	(8.19)
PropAge	-1.269***	-1.903***	-1.447***
	(-57.27)	(-84.02)	(-19.87)
List Agent's Sales in Prior Year	-0.009***	0.061***	0.021***
	(-4.01)	(28.96)	(8.05)
DOM in Prior 3 Months	0.018***	-0.042***	
	(22.96)	(-49.52)	
Pct of Bachelor+ Degree	0.195***		
	(76.38)		
Property Attributes	Yes	Yes	Yes
Location FE	None	MSA	Zip Code
YYQQ FE	Yes	Yes	Yes
N	6167389	6173617	6237995
adj. R^2	0.095	0.145	0.162

We report in this table the results of the listing profiles of those ending with 900. All the regressions are OLS regressions. The dependent variable is a left-digit dummy x 100. Right-hand variables include listing price pair fixed effects or listing price as continuous variable, property age, living area, lot size, average sale to list ratio of the listing agent in the past year, total sales of the listing agent in the past year, MSA fixed effects, year fixed effect effects, quarterly dummies. Data is the complete listings from MLS data in the 14 largest MSAs. Standard errors are clustered around Zip Codes. t–statistics are in parentheses.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table III Baseline Effects on Listing Outcomes

	Overall Sample w/o Price Pair Control					*Overall Sample w/ Price Pair Control*				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	SOLD	DOM	Log(Price)	Price	SALE/LIST	SOLD	DOM	Log(Price)	Price	SALE/LIST
Smaller Left Digit	5.559***	-3.181***	-4.645***	-17438***	0.206***	5.187***	-3.712***	0.068***	328***	0.085***
	(40.67)	(-16.01)	(-31.25)	(-40.74)	(16.49)	(33.75)	(-15.84)	(5.65)	(11.02)	(7.47)
Property Attributes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Zip-Code FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
YYQQ FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Price Pair FE	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
N	7128136	3368000	3368000	3368000	3368000	7128136	3368000	3368000	3368000	3368000
adj. R^2	0.162	0.1	0.785	0.739	0.107	0.178	0.101	0.993	0.994	0.124

	PSM Matched Sample				
	(11)	(12)	(13)	(14)	(15)
	SOLD	DOM	Log(Price)	Price	SALE/LIST
Smaller Left Digit	3.794***	-3.076***	0.103***	431***	0.122***
	(28.64)	(-14.07)	(7.86)	(13.44)	(9.78)
Property Attributes	Yes	Yes	Yes	Yes	Yes
Zip-Code FE	Yes	Yes	Yes	Yes	Yes
YYQQ FE	Yes	Yes	Yes	Yes	Yes
Price Pair FE	Yes	Yes	Yes	Yes	Yes
N	6058734	2983925	2983925	2983925	2983925
adj. R^2	0.188	0.097	0.992	0.993	0.117

We report the baseline left-digit effects on listing outcomes. All the regressions are OLS regressions with standard errors are clustered around Zip Codes. The dependent variable is column title. *Price* are contract price of the listing. *DOM* and *Price* are available for sold listings. Right-hand variables include listing price pair fixed effects, left-digit dummy, property age, living area, lot size, zip-code fixed effects, and year and quarter fixed effect effects. *DOM* is included as additional control variable all the regressions of *Price*. Data is the listings with rightmost digits at 900 and 1,000 from MLS data in the 14 largest MSAs in the country. t–statistics are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table IV Market Conditions and Educational Level

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Bargaining Power of Buyer and Seller										
	Tight (Seller) Markets					Soft (Buyer) Markets				
	SOLD	DOM	Log(Price)	Price	SALE/LIST	SOLD	DOM	Log(Price)	Price	SALE/LIST
Smaller Left Digit	4.760***	-3.337***	0.014	215***	0.034**	5.459***	-4.036***	0.094***	378***	0.108***
	(25.22)	(-14.29)	(0.82)	(5.51)	(2.10)	(29.56)	(-11.43)	(5.14)	(8.66)	(6.26)
Property Attributes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Zip-Code FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
YYQQ FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Price Pair FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2336440	1148306	1148306	1148306	1148306	2320294	1070804	1070804	1070804	1070804
adj. R^2	0.208	0.097	0.993	0.994	0.119	0.160	0.097	0.993	0.993	0.134
Panel B: Demographics of Markets										
	Less Educated Markets					More Educated Markets				
	SOLD	DOM	Log(Price)	Price	SALE/LIST	SOLD	DOM	Log(Price)	Price	SALE/LIST
Smaller Left Digit	5.317***	-4.657***	0.101***	476***	0.113***	5.837***	-2.234***	-0.008	64	0.016
	(20.79)	(-10.71)	(4.67)	(10.21)	(5.46)	(19.71)	(-6.24)	(-0.44)	(1.21)	(0.91)
Property Attributes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Zip-Code FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
YYQQ FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Price Pair FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2874617	1340975	1340975	1340975	1340975	1742703	908443	908443	908443	908443
adj. R^2	0.187	0.096	0.993	0.994	0.110	0.201	0.110	0.994	0.994	0.120

The results in Panel A are based on subsamples of different market conditions, defined on the average DOM in the prior month at zip-code level, which determine different bargaining power of buyer and seller. Results in Panel B is based on subsamples of different education level, defined as percent of bachelor degree or higher at county level, which measures financial sophistication of buyers and sellers. All the regressions are OLS regressions with standard errors are clustered around Zip Codes. The dependent variable is column title. *DOM* and *Price* are only available for sold properties. All right-hand variables and data used are the same as baseline regression. t–statistics are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table V Role of Seller Realtors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Baseline Specification				Realtor Fixed Effects				Top Performers			
	SOLD	DOM	Log(Price)	Price	SOLD	DOM	Log(Price)	Price	SOLD	DOM	Log(Price)	Price
Smaller Left Digit	0.674***	-3.251***	0.000	14.9	1.251***	-5.531***	0.003***	359.7***	0.953***	-3.765***	0.001	172.5***
	(10.17)	(-13.20)	(0.55)	(0.29)	(16.11)	(-13.09)	(3.31)	(5.57)	(11.5)	(-9.38)	(0.87)	(2.58)
x Above Median (# Realtor's Sales)									0.573***	-3.398***	0.004***	360.6***
									(8.73)	(-13.14)	(4.32)	(6.33)
Property Attributes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Zip-Code FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Price FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
List Agent FE	No	No	No	No	Yes	Yes	Yes	Yes	No	No	No	No
N	1710370	1559771	1559771	1559771	1710370	1559771	1559771	1559771	1710370	1559771	1559771	1559771
adj. R^2	0.367	0.175	0.703	0.981	0.298	0.091	0.683	0.98	0.298	0.091	0.683	0.98

Columns (1)–(4) present the results of baseline regressions based on the same subsample used in next eight columns. The regression for the results in columns (5)–(8) include additional realtor fixed effects to the baseline regression and include additional interaction terms of smaller left digits and listings by top-performing realtors, who had above median sales in the MSA in previous year, are included in the regressions for the results in columns (9)–(12). All the regressions are OLS regressions with standard errors are clustered around Zip Codes. The dependent variable is column title. Price are contract price of the listing. DOM and Price are available for sold listings. Other right-hand sided variables and data used are the same as baseline regression. t statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table VI Search Filters

	(1) SOLD	(2) DOM	(3) Log(Price)	(4) Price
Smaller Left Digit	5.249***	-7.258***	0.004***	468.9***
	34.73	(-21.54)	4.57	(8.15)
x Listing Price @ \$100,000	1.238***	1.026	-0.005**	-1256.9***
	4.21	1.2	(-2.31)	(-6.18)
x Listing Price @ \$200,000	-1.773***	1.712	-0.013***	-1549.5***
	(-4.09)	1.46	(-3.35)	(-5.61)
x Listing Price @ \$300,000	-2.447***	4.497***	0.003	-1594.0***
	(-4.92)	3.15	0.32	(-3.63)
x Listing Price @ \$400,000	-3.090***	5.214***	-0.024**	-2525.9***
	(-5.20)	2.82	(-2.20)	(-3.23)
x Listing Price @ \$500,000	-1.846**	6.677**	-0.022	-652.2
	(-2.48)	2.36	(-1.51)	(-0.53)
x Listing Price @ \$600,000	-3.983***	4.608	-0.012	2033.1
	(-4.49)	1.45	(-0.31)	(0.79)
x Listing Price @ \$700k \$800k, \$900k, \$1M	-4.836***	2.653	-0.01	1793.8
	(-5.92)	0.65	(-0.23)	(0.52)
Property Attributes	Yes	Yes	Yes	Yes
Zip-Code FE	Yes	Yes	Yes	Yes
YYQQ FE	Yes	Yes	Yes	Yes
Price Pair FE	Yes	Yes	Yes	Yes
N	7128136	3436607	3436607	3436607
adj. R^2	0.178	0.098	0.724	0.977

When perspective buyers search for listings they tend to search by ranges between two numbers at multiples of 100,00, so we define the search as listings with Listing Price near thresholds at 100,000, 200,000 etc. All the regressions are OLS regressions with standard errors clustered around Zip Codes. The dependent variable is column title. *Price* are contract price of the listing. *DOM* and *Price* are only available for sold properties. All right-hand variables and data used are the same as baseline regression. t–statistics are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table VII Effect of Buyer–Side Factors

	Panel A: Concessions		
	(1)	(2)	(3)
	MLS	Matched Mortgages	
	Contract Price	Contract Price	Final Price
Smaller Left Digit	404.4***	388.3***	271.8***
	(7.20)	(4.88)	(3.40)
x New Homes	250.914		
	(1.45)		
Zip-Code FE	Yes	Yes	Yes
YYQQ FE	Yes	Yes	Yes
Price Pair FE	Yes	Yes	Yes
N	3436607	233191	233191
adj. R^2	0.977	0.991	0.991

	Panel B: Credit Supply		
	DOM	Log(Price)	Price
Smaller Left Digit	1.180*	-0.002***	-171.5**
	(1.96)	(-4.16)	(-2.19)
x Borrowing at 70-79% CLL	-2.594**	0.006***	1403.2***
	(-2.27)	(8.74)	(7.35)
x Borrowing at 80-89% CLL	-2.243*	0.008***	2003.9***
	(-1.79)	(8.72)	(7.02)
x Borrowing at 90-99% CLL	-2.877*	0.010***	3090.2***
	(-1.69)	(12.15)	(10.32)
x Borrowing at 100% CLL	-5.025**	0.015***	5872.0***
	(-2.33)	(10.85)	(10.35)
Property Attributes	Yes	Yes	Yes
Zip-Code FE	Yes	Yes	Yes
YYQQ FE	Yes	Yes	Yes
Price Pair FE	Yes	Yes	Yes
N	153,817	153,817	153,817
adj. R^2	0.091	0.992	0.992

In Panel *A*, we measure non-price concessions as the difference between contract price and final sales price derived from the mortgage loan amount, as well as the difference between new homes, those built in 0-2 years, and those built 2-5 years ago. In Panel *B* we explore the effect of more credit supply on the left-digit effects of perspective buyers. All the regressions are OLS regressions with standard errors clustered around Zip Codes. The dependent variable is column title. *DOM* and *Price* are only available for sold properties. All right-hand variables and data used are the same as baseline regression. t–statistics are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table VIII Characteristics of Buyers of Left-Digit Listed Properties

	(1)	(2)
	Smaller Left Digit x 100	
FICO $\leq$ 620 Dummy	-0.037	1.660***
	(-0.08)	(-4.20)
Minority	-0.348	0.372*
	(-1.47)	(-1.70)
Backend Ratio	-8.127***	2.880***
	(-9.16)	(-3.47)
Ln(Income)	-6.293***	-0.690***
	(-29.96)	(-2.85)
Mortgage Attributes	Yes	Yes
Origination YYQQ FE	Yes	Yes
MSA FE	Yes	Yes
Price Pairs	No	Yes
N	217880	217880
adj. R^2	0.074	0.285

All the regressions are OLS regressions with standard errors clustered around Zip Codes. The dependent variable is a left-digit dummy x 100. Right-hand sided variables include listing price pair fixed effects, high LTV dummy, low FICO dummy, young household dummy, low income dummy, first-time homebuyer dummy, minority borrower dummy, investment property dummy, loans originated by broker dummy, backend debt to income ratio, MSA fixed effects, and origination year and quarter fixed effect. t–statistics are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table IX Ex Post Mortgage Performance of Buyers of Left-Digit Listed Properties

	(1) Rate	(2) Resale Return	(3) Default	(4) Refinance
Smaller Left Digit	0.170***	-4.159***	-0.005	0.195***
	(12.70)	(-3.17)	(-0.62)	(-6.27)
Negative Rate Change			-0.290***	-2.925***
			(-36.17)	(-67.28)
x Smaller LeftDigit				0.294***
				(-8.53)
MtM CLTV			0.012***	-0.067***
			(-23.86)	(-61.16)
Positive Rate Change			0.313***	-1.311***
			(-20.76)	(-24.41)
Borrower Attributes	Yes	Yes	Yes	Yes
Mortgage Attributes	Yes	Yes	Yes	Yes
Time FE	YYMM	YYMM	YYQQ	YYQQ
Location FE	MSA	MSA	State	State
Price Pairs	Yes	Yes	Yes	Yes
Sale YYQQ FE		Yes		
N	247785	68110	3858475	3858475
adj. R^2	0.241	0.362	0.009	0.022

The dependent variable is the column title. The regressions for the results in columns (1) and (2) are OLS regressions with standard errors clustered around Zip Codes. Right-hand variables include listing price pair fixed effects, left-digit dummy, LTV, borrower FICO, investment property dummy, loans originated by broker dummy, backend debt to income ratio, MSA fixed effects, origination year and month fixed effect. The regressions for the results in columns (3) and (4) are Cox hazard model regressions using additional regressors, such as marked to market CLTV, positive interest rate change, negative interest rate change from origination. Default and refi regressions are based on loan-quarter panel data. t–statistics are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.