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Analysis of Even Pricing in Real Estate Markets: Different Asset Types and Implications

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This study examines price clustering in different real estate markets. Using a novel data set, we document that prices are clustered around even figures, and exact prices are not common in the residential, commercial and land markets. Prices increase in multiples of five hundred, five thousand or fifty thousand depending on the market, and particular digits can predict the prices. The magnitude of even pricing is comparable to months' worth of disposable income and has potential implications on the financial well-being of the market participants.

Keywords

Even pricing, Real estate markets, Price clustering

JEL: G41, R31, R33

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1. Introduction

Real estate markets are an important part of the economy and have a size comparable to the equity markets. The total value of the global real estate market, with 79% being the residential market, equals to 326.5 trillion dollars whereas the total value of the global equity market is worth 109.5 trillion dollars.[1] Market participation rates are also high; home ownership is more than 70% as opposed to the global stock market participation of around 20% (Giannetti and Koskinen 2010).[2] Furthermore, a residential property transaction corresponds to a significant portion of the wealth of an average individual who is involved in the process. Housing wealth accounts for almost two-thirds of the total wealth of a median household, and tends to move together with household consumption (Iacoviello 2011), thus, price efficiency in the real estate markets is of importance to household well-being. For instance, the overall median asking price of a multi-unit housing is 490,000TRY in our data set. Even one percent of the median price is 4,900TRY while the monthly disposable median income during the same period in Turkey is 1,324TRY.[3]

Studies, including Ohnishi et al. (2011), show that residential price distributions are leptokurtic and heavily clustered. Moreover, fat tails are not the only inconsistency related to the normal distribution assumption in housing prices. Empirically, the distribution is heavily clustered at particular points which results in spikes in a histogram. These clusters can be, for example, grouping of prices around even-ending or just below (charm) prices. This grouping can be driven by different motives of price setters including costly information acquisition, negotiation processes and cognitive ease.

In our study, we examine whether price clustering exists, and the possible determinants by analyzing different real estate markets including the residential, commercial and land markets with the use of a novel data set for the metropolitan city of Istanbul, Turkey. We first examine the residential sales market in detail and then extend our analyses to the commercial, land and rental housing markets. We show that there is a tendency to anchor prices to even numbers. Residential sales prices usually end with zeros and multiples of five thousand or fifty thousand, coupled with the observation that price endings closer to these endings are particularly avoided. Furthermore, similar price patterns exist for the different property types. This observed pricing anomaly cannot be attributed to price levels, frictional explanations such as opportunity cost of information acquisition or taxes, although cognitive ease and ease in negotiation can be potential explanations for such pricing patterns.

[1] Based on Refinitiv data for 2021.
[2] OECD housing tenure distribution for 2019.
[3] Turkish Statistical Institute annual equivalised household disposable income statistics for 2017 at USD/TRY = 3.66 (as of October 2017).

Our study contributes to the literature in multiple ways. To the best of our knowledge, this is the first study to analyze even pricing behavior in different real estate markets including commercial and land markets. We also show that there is a tendency to avoid prices with even-endings, and using a novel set, we document even pricing for the first time in an emerging market. The examination of different real estate markets help us to provide potential explanations for the observed pricing behavior.

The remainder of the paper is organized as follows. Section 2 summarizes the related literature. Section 3 explains our methodology and data. In Section 4, we present the empirical evidence and Section 5 concludes.

2. Literature Review

An important work in the real estate literature is that of Palmon et al. (2004) who document and analyze clustering in residential prices. The authors group house prices according to the last three digits of the listing prices. In their sample, more than half of the observations are "just below" prices (prices ending with 9) and 20% of the houses have even-ending pricing with three zeros. Similarly, Beracha and Seiler (2014) report that more than 75% of the prices are associated with a round or "just below" pricing. Repetto and Solis (2020) also observe just below pricing for the Swedish housing market.

There are alternative explanations for the clustering behavior including costly information acquisition, cognitive ease and negotiation processes. Studies on costly information acquisition argue that investors use coarse pricing sets where the marginal cost of acquiring additional information equals the marginal benefit (Ball et al. 1985). Using a coarse pricing set results in price clustering; prices deviate from fundamental values due to missing or costly information.

Studies that analyze cognitive ease reveal that people rely on round numbers like multiples of ten as cognitive reference points (Rosch 1975), the use of just below and even prices is positively related to the number of listings of a broker (Palmon et al. 2004), transaction prices in the used car market change with even mileage thresholds due to the inattention of buyers (Lacetera et al. 2012), the frequency of limit order submissions that end with zeros is correlated with the performance of investors (Kuo et al. 2015) and professional stock traders form cognitive reference points of even price thresholds (Bhattacharya et al. 2012).

Studies like Harris (1991) take the negotiation perspective and show that traders use discrete price sets to simplify negotiation. Moreover, rounded figures affect the total number of offers to reach an agreement (Backus et al., 2019). Although there is no consensus on the immediate impact, listing price characteristics such as being round or just below affect the final transaction price (Beracha and Seiler 2014, Cardella and Seiler, 2016). Cardella and Seiler (2016) argue that when the sellers decide the listing price, the price sets the grounds for negotiation and determines the time that the property is on the market. A price set too high may result in illiquidity and no final transaction. A price set too low results in a short time on the market (TOM), although there will be a value loss for the seller. Therefore, the seller tries to optimize the listing price which will generate the highest sale price.

3. Methodology and Data

Palmon et al. (2004) group real estate prices by using the last three digits, and find that 50% of the observations end with 9 and 20% have even-endings with three zeros. Beracha and Seiler (2014) also report that more than 75% of the prices are either round or end with 9.

In line with these two studies, we define a digit group variable D, and categorize a six digit price P_i by its fifth digit from the right if the price ends with four zeros.[4] Otherwise, P_i is categorized as "other".

$$P_i = \overline{d_{6_i} d_{5_i} d_{4_i} d_{3_i} d_{2_i} d_{1_i}}$$

$$D = \begin{cases} d_{5_i}, if \overline{d_{4_i} d_{3_i} d_{2_i} d_{1_i}} = '0000' \\ other, if \overline{d_{4_i} d_{3_i} d_{2_i} d_{1_i}} \neq' 0000' \end{cases}$$

We employ a standard hedonic pricing model to understand the pricing dynamics.[5] The logarithm of prices is regressed on property characteristics including area, number of bedrooms, proximity to public services, and districts.

$$log(P_i) = B_i + A_i + D_i + S_i + u_i \tag{1}$$

where P_i denotes the house price and the dependent variable is the log price of unit *i*. B is the set of controls regarding the structural characteristics of the building including property type and age. A is the set of controls for apartment characteristics such as the area of the unit, and number of bedrooms and bathrooms. D is the set of district dummy variables for fixed effects in the administrative areas. *S* is the set of controls for proximity to public services such as distance of the housing unit *i* to the closest hospital or school in meters.[6]

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[4] Similarly, we categorize seven digit prices by their sixth digit from the right. We focus on the fifth (sixth) digit when we examine six (seven) digit prices as it is the most important clustering digit. The findings in the literature show that the digit of concern changes with the level of prices (for example; Allen and Dare (2004) and Beracha and Seiler (2014(). In line with the literature, when we repeat our analyses with the fourth (fifth) digit for six (seven) digit prices, results omitted for brevity reveal that the findings are similar but less significant.

[5] A number of studies in the literature including Morali and Yilmaz (2022) argue that a standard hedonic pricing model would suffice.

[6] We have 23 property characteristics, 14 controls for proximity to public services and 39 district variable. The definitions of the variables are in the Appendix.

For the analysis, we randomly divide the data into two groups: the training and prediction subsamples (15% and 85% of the data, respectively).[7] The coefficients of the model are estimated by using the training sample and the analysis is performed on the prediction sample by using the coefficients from the training data set:

$$log(P) = \beta_{training} X + u \tag{2}$$

$$u_{prediction} = log\left(P_{prediction}\right) - \overline{P}_{training} \tag{3}$$

The residuals of the prediction sample are grouped by their price endings and regressed on D to examine whether there exists a pricing anomaly:

$$u_{prediction} = \beta_0 + \beta_1 D + v \tag{4}$$

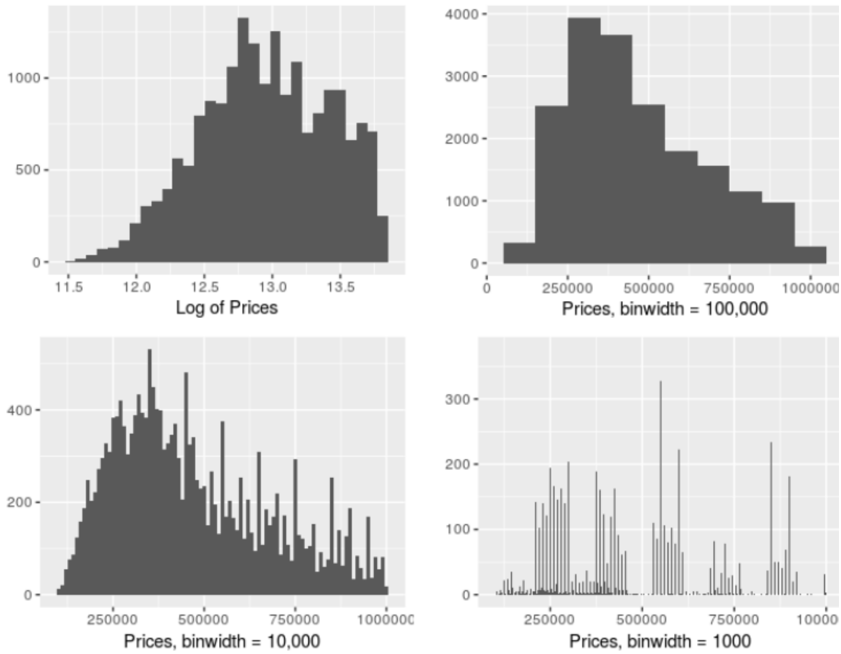
Data are taken from a leading online portal in Turkey - HurriyetEmlak.com. There are 59,935 listings for Istanbul as of October 15, 2017 from the residential, commercial and land markets. Observations with six and seven digit (four digit) prices are used for the sales (rental) listings as they are the most commonly used price quotations, and constitute almost all of the observations. Table 1 presents the descriptive statistics for different real estate property types and Figure 1 plots our sample data for different bin widths and illustrates spikes at specific points.

Table 1 Descriptive Statistics for Prices of Properties in Different Real Estate Markets

	N	Mean	S.D.	Min.	Median	Max.
Housing for Sale	22,978	682,741	595,745	100,000	490,000	9,500,000
Commercial	9,242	1,395,613	1,618,086	100,000	770,000	9,950,000
Land	5,053	407,506	243,180	100,000	350,000	999,900
Rental Housing	22,662	2,741	1,681	1,000	2,200	9,900

[7] In unreported analyses for brevity, we repeat our calculations by using both random selections of different 15% and 85% subsamples, and also dividing our data into 10% and 90%, 50% and 50%, and 90% and 10% which do not change our results.

Figure 1 Histogram Plots of Listing Prices with Difference Bin Widths



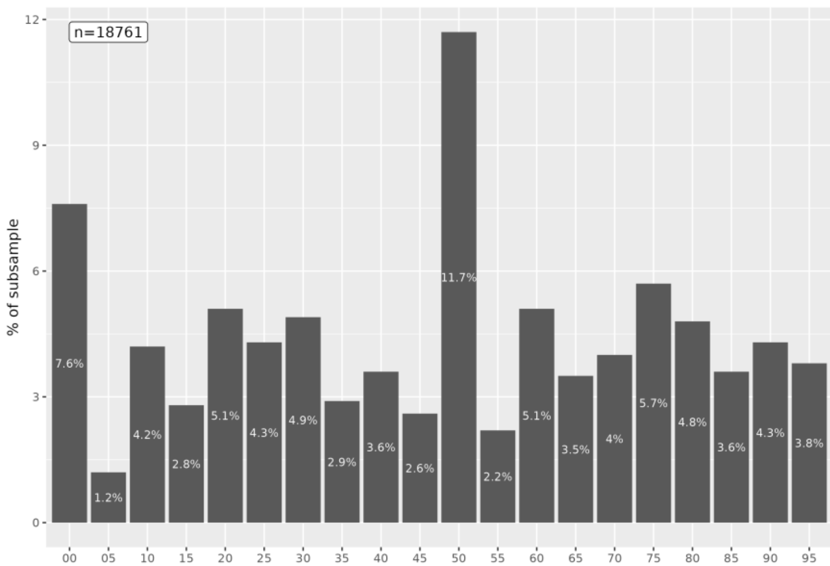
Before we perform our analyses, we need to consider the fact that transaction prices are not publicly available in the Turkish real estate market and listing prices are the key indicators to convey information to the market participants to estimate property worth. However, we acknowledge that listing prices are ask prices and can be different from the transaction prices due to, for example, negotiation. Real estate markets differ from other financial markets where the buyer pays the spot price, because the ask price in the real estate market is, in general, a starting point for negotiation. [8] Findings show that listing prices act as anchors for transaction prices (Northcraft and Neale 1987, Thomas and Morwitz 2005, Janiszewski and Uy 2008, Mason et al. 2013) and studies like Harris (1991) argue that if buyers and sellers want to speed up the negotiation, they may not bother using small price increments; thus, the negotiated prices tend to be rounded. Palmon et al. (2004) document that transaction prices cluster even more than the listing prices.

[8] The average margin for negotiation may differ by region. One possible reason is the liquidity of property. The literature suggests that more illiquid properties tend to have a longer TOM [Forgey et al. (1996), Jud et al. (1996), Kluger and Miller (1990)). Consequently, in the effort to account for the effect of liquidity and reduce the difference in margins of negotiations in different areas, we focus on listings that are active for two months or less as this is the longest time allowed for a listing to be active on HurriyetEmlak.com without a renewal action.

4. Results

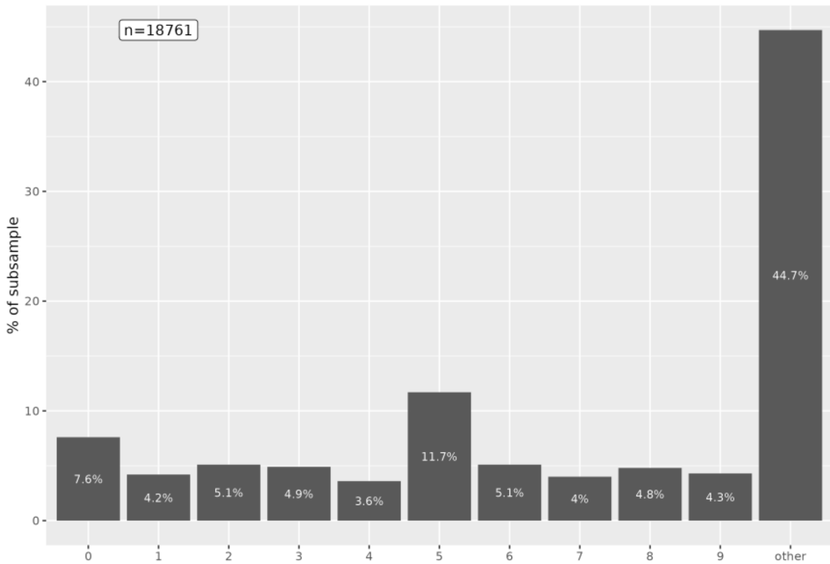
We start with six-digit residential sales prices which consist of 81.6% of the observations and later continue with the remaining 18.4% which are seven figure prices. Figure 2 shows the prices by the last five digits, excluding observations less than 1% of the sample for brevity. Exact figures such as $313,875 are uncommon and prices cluster around even figures like $315,000 rather than $314,000. Price increments of 5,000 are more available than any other, and endings of “00,000” or “50,000” are more popular at the expense of the ones around them (“05,000”, “45,000” or “55,000”). These findings are in line with studies such as Palmon et al. (2004) and Beracha and Seiler (2014).

Figure 2 Fourth and Fifth Digits of Six Digit Residential Prices



Next, we focus on endings with “0,000” and track the changes in the fifth digit. A unit change at the fifth digit implies a change of 10,000; that is, 2% of our sample median house price (490,000TRY) and is equivalent to more than seven months of the disposable income of median households, and hence, economically significant. Figure 3 shows the histogram for different endings defined by D, the fifth digit. There are 55.3% of the prices that have “0,000” endings and the fifth digit clusters around 0 and 5; 24.7% with “0,000” endings have 0 while 31.2% have 5 as the fifth digit; and the frequency of the other numbers as the fifth digit is much less than what a uniform distribution would imply, i.e. 10%. This indicates increments of 50,000TRY in addition to the increments of 5,000TRY observed in Figure 2. Even the 5,000TRY increment is almost 1% of the median house price of 490,000TRY and 3.8 times the monthly disposable income.

Figure 3 Fifth Digit of Six Digit Residential Prices



To further analyze the impact of clustering, we first regress the logarithm of prices on all available property characteristics including the area and number of bedrooms. Table 2 presents the summary statistics of the available numerical characteristics of housing properties for sale, and the summary statistics for the categorical characteristics such as the heating type are provided in the Appendix. Table 2 shows that the average age of the residential properties for sale is 7.4 years old while the average property measures 112.12 in square meters, and has around two bedrooms, one living room and one bathroom. On average, the residential unit is in closer proximity to schools and hospitals compared to universities, shopping malls and fire stations.

As we explain in the methodology section, we divide the data randomly into two groups: training and prediction subsamples. We estimate the coefficients of the model by using the training sample and perform the analysis for the prediction sample with the coefficients from the training data set. Table 3 presents the results of the regression model for the training subsample as in Equations (1) and (2), and the residuals of the analysis are calculated by using Equation (3). The regression results for the training sample shows that age and the number of living rooms have negative impacts on listing prices. As the property for sale increases in age, the prices go down and more living roomsare related to lower value. This negative effect of the number of living rooms is because most residential properties have one living room, and those with more tend to be the ones with odd features or modified layouts, which are not as common and more difficult to sell. On the other hand, property area, and number of bedrooms and bathrooms pertain to higher prices as a larger square footage, and more bedrooms and bathrooms add to the value of the property.

Table 2 Summary Statistics of Numerical Characteristics of Housing Properties for Sale

	N	Mean	S.D.	Min.	Max.
Age (years old)	18,761	7.40	11.01	0	50
Area (square meters)	18,761	112.14	38.12	30	400
# Bathrooms	18,761	1.35	0.53	1	5
# Livingrooms	18,761	1.05	0.25	0	4
# Bedrooms	18,761	2.39	0.86	1	7
Dist. to fire station	18,761	1,648.02	1,021.58	6.01	9,017.45
Dist. to hospital	18,761	892.10	738.18	4.18	10,844.95
Dist. to mall	18,761	1,598.86	1,072.49	0.06	14,645.27
Dist. to police station	18,761	1,076.00	756.53	6.61	9,685.61
Dist. to transportation	18,761	1,509.23	2,379.96	11.02	45,523.78
Dist. to priv. kindergarten	18,761	417.73	355.96	1.67	9,168.73
Dist. to priv. elem. sch.	18,761	814.88	592.96	5.60	15,801.18
Dist. to priv. high sch.	18,761	897.58	637.98	7.15	15,315.44
Dist. to priv. middle sch.	18,761	769.23	530.83	5.60	11,090.74
Dist. to pub. kindergarten	18,761	1,951.08	1,814.88	9.57	15,169.77
Dist. to pub. elem. sch.	18,761	393.08	293.77	3.03	6,730.28
Dist. to pub. high sch.	18,761	558.69	376.31	4.02	8,040.03
Dist. to pub. middle sch.	18,761	410.09	298.78	4.26	5,926.49
Dist. to university	18,761	1,597.11	1,337.80	17.33	15,328.01

Notes: Age is the age of the building. Area is the area of the housing unit in square meters. # Bathrooms, # Livingrooms and #Bedrooms are the number of bathrooms, living rooms and bedrooms within the property, respectively. Dist. variables are the distance in meters to the closest public services. The definitions of the variables are explained in detail in the Appendix

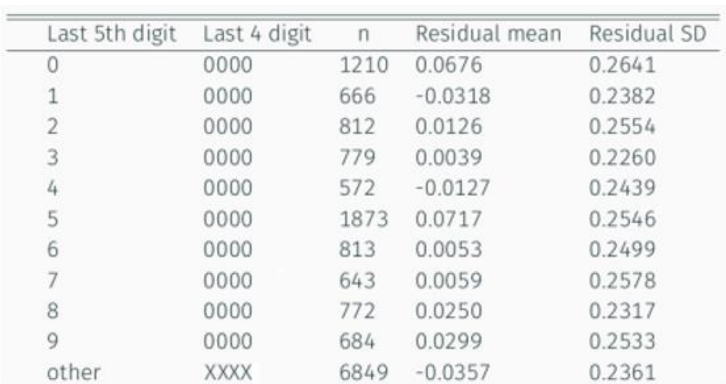
Table 3 Regression of Housing for Sale Prices on Property Characteristics with Training Set

Age	-0.001361*
	(0.010)
Area	0.005376***
	(0.000)
#Bathrooms	0.07205***
	(0.000)
#Livingrooms	-0.04811*
	(0.023)
#Bedrooms	0.02837**
	(0.008)
Constant	0.1284***
	(0.000)
Observations	2,814
R^2	0.7446

Note: The table shows the coefficients for the regression of the natural logarithm of housing for sale prices on property characteristics. p-statistics are given in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

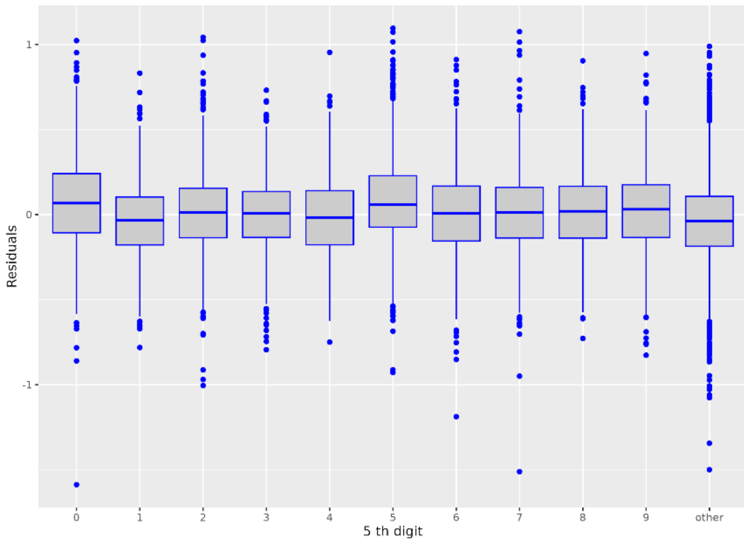
Next, we group the residuals of the prediction sample by their price endings and regress on *D* to understand whether there is a pricing anomaly. Figure 4 shows the within group statistics of the residuals and a box plot for visual inspection which also confirms clustering around zero and five.

Figure 4 Residuals of Hedonic Pricing Equation by Price Ending



Last 5th digit	Last 4 digit	n	Residual mean	Residual SD
0	0000	1210	0.0676	0.2641
1	0000	666	-0.0318	0.2382
2	0000	812	0.0126	0.2554
3	0000	779	0.0039	0.2260
4	0000	572	-0.0127	0.2439
5	0000	1873	0.0717	0.2546
6	0000	813	0.0053	0.2499
7	0000	643	0.0059	0.2578
8	0000	772	0.0250	0.2317
9	0000	684	0.0299	0.2533
other	XXXX	6849	-0.0357	0.2361

(Figure 4 Continued)



After the estimations with the prediction subsample as in Equations (2) and (3), the existence of any clustering effect in the predicted residuals are examined by Equation (4). Table 4 shows the coefficient estimates of Equation (4) - the regression of residuals on the fifth digit of the prices while the last four digits are all zeros, which seem to explain some of the variation in the predicted residuals. The coefficients are significant with zero and five has the highest impact in magnitude. An analysis of variance (ANOVA) which is used to test whether the means of the residuals are zero also rejects the null hypothesis, thus suggesting that the group means are not jointly zero and signal an anomaly.

4.1 Levels, Seven Digit Prices and Different Real Estate Markets

4.1.1 Price Levels

Given the methodology, clustering can be related to price levels and there may be the tendency to round higher numbers more. When we examine the fifth digit of prices, a unit change in the fifth digit can be as high as 6% (1%) of the price of real estate worth around 100,000TRY (900,000TRY). Therefore, we first determine the correlation between the fifth and sixth digits to understand whether the two are linked. Cramer's V is 0.096 which implies a small association (Cohen 1988). Next, we add both the fifth and sixth digits to the pricing equation to check the effect of the digit groups on even-endings while controlling for the sixth digit. The results in Table 5 confirm that the price levels have an effect; however, clustering still prevails as Ds remain significant. Interestingly, the coefficients on the digit group variables are negative and decrease in magnitude from one to five while they are positive and increase in magnitude from six to nine. This pattern implies a tendency to round down prices when the fifth digit is less than five and round up prices when the fifth digit is more than five.

Table 4 Regression of Regression Residuals on Fifth Digit (D) of Six Digit Prices

zero	0.106***
	(0.008)
one	0.003
	(0.010)
two	0.047***
	(0.009)
three	0.039***
	(0.009)
four	0.025**
	(0.011)
five	0.114***
	(0.006)
six	0.045***
	(0.009)
seven	0.045***
	(0.010)
eight	0.056***
	(0.009)
nine	0.055***
	(0.010)
constant	-0.036***
	(0.003)
Observations	15,763
R^2	0.029

Notes: The table shows the coefficients for the regression of predicted residuals on the fifth digit of six digit prices. The fifth digit ranges from zero to nine and the remaining four digits are all zeros. p-statistics are given in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5 Regression of Price Levels on Fifth Digits (D) of Six Digit Prices

one	-0.110***	(0.007)
two	-0.076***	(0.006)
three	-0.056***	(0.006)
four	-0.035***	(0.007)
five	-0.006	(0.004)
six	0.014**	(0.006)
seven	0.039***	(0.007)
eight	0.066***	(0.006)
nine	0.085***	(0.006)
Constant	12.083***	(0.032)
Observations	3,088	
R^2	0.981	

Note: The table shows the coefficients for the regression of price levels on the fifth digits of six digit prices while controlling for the sixth digits. The fifth digit ranges from zero to nine and the remaining four digits are all zeros. The results for the sixth digit are omitted for brevity. p-statistics are given in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

4.1.2 Seven Digit Prices

Next, we focus on seven figure prices - 1,000,000TRY[9] and higher. This group constitutes 18.4% of the residential sample for sales and are relatively higher-priced properties. We use a similar methodology as the analysis for six digit prices, and focus on the endings of “00,000” and the sixth digit as the grouping variable. Figure 5 shows that seven figure prices are distributed in “50,000” increments as opposed to the “5,000” increments of the six digit prices. The ANOVA shows that the digit groups that explain the residuals still remain significant and the group means of the residuals are not jointly zero, hence, confirming the pricing anomaly.

The clustering and more sparse increments for higher prices rule out the precision explanation. If people can be precise about the price with “5,000” increments in the six figure sample, they can also be as precise in the seven figure sample. This is in line with the mental accounting phenomenon in Tversky and Kahneman (1981); sellers and brokers consider the minimal account associated with the decision to trade rather than trying to value the property precisely. Moreover, the valuation of real estate properties requires accumulation of a considerable amount of information. It may be the case that the owners of the relatively more expensive properties might have a higher opportunity cost of time for information acquisition. Therefore, one might

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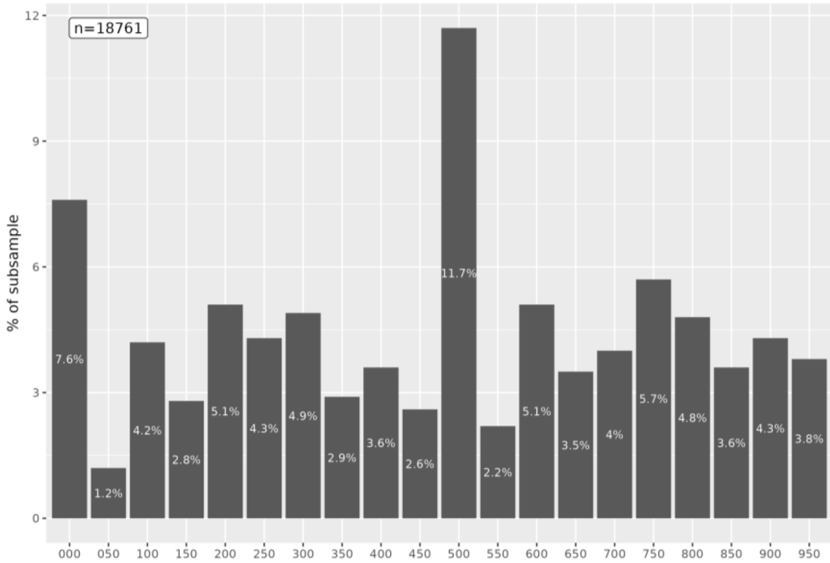
[9] USD/TRY = 3.66 as of October 2017.

argue that the one digit increase in price increment could be due to information friction; the increased cost of obtaining information for sellers rather than individual heuristics. However, there is a specific market for acquiring information and the potential change in wealth is relatively higher such that outsourcing the valuation process to obtain a more precise price can prove profitable. For example; the minimum real estate property valuation fee is 445TRY which is less than 1% of the 50,000TRY increments for the seven figure prices. [10]

Figure 5 Fourth, Fifth and Sixth Digits of Seven Digit Residential Prices



4.1.3 Different Real Estate Prices

Finally, we examine the commercial property and land markets for sale, and the rental housing market. We apply the same methodology used for the residential market, and report similar results.[11] Figure 6 shows the distributions of the price endings for different property types confirming those for the housing market for sale.

[10] Capital Markets Board of Turkey, 2017

[11] For the rental housing market, we focus on the four digit prices as the median rental housing price is 2,200TRY and the 22,662 rentals with four figure price levels consist of 93% of all observations.

Figure 6 (a) Price Endings for Commercial Prices

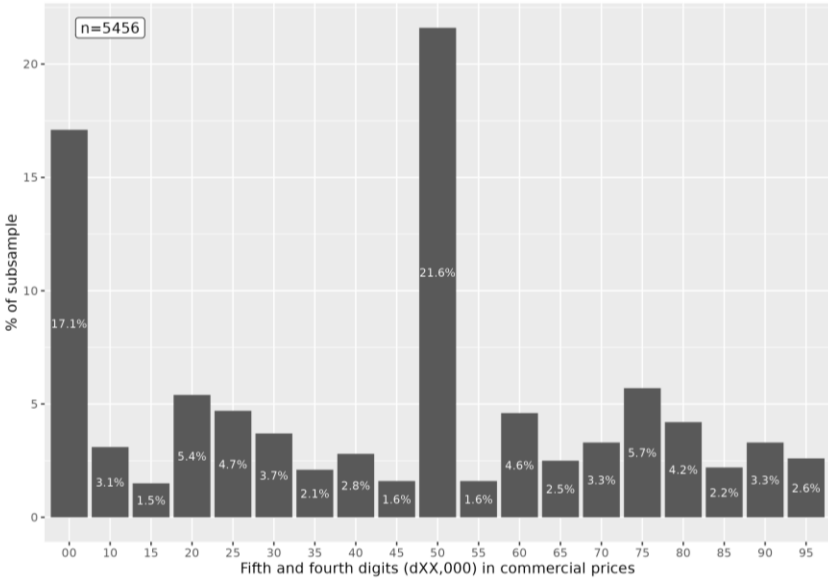


Figure 6 (b) Price Endings for Land Prices

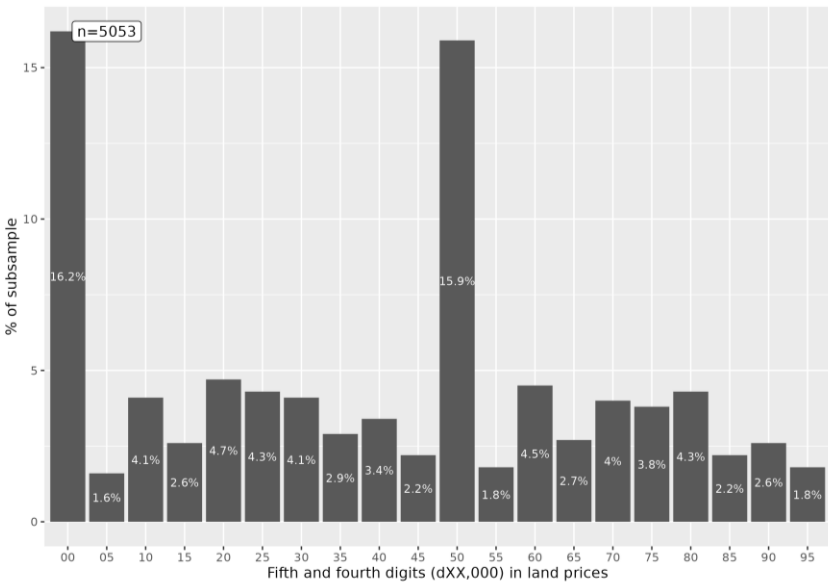
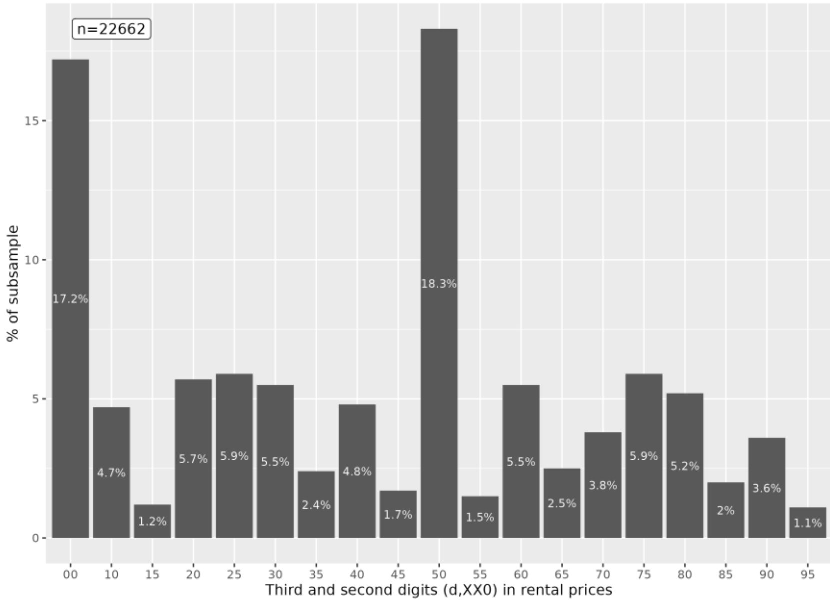


Figure 6 (c) Price Endings for Rental Prices



The analyses for the different real estate markets confirm the clustering behavior and provide evidence that the effect is not solely due to specific price levels or the inability to be precise in valuation. Moreover, the analyses show that information friction or taxes cannot be the main drivers as friction such as fees paid or the taxation schedule of transactions are vastly different in different markets. Our findings support the cognitive hypothesis that even pricing can be due to the tendency of relying on round numbers. Individuals have cognitive limitations and round numbers are naturally easier to deal with. The negotiation process can also relate to even pricing. However, round prices may increase the length of the negotiation process, and price clustering can occur if the participants think that round prices ease negotiation (Harris 1991).
When we consider the median price levels and the respective price increments for different real estate markets, the magnitude of even pricing is around 1% for most property types, except for the commercial and rental properties. The impact of clustering is 0.6% and 22% of the median commercial and rental price levels, respectively. All the different levels of even pricing amounts are equivalent to months' worth of median disposable income and economically significant. Therefore, a possible mispricing of a property may result in potential wealth loss for the transacting parties.

5. Concluding Remarks

Any digit sequence in prices should not have any impact on the prices themselves; nevertheless, we show that there is price clustering in the real estate markets. Even price endings of zeros and increments in multiples of five hundred, five thousand, and fifty thousand are far more common than what normally distributed price data or uniformly distributed price ending data would predict. This clustering is at the expense of the most immediate endings around clusters.

The even pricing phenomenon is prevalent in a wide range of markets including rental housing, and residential, commercial and land markets for sale which are vastly different in price levels, liquidity, participant information and tax practices. Moreover, the average rounding margin is not only higher than the expert valuation costs that can be paid to obtain more precise valuations but also economically significant as it is comparable to months' of median disposable income which may have implications for the financial well-being of the participants in the real estate markets as housing wealth and household consumption tend to move together.

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Appendix

Table A1 Control Variables and Definitions

Property_apt	Type of housing, apartment
Property_res	Type of housing, residence
Age	Age of the building
Area	Area of the property in square meters
# Bathrooms	Number of bathrooms
# Livingrooms	Number of living rooms
#Bedrooms	Number of bedrooms
Heating_ind.(C)	Type of heating: combi-boiler
Heating_ind.(A/C)	Type of heating: A/C
Heating_ind.(S)	Type of heating: stove
Heating_ind.(B)	Type of heating:boiler
Heating_central(CA)	Type of heating: central with allocator
Heating_central(G)	Type of heating: geothermal
Heating_central(C)	Type of heating: central
Floor_below ground	Property located at below ground level

Floor_ground	Property located on ground floor
Floor_half	Property located on semi-ground floor
Floor_first	Property located on first floor
Floor_mid	Property located on 2^{nd} to 5^{th} floors
Floor_high	Property located on 6^{th} to 12^{th} floors
Floor_veryhigh	Property located on 13^{th} and higher floors
Floor_top	Property located on top floor
Gated	Whether building is gated community
Dist. to fire station	Distance to closest fire station
Dist. to hospital	Distance to closest hospital
Dist. to mall	Distance to closest shopping mall
Dist. to police station	Distance to closest police station
Dist. to transportation	Distance to closest public transportation
Dist. to priv. kindergarten	Distance to closest private kindergarten
Dist. to priv. elem. sch.	Distance to closest private elementary school
Dist. to priv. middle sch.	Distance to closest private middle school
Dist. to priv. high sch.	Distance to closest private high school
Dist. to pub. kindergarten	Distance to closest public kindergarten
Dist. to pub. elem. sch.	Distance to closest public elementary school
Dist. to pub. middle sch.	Distance to closest public middle school
Dist. to pub. high sch.	Distance to closest public high school
Dist. to university	Distance to closest university campus
District	Dummies that correspond to the 39 districts in Istanbul

Table A2 Summary Statistics of the Categorical Characteristics of Housing Properties for Sale

	N
Property_apt	18,004
Property_res	757
Heating_ind.(C)	14,810
Heating_ind.(A/C)	57
Heating_ind.(S)	77
Heating_ind.(B)	37
Heating_central(CA)	2,440
Heating_central(G)	40
Heating_central(C)	1,300
Floor_below ground	358
Floor_ground	2,138
Floor_half	1,516
Floor_first	2,804
Floor_mid	6,404
Floor_high	2,004
Floor_veryhigh	512
Floor_top	3,025
Not gated	17,052