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PRICE CLUSTERING BEHAVIOR IN VIRTUAL REAL ESTATE MARKETS

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Abstract

We analyse 21,209 intraday transactions in the virtual real estate market and document significant price clustering at round numbers 0, 00, and 000 as ending digits, consistent with the negotiation hypothesis. The clustering increases with price level and pricing uncertainty proxied by the number of buyers and sellers in the NFT market. Moreover, market venue influences price clustering dynamics. Digits 9, 99, and 999 as ending prices are overrepresented in the sample, consistent with the left digit effects. However, we do not find support for the psychologically feeling right hypothesis or the strategic trading hypothesis.

JEL: O30, G10, G40, R30

Keywords: Price Clustering, Virtual Real Estate, Nonfungible Tokens, Behavioral Finance

1. Introduction

Decentraland, a virtual platform operating in the metaverse, offers non-fungible tokens (NFTs) in the form of virtual land parcels via the MANA cryptocurrency. These parcels can be freely traded among users, and all transactions are securely recorded in an Ethereum smart contract. In an explorative study, Dowling (2022) analyses 4,936 trades in the Decentraland and rejects both martingale and adaptive market efficiency. In this paper, we demonstrate pricing inefficiency through a direct measure – price clustering.

Studies show that the dollar digits cluster on 0 and 5 for a variety of assets, including stocks, commodities, and cryptocurrencies (Urquhart, 2017; Hu et al., 2019).[1] For the real estate market, Morali and Yilmaz (2023) find price clustering around even figures in residential, commercial, and land markets, with infrequent use of exact prices.

Our study focuses on analysing intraday transactions involving the MANA cryptocurrency of land parcels on the NFT trading platforms Decentraland and OpenSea. We find that the ending digit of sales prices shows significant clustering in 0, which represents a round number associated with a coarser price grid that simplifies and expedites negotiations. The extent of price clustering reduces as

[1] Price clustering has been observed in markets such as stocks (Harris, 1991; Hu et al. 2017), gold (Ball et al.,1985), derivatives (Schwartz et al., 2004), IPO and SEO markets (Kandel et al., 2001; Chiao et al., 2020), analyst forecasts (Dechow and You, 2012), drug prices (Hu et al., 2022), real estate prices (Palmon et al., 2004), and foreign exchange (Sopranzetti and Datar, 2002).

the number of buyers and sellers in the NFT market increases. Moreover, price clustering varies monotonically with price levels. Additionally, we investigate the occurrence of integer pricing, specifically examining the likelihood of sales prices ending with one zero (0), two zeros (00), and three zeros (000). Through logistic regression analysis, we identify two key determinants of price clustering: the price level and the level of pricing uncertainty. Both factors contribute to a higher likelihood of rounding in sales prices.

There is also a left-digit effect for ending digits 9, 99, and 999, which are just below a change in the leftmost digit. Surprisingly, the ending digit 5 is lower in frequency compared to 9, which is inconsistent with the typical psychological preference for digits such as 0 and 5. Furthermore, we find that the ending digit 1 has the lowest proportion, which contradicts the hypothesis of strategic trading.

By conducting a comprehensive analysis of 21,209 intraday transactions within the virtual real estate market, our research reveals unique insights into market efficiency and price negotiations in the metaverse. Like conventional markets, the virtual real estate market is susceptible to behavioral biases, including the left digit effect, a phenomenon frequently observed in consumer markets.

2. Hypotheses and Data

We examine four hypotheses regarding transaction price clustering in the metaverse real estate market.

The first hypothesis focuses on price negotiation and suggests that round numbers or coarser price grids reduce search costs in negotiations by expediting price discovery (Ball et al., 1985; Harris, 1991). According to the price negotiation hypothesis, as price level or pricing uncertainty increases, we anticipate an increase in price clustering.

The second hypothesis pertains to psychological factors, as rounded numbers are associated with a sense of "feeling right," while non-rounded numbers are more cognitively oriented. The preferred order for selecting ending digits is as follows: 0, 5, and others. Wadhwa and Zhang (2015) argue that people opt for round numbers because they find them psychologically appealing and easier to recall. However, the psychologically feeling right hypothesis would not predict positive correlations between price clustering and price level or pricing uncertainty.

The third hypothesis, known as the strategic trading hypothesis, asserts that individuals strategically choose prices by opting for values just above or below round numbers (Sonnemans, 2006). For instance, when prices cluster at 10-unit increments, strategic traders might gain an advantage by placing buy (sell) orders at the ending digit 9 (11).

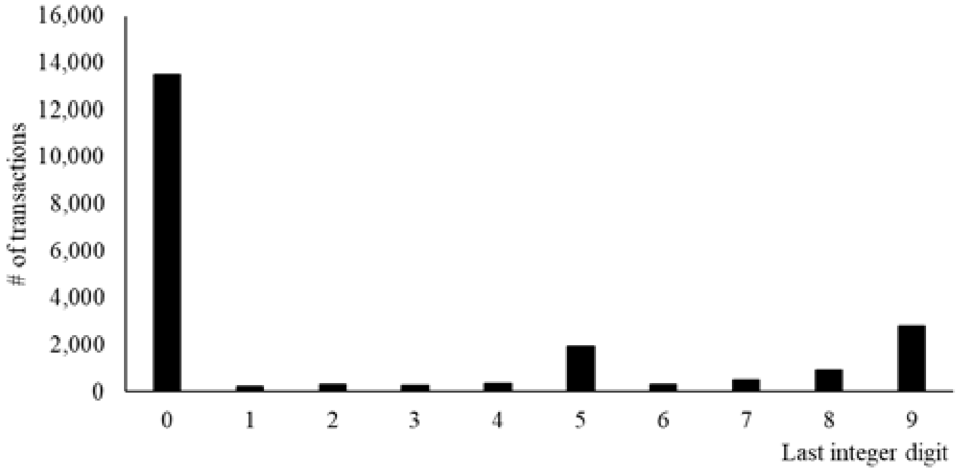
The fourth hypothesis focuses on the left digit effect, which has been examined by Manning and Sprott (2009) in relation to its impact on consumer choices. Their findings indicate that price endings on 9 have an influence on consumer behaviour. For instance, when comparing prices like 1.99 and 2.00, the left digits are 1 and 2, respectively. Thomas and Morwitz (2005) argue that consumers often exhibit behaviour characterised by being conscious of smaller expenses (penny-wise) but less concerned about larger ones (pound-foolish). Based on the left-digit effect hypothesis, we anticipate observing a higher proportion of prices ending with the digit 9. However, the strategic trading hypothesis suggests that both 1 and 9 would have higher frequencies as ending digits.

To test these hypotheses, we collect virtual real estate intraday transaction data utilising the methodology outlined by Nadini et al. (2021). Our dataset comprises 21,209 intraday transactions spanning from October 11, 2018, to April 11, 2021. We obtain the number of unique buyers and sellers in the NFT market for investor interest from https://nonfungible.com/market-tracker. The cryptocurrency MANA prices, and the S&P 500 market data are from Yahoo! Finance.

3. Results and Discussions

Do prices of virtual lands display clustering behaviour? Figure 1 illustrates the transaction frequency for prices ending in digits 0 through 9. Notably, prices ending in 0 exhibit the highest frequency, followed by prices ending in 9 and 5.

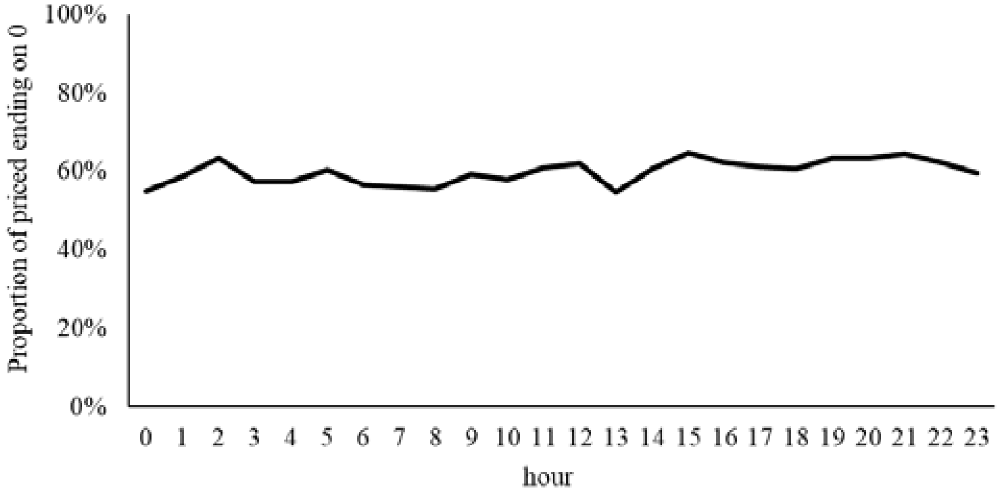
Figure 1: Distribution of the ending integer digit for virtual land prices



Note: We collect intraday transaction data for virtual land using the methodology outlined by Nadini et al. (2021). We provide an overview of the distribution of ending integer digits for virtual land prices denominated in MANA dollars.

Figure 2 shows the intraday variations in price clustering, specifically focusing on prices ending in 0 within hourly intervals. The clustering pattern remains consistent throughout the 24-hour day. These findings align with previous studies on cryptocurrency price clustering conducted by Hu et al. (2019) and Quiroga-Garcia et al. (2022).

Figure 2: Intraday variations in price clustering



Note: We collect intraday transaction data for virtual land using the methodology outlined by Nadini et al. (2021). We illustrate the proportion of prices ending on 0 throughout the day by hourly intervals using the UTC time.

Table 1 presents the frequencies of four different types of ending digits in the prices of virtual lands. For fractional prices, we truncate the values to four decimal places. It is worth noting that 12.6% of prices end in a fraction.[2] Within this group of 2,671 transactions, 1,085 or 40.6% of them end with .9999, providing support for the left digit effect hypothesis. However, the majority of prices (87.4%) for virtual lands end in integer values of the MANA currency.

Table 1: Price Clustering for Virtual Land Parcels

Panel A: Overall sample								
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Decimal	Count	Percent	Last one integer digit	Percent	Last two integer digits	Percent	Last three integer digits	Percent
.0000	1,567	7.4%	0	63.7%	00	43.5%	000	21.0%
.0001	8	0.0%	9	13.2%	99	8.2%	500	9.4%
.002	3	0.0%	5	9.2%	50	7.6%	999	5.3%
.1910	1	0.0%	8	4.5%	10	3.9%	900	3.7%
.3455	1	0.0%	7	2.5%	90	2.4%	010	3.5%
.5	1	0.0%	4	1.6%	15	1.7%	800	1.9%
.7886	1	0.0%	2	1.4%	88	1.5%	015	1.6%
.8019	1	0.0%	6	1.4%	30	1.4%	200	1.5%
.9	1	0.0%	3	1.3%	25	1.3%	100	1.4%
.99	1	0.0%	1	1.1%	80	1.3%	400	1.3%
.998	1	0.0%			Other	27.1%	Other	49.4%
.9999	1,085	5.1%						
Total obs with decimals	2,671	12.6%						
Grand total obs					21,209			

Panel B: Strategic trading vs. left digit effect			
Last integer digit	Chance proportion	Actual proportion	Difference
1	10.0%	1.1%	-8.9%***
9	10.0%	13.2%	3.2%***

Note: This table reports the summary statistics for the variables in this study. All variables are in a monthly frequency. The time span is from January 2008 through December 2014. The variables are as follows: ADR mispricing, investor attention (Wikipedia country page views are the proxy of investor attention), volume, market value, absolute returns (|Returns|), inverse price (1/P), dividend yield and the crisis dummy that assumes the value of 1 between January 2008 and June 2009, and zero otherwise. The data on ADRs is obtained from DataStream. The country-specific investor attention measure, Wikipedia page views, is obtained from the Wikipediatrends.com website.

In the real estate market, prices often end with triple zeros (000) to facilitate negotiation and price formation. Analysing the rightmost one, two, and three digits of prices in the integer MANA group, we find that ends in 0, 00, and 000 prevail over other digits. Notably, 21.0% of prices end with 000, which is comparable to the 19.6% reported by Palmon et al. (2004) for real estate listing prices clustering on 000, but much lower than the 50.5% clustering on 000 for transaction prices.

We also observe an overrepresentation of ending digits 9, 99, and 999 compared to other digits. These proportions are consistent with the left digit effect hypothesis, as the frequencies of 9 and 99 immediately trail the frequency of prices ending in round numbers 0 and 00. Since digit 5 ranks after

[2] The transactions with fractional price endings are associated with items for sale in the virtual land.

9, the findings do not support the hypothesis that digit 5 would have a higher proportion due to its psychological appeal.

To test the strategic trading hypothesis, we compare the ending digits 1 and 9 to their chance proportions using one proportion z-tests. Table 1, Panel B reveals that the proportion of ending digit 1 is significantly lower than the chance frequency. Furthermore, it ranks last in Panel A, Column (4). These results support the use of a coarser price grid to reduce search costs but reject the strategic trading hypothesis.

To further investigate the negotiation hypothesis, we analyze price clustering behaviour across different price levels and in relation to pricing uncertainty. Table 2 presents the findings on price clustering by price level. We sort the sample by transaction prices and partition the sample into three equal categories: low, medium, and high price groups. The results show that clustering in round number 0 as the ending digit increases monotonically from 39.4% for the low-price group, to 69.9% for the medium-price group, and further to 81.8% for the high-price group. Conversely, clustering around digits 9 and 5 decreases as the price level rises.

Table 2: Price Clustering for Virtual Land Parcels by Price Level

	Price level		
Last integer digit	Low (avg= 76 MANA, N=7069)	Medium (avg= 6,360 MANA, N=7070)	High (avg= 41,999 MANA, N=7070)
0	39.4%	69.9%	81.8%
1	2.1%	0.7%	0.6%
2	3.3%	0.7%	0.3%
3	2.6%	0.9%	0.5%
4	3.5%	0.8%	0.4%
5	18.9%	5.6%	3.1%
6	2.6%	1.0%	0.7%
7	4.8%	1.8%	1.0%
8	7.2%	4.2%	2.0%
9	15.6%	14.3%	9.6%

Note: We collect intraday transaction data for virtual land using the methodology outlined by Nadini et al. (2021). The transactions are denominated in MANA cryptocurrency. Column 1 shows the MANA dollar digit of the land prices. We partition the sample based on price level into three categories: Low, Medium, and High. The average price is in parentheses under each category. Count refers to the number of observations for each digit. Percent is Count divided by the total number of observations.

Table 3 focuses on price clustering in relation to pricing uncertainty, which is proxied by two measures. The first measure is the market venue for the transactions. Investors can either use the NFT trading platform OpenSea or buy land directly through the Decentraland Marketplace. Bessembinder (1999) documents higher adverse selection costs for Nasdaq-listed stocks compared to NYSE-listed stocks. In our study, using z-tests to compare the difference in proportions between Decentraland and OpenSea, we find significantly higher price clustering in the secondary market Opensea, relative to the primary market Decentraland, which suggests that the secondary market entails more uncertainty.

Table 3: Price Clustering for Virtual Land Parcels by Price Level by Uncertainty Measures

Panel A: By market				
Last integer digit	**Decentraland**	**OpenSea**	**Difference**	
0	60.2%	77.3%	17.1%	***
1	1.2%	0.7%	-0.5%	**
2	1.7%	0.6%	-1.1%	***
3	1.5%	0.6%	-1.0%	***
4	1.9%	0.3%	-1.6%	***
5	10.8%	2.8%	-8.0%	***
6	1.5%	1.2%	-0.3%	
7	2.8%	1.3%	-1.5%	***
8	4.6%	3.9%	-0.8%	*
9	13.7%	11.3%	-2.4%	***

Panel B: By investor interest			
	Investor Interest		
Last integer digit	**Low**	**Medium**	**High**
0	75.4%	60.3%	55.4%
1	0.8%	1.3%	1.4%
2	0.5%	1.4%	2.4%
3	0.6%	2.1%	1.3%
4	0.5%	2.1%	2.1%
5	3.8%	11.1%	12.7%
6	0.9%	1.3%	2.0%
7	1.2%	2.6%	3.7%
8	4.0%	4.5%	5.0%
9	12.3%	13.3%	14.0%

*Note: We collect intraday transaction data for virtual land using the methodology outlined by Nadini et al. (2021). The transactions are denominated in MANA cryptocurrency. We use two measures of uncertainty: market venue and investor interest. Decentraland is the main market that is associated with more information relative to the secondary market Opensea. For investor interest, we use the aggregate number of unique buyers and sellers in the NFT market from https://nonfungible.com/market-tracker. We partition the sample based on investor interest into three categories: Low, Medium, and High. Count refers to the number of observations for each digit. Percent is Count divided by the total number of observations. *, **, and *** indicate significance levels based on p-values derived from z-tests to compare the difference in proportions between Decentraland and OpenSea at 10%, 5%, and 1%, respectively.*

The second measure of pricing uncertainty is investor interest, calculated as the aggregate number of buyers and sellers in the NFT market. Information production increases as more participants enter the market, reducing uncertainty. Table 3, Panel B, illustrates a monotonic decrease in price clustering with the intensity of investor interest.

To analyse the determinants of price clustering in a multivariate analysis framework, we employ logistic regressions with a binary dependent variable for price clustering as shown below.

*Price Clustering = a + b1*Medium price + b2*High price + b3*Market + b4*Investor interest*

*+ b5*MANA volatility + b6*Stock market volatility*

The dependent variable *Price Clustering* is *zero-ending*, which takes on a value of 1 if the price ends with zero and 0 otherwise. Table 4 reports the results for the logistic regression. After controlling return volatilities in the cryptocurrency and stock markets, we find statistically significant coefficients for price level and the uncertainty measures at the 1% level based on p-values derived from the Wald statistic. By comparison, Morali and Yilmaz (2023) also find increases in rounding as price levels go up. These results provide support for the negotiation hypothesis.

Table 3: Price Clustering for Virtual Land Parcels by Price Level by Uncertainty Measures

Variable	Coefficient	
Intercept	-0.270	***
Medium price	1.307	***
High price	1.928	***
Market	0.278	***
Investor interest	0.022	
MANA volatility	-0.170	***
Stock market volatility	-0.046	
N	21,209	
p-value of likelihood ratio	<0.0001	

Note: To analyse the determinants of price clustering in a multivariate analysis framework, we employ logistic regressions with a binary dependent variable for price clustering as shown below.

*Price Clustering = a + b1*Medium price + b2*High price + b3*Market + b4*Investor interest*

*+ b5*MANA volatility + b6*Stock market volatility*

*The dependent variable Price Clustering is zero-ending, which takes on a value of 1 if the price ends with zero and 0 otherwise. The explanatory variables include price dummies and proxies for uncertainty along with control variables. We rank the transactions by price into three groups. If it is in the middle group, dummy variable Medium Price is 1 and 0 otherwise. If it is in the high-priced group, dummy variable High Price is 1 and 0 otherwise. Dummy variable Market is 1 for transactions in the secondary market Opensea and 0 for transactions in the primary market Decentraland. For investor interest, we use the aggregate number of unique buyers and sellers in the NFT market from https://nonfungible.com/market-tracker. We partition the sample based on investor interest into three categories: Low, Medium, and High, and use the ranking as dummy variable Investor interest. Control variables include daily return volatilities of prior month for both the MANA and the stock market proxied by the S&P 500 index. *, **, and *** indicate significance levels based on p-values derived from the Wald statistic at 10%, 5%, and 1%, respectively.*

4. Conclusion

In the context of virtual real estate transactions, our findings reveal significant price clustering at round numbers such as 0, 00, and 000, which provides strong support for the negotiation hypothesis. These results are consistent with the observed price clustering patterns in the tangible real estate market. Additionally, we observe evidence of left digit effects, as digits 9, 99, and 999 appear with higher frequencies as ending prices. However, we do not find support for the psychologically feeling right hypothesis or the strategic trading hypothesis. These findings suggest that factors other than psychological appeal or strategic trading behaviour play a more prominent role in price clustering within the virtual real estate market.

Overall, our results lend support to the negotiation hypothesis and the left-digit effect hypothesis. Furthermore, our analysis reveals lower price clustering on Decentraland compared to Opensea as the venue for virtual land transactions. This highlights the potential influence of the market venue on price clustering dynamics. Our research offers both theoretical and practical insights. Theoretical findings reveal the significance of price clustering and the persistence of behavioural biases in the virtual real estate market, providing a bridge between the real and virtual worlds in terms of human decision-making. For practitioners and regulators, price clustering studies help in designing the virtual real estate market to encourage liquidity, facilitate negotiations, and reduce search costs. Future studies could explore the impact of virtual land location on price clustering in order to gain further insights into this phenomenon.

References

Ball, Clifford A., Walter N. Torous, and Adrian E. Tschoegl, 1985, The degree of price resolution: The case of the gold market, Journal of Futures Markets 5, 29-43.

Bessembinder, Hendrik, 1999, Trade execution costs on NASDAQ and the NYSE: A post-reform comparison, Journal of Financial and Quantitative Analysis 34, 387-407.

Chiao, Cheng-Huei, Bill Hu, Ying Huang, and Jim Washam, 2020, Priced on the note: The case of Japanese IPOs, Applied Economics 52, 3406-3417.

Dechow, Patricia M., and Haifeng You, 2012, Analysts' motives for rounding EPS forecasts, The Accounting Review 87, 1939-1966.

Dowling, Michael, 2022, Fertile LAND: Pricing non-fungible tokens, Finance Research Letters 44, 102096.

Harris, Lawrence, 1991, Stock price clustering and discreteness, Review of Financial Studies 4, 389-415.

Hu, Bill, Joon Ho Hwang, Christine Jiang, Jim Washam, and Li Zeng, 2022, Down to the cents: The case of international drug prices, Finance Research Letters 46, 102357.

Hu, Bill, Christine Jiang, Thomas McInish, and Yixi Ning, 2019, Price clustering of Chinese IPOs: The impact of regulation, cultural factors, and negotiation, Applied Economics 51, 3995-4007.

Hu, Bill, Christine Jiang, Thomas McInish, and Haigang Zhou, 2017, Price clustering on the Shanghai Stock Exchange, Applied Economics 49, 2766-2778.

Hu, Bill, Thomas McInish, Jonathan Miller, and Li Zeng, 2019, Intraday price behavior of cryptocurrencies, Finance Research Letters 28, 337-342.

Kandel, Shmuel, Oded Sarig, and Avi Wohl, 2001, Do investors prefer round stock prices? Evidence from Israeli IPO auctions, Journal of Banking & Finance 25, 1543-1551.

Manning, Kenneth C, and David E Sprott, 2009, Price endings, left-digit effects, and choice, Journal of Consumer Research 36, 328-335.

Morali, Orcun, and Neslihan Yilmaz, 2023, Analysis of even pricing in real estate markets: Different asset types and implications, International Real Estate Review 26.

Nadini, Matthieu, Laura Alessandretti, Flavio Di Giacinto, Mauro Martino, Luca Maria Aiello, and Andrea Baronchelli, 2021, Mapping the NFT revolution: market trends, trade networks, and visual features, Scientific reports 11, 1-11.

Palmon, Oded, Barton Smith, and Ben Sopranzetti, 2004, Clustering in real estate prices: Determinants and consequences, Journal of Real Estate Research 26, 115-136.

Quiroga-Garcia, Raquel, Natalia Pariente-Martinez, and Mar Arenas-Parra, 2022, Evidence for round number effects in cryptocurrencies prices, Finance Research Letters 47, 102811.

Schwartz, Adam L., Bonnie F. Van Ness, and Robert A. Van Ness, 2004, Clustering in the futures market: Evidence from S&P 500 futures contracts, Journal of Futures Markets 24, 413-428.

Sonnemans, Joep, 2006, Price clustering and natural resistance points in the Dutch stock market: A natural experiment, European Economic Review 50, 1937-1950.

Sopranzetti, Ben J., and Vinay Datar, 2002, Price clustering in foreign exchange spot markets, Journal of Financial Markets 5, 411-417.

Thomas, Manoj, and Vicki Morwitz, 2005, Penny wise and pound foolish: The left-digit effect in price cognition, Journal of Consumer Research 32, 54-64.

Urquhart, Andrew, 2017, Price clustering in Bitcoin, Economics Letters 159, 145-148.