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Effects of Price Clustering on African Stock Markets

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Abstract: The phenomenon of price clustering refers to the empirical finding that some prices in financial markets occur significantly more frequently than others. The phenomenon is important theoretically as it challenges the efficient market theory and empirically as it suggests that predictability patterns can be used by investors to devise strategies and investments capable of generating abnormal returns. In this paper, we study the phenomenon for the first time in the context of African markets. Our study includes data from the period spanning 2018-2022 for the stock markets of Egypt, Kenya, Morocco, Nigeria, South Africa, and Tunisia. Our results provide compelling evidence of price clustering within all markets under analysis. Univariate analysis confirms widespread clustering, particularly favoring closing prices ending in zero and five. The results of the multivariate analysis suggest that stocks with higher prices, lower turnover, and lower liquidity tend to exhibit a higher level of clustering. Contrary to the expectations of the Panic Selling Hypothesis, a more intense clustering did not occur during the COVID-19 pandemic. Collectively, our results offer partial support for the Attraction Hypothesis and the Negotiation/Price Resolution Hypothesis.

Keywords: price clustering; COVID-19 pandemic; efficient market theory; behavioral finance; African stock markets.

JEL classification: G01; G12; G14; G40.

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1. INTRODUCTION

The Efficient Market Hypothesis (EMH) has been a cornerstone in financial theory, asserting that market prices incorporate all available information, rendering attempts to predict future price movements futile (Fama, 1965). According to the EMH, asset prices should reflect all available market information, resulting in evenly distributed prices without apparent clustering around specific digits. However, empirical research over time has revealed instances where market prices exhibit patterns challenging the fundamental principles of EMH. One such pattern is the phenomenon of price clustering, initially identified in studies by Osborne (1962) and Niederhoffer (1965).

Early investigations found that prices in the US market often cluster around whole numbers or fractions. Numerous subsequent studies on price clustering in the US market, including those by Harris (1991), Christie *et al.* (1994), and Ikenberry and Weston (2008), among others, expanded our understanding. As time progressed, evidence surfaced indicating stock price clustering in other markets, such as Australia (Aitken *et al.*, 1996), Singapore (Hameed and Terry, 1998), various Asia-Pacific markets (Brown *et al.*, 2002), Tokyo (Ohta, 2006; Aşçıoğlu *et al.*, 2007), and more. Price clustering, however, extends beyond stock markets alone, affecting diverse asset types and markets, including the commodity market (Ball *et al.*, 1985), derivatives (Ap Gwilym *et al.*, 1998), foreign exchange market (Mitchell, 2001), betting market (Brown and Yang, 2016), and cryptocurrencies (Urquhart, 2017; Baig *et al.*, 2019).

With numerous studies, various hypotheses emerged to explain this clustering phenomenon. Ball *et al.* (1985) proposed the Price Resolution Hypothesis, Harris (1991) suggested the Negotiation Hypothesis based on increased uncertainty, Curcio and Goodhart (1991) introduced the Attraction Hypothesis related to individual number preferences, and Christie *et al.* (1994) proposed the Collusion Hypothesis, implying collusion among market participants. More recently, the Panic Selling Hypothesis (Narayan and Smyth, 2013) posits that during crises, the clustering effect intensifies.

This paper represents a pioneering effort dedicated to exploring price clustering in African stock markets. Our primary goal is to contribute to existing literature by compiling comprehensive evidence on price clustering in six African nations: Egypt, Kenya, Morocco, Nigeria, South Africa, and Tunisia. These markets, with market capitalization values in 2018 relative to their GDPs of 16%, 24.32%, 47.97%, 7.47%, 19.51%, and 214.11%, respectively, have gained significance within the African continent. Our research spans the onset of the COVID-19 pandemic, allowing us to examine whether the pandemic influenced price clustering within these markets. To achieve this, we divided the sample from each market into three distinct periods, facilitating an in-depth analysis of the pandemic-induced financial crisis' impact on variations in price clustering.

Following methodologies outlined by Ikenberry and Weston (2008) and Lobão *et al.* (2019), our approach includes both univariate and multivariate analyses. The initial analysis aims to ascertain the uniformity of the frequency distribution of last digits and discern any disparities in price clustering between the periods. Subsequently, the multivariate analysis explores factors contributing to fluctuations in price clustering, including the influence of the COVID-19 crisis.

In summary, our study provides compelling indications of price clustering within the examined markets. However, it offers limited validation for the Attraction Hypothesis and the Price Negotiation and Resolution Hypothesis. Surprisingly, the impact of the COVID-19 pandemic on the extent of price clustering does not align with the anticipated outcomes documented in the Panic Selling Hypothesis.

Price clustering is a focal point in financial research, offering insights into investor behavior, market efficiency, and the impact of various market mechanisms on price formation. Understanding the patterns and drivers of price clustering contributes to a deeper comprehension of how financial markets operate and how investor psychology interacts with market structure.

The subsequent sections structure the paper as follows. Section 2 delves into existing literature, offering a comprehensive review of price clustering concepts, hypotheses, and empirical findings. Section 3 describes the research questions, the data used for the analysis, as well as the methodology adopted. Section 4 presents the outcomes revealed by univariate and multivariate analysis for each sample. Finally, Section 5 summarizes the main conclusions and presents future avenues of research.

2. LITERATURE REVIEW

2.1 Price Clustering Definition

Price clustering denotes the recurring tendency of financial asset prices, including stocks, commodities, and currencies, to aggregate around specific numerical values or price levels sharing common ending digits or fractions. Instead of a uniform distribution, price clustering leads to a disproportionate frequency of certain endings, often round numbers or fractions. Rooted in psychological, cognitive, and market structure factors, investor behavior, influenced by perceptions of significance, contributes to increased trading activity around these levels. Market mechanics and regulations also play a role, impacting liquidity at specific price levels. Pioneers Osborne (1962) and Niederhoffer (1965) documented this phenomenon during the 1960s, challenging the expectations of the efficient market hypothesis.

Following their work, various hypotheses emerged, such as the Price Resolution Hypothesis (Ball *et al.*, 1985), Negotiation Hypothesis (Harris, 1991), Attraction Hypothesis (Curcio and Goodhart, 1991), Collusion Hypothesis (Christie *et al.*, 1994), and Panic Selling Hypothesis (Narayan and Smyth, 2013). Besides those, the Culture Hypothesis (Curcio and Goodhart, 1991), and the Strategic Trading Hypothesis (Sonnemans, 2006) are two other theories mentioned in the literature, albeit not tested in this paper.

2.2 Price Resolution Hypothesis

The Price Resolution Hypothesis, articulated by Ball *et al.* (1985), delves into the intricate dynamics of price clustering, asserting that this phenomenon arises from the deployment of coarser price grids. These grids are influenced by the amount of information available in the market and the inherent uncertainty investors face regarding the underlying value of each asset. According to this hypothesis, larger companies, endowed with greater information access due to comprehensive analyses and rankings by analysts, exhibit lower degrees of clustering. The reasoning is that as the value of the asset increases, market participants are more inclined to employ a coarser price grid, negotiating at round prices. Notably, the high liquidity of larger companies minimizes information asymmetry, subsequently reducing trade uncertainty and contributing to less clustering. In essence, the hypothesis contends that as market information increases, uncertainty decreases, resulting in a higher degree of price resolution and a lower probability of price clustering.

Ikenberry and Weston (2008) further explored the implications of the Price Resolution Hypothesis by examining the impact of decimalization on the clustering phenomenon in US stock prices. Their study revealed a reduction in price clustering post-decimalization, indicating that finer tick sizes allowed for higher price granularity, thereby deviating from previous clustering patterns. Furthermore, the shift to decimal pricing altered investors' perspectives and trading approaches towards stocks, subsequently impacting the clustering tendencies of stock prices. The empirical substantiation of the Price Resolution Hypothesis is evident in various studies conducted by researchers such as Harris (1991), Aitken *et al.* (1996), Ap Gwilym *et al.* (1998), Ohta (2006), Narayan and Smyth (2013), and more recently, Lobão *et al.* (2019).

2.3 Negotiation Hypothesis

Harris (1991) expanded the Price Resolution Hypothesis into the Negotiation Hypothesis, suggesting that negotiation convenience leads to clustering around round numbers or fractions. As negotiating costs rise, observed price clustering increases. Aitken *et al.* (1996) and Hameed and Terry (1998) provided supporting evidence, emphasizing the influence of negotiation costs, trading volume, and price levels on clustering. Additional investigations by Ap Gwilym *et al.* (1998), Palao and Pardo (2012), Narayan and Smyth (2013), Hu *et al.* (2019), Lobão *et al.* (2019), Narayan (2022), and Lobão (2024) further substantiated this hypothesis's explanatory power.

2.4 Attraction Hypothesis

Curcio and Goodhart (1991) investigated the clustering phenomenon of bid and ask prices within the foreign exchange market, recognizing its significance for the bid-ask spread and, consequently, traders' transaction costs and market liquidity. The Attraction Hypothesis proposed by Curcio and Goodhart (1991) posits that each number possesses a "gravitational" force, with certain values perceived as more attractive. Rooted in behavioral psychology, this theory suggests a preference for prices ending in zero followed by five, and an inclination towards even numbers, particularly the digits two and eight. Their conclusion highlights the correlation between price clustering, trading costs, and participants' desired price resolution. Aitken *et al.* (1996) corroborate the Attraction Hypothesis in the Australian Stock Exchange, revealing a tendency for price clusters ending in digits zero and five. The nuanced interplay of market dynamics and psychological factors influencing price clustering is further emphasized by Kandel *et al.* (2001) in their examination of stock price levels during initial public offerings (IPOs) in the Israeli market. Brown *et al.* (2002), Aşçıoğlu *et al.* (2007), Narayan *et al.* (2011), Palao and Pardo (2012) and Lobão *et al.* (2019) also confirmed the Attraction Hypothesis in their studies, concluding that prices ended at zero (0) were preferred, followed by those ending in five.

2.5 Collusion Hypothesis

The Collusion Hypothesis, proposed by Christie *et al.* (1994), suggests that price clustering may stem from tacit collusion among market participants. This hypothesis implies that traders or investors may coordinate their activities to keep prices close to certain levels, potentially benefiting their interests. However, proving such coordination empirically is challenging.

Christie *et al.* (1994) evidenced how the multi-dealer structure in the NASDAQ market creates an incentive to maintain uncompetitive offer-sale spreads, increasing profit margins per transaction and causing price clustering. Huang and Stoll (1996) argue that collusion in markets with multiple dealers is rare, and Aşçıoğlu *et al.* (2007) find indications of price clustering even in an electronic trading market that does not permit explicit collusive behavior. While some studies support the notion of collusion, such as Barclay (1997), Bessembinder (1997), and Geoffrey Booth *et al.* (2000), the empirical evidence remains mixed.

2.6 Panic Selling Hypothesis

The Panic Selling Hypothesis, proposed by Narayan and Smyth (2013), posits that political instability has a positive effect on price clustering. In times of anxiety or fear among market participants due to adverse news or uncertain economic conditions, a rush to sell assets may occur, leading to a concentration of sell orders at specific price levels. This hypothesis underscores the influence of market psychology and emotional reactions on price clustering, particularly during market uncertainty. Lobão *et al.* (2019) found support for the Price Resolution, Negotiation, and Attraction Hypotheses in their analysis of price clustering in European and American banks during the 2008 global financial crisis. Contrary to expectations, they identified a reduction in price clustering during the crisis, challenging the Panic Selling Hypothesis. Narayan (2022) explored price clustering in the oil market during the COVID-19 pandemic, aligning with the Panic Selling Hypothesis and revealing potential shifts in investor behavior and market dynamics during crises.

3. DATA AND METHODOLOGY

3.1 Hypotheses

Our research questions are inspired by theories discussed in the literature, leading to the formulation of hypotheses. Initially, we aim to empirically verify the presence of price clustering in the analyzed markets. Hypothesis H_1 posits that the final digits of daily closing prices do not follow a uniform distribution, aligning with the "gravitational" influence of each number as proposed by Curcio and Goodhart (1991).

H1*: The final digits of daily closing prices do not present a uniform distribution.*

Subsequently, if evidence of price clustering is found, we explore the impact of COVID-19 on clustering patterns. Hypothesis H_2 anticipates an increase in price clustering during the COVID-19 period, aligning with the Panic Selling Hypothesis (Narayan and Smyth, 2013) and the Price Resolution Hypothesis (Ball *et al.*, 1985).

H2*: There is an increase in price clustering in the markets during the period of COVID-19, compared to the previous or subsequent period.*

Following the Negotiation Hypothesis (Harris, 1991) and the Price Resolution Hypothesis (Ball *et al.*, 1985), we propose additional hypotheses related to variables influencing price clustering:

H3a*: Stock with higher prices exhibit higher price clustering.*

H3b*: Stocks with lower capitalization exhibit higher price clustering.*

H3c*: Stocks with lower turnover exhibit higher price clustering.*

H3d*: Higher market volatility is associated with higher price clustering.*

H3e*: Stock with lower liquidity exhibit higher price clustering.*

3.2 Data

We analyze price clustering effects using daily closing prices of shares listed in six African markets over five years (January 1st, 2018, to December 31st, 2022): Egypt, Kenya, Morocco, Nigeria, South Africa, and Tunisia. We follow Lobão (2018) criteria to select these markets. We use the daily closing prices of the stocks listed in Egypt (29 stocks quoted on the EGX 30 Index), Kenya (17 stocks from the NSE 20 Index), Morocco (46 stocks from the MASI Index), Nigeria (75 stocks from the NSE All Share Index), South Africa (103 stocks from the FTSE/JSE All Share), and Tunisia (78 stocks from the Tunindex). To ensure a fair examination of the clustering effect, we exclude prices hindered by tick sizes that prevent specific digit endings, following the standard practice in price clustering studies. Daily data is retrieved from Datastream by Refinitiv.

For COVID-19 analysis, we split the sample into three periods standardized across markets: before, during, and after COVID-19. Period start and end dates for each market are detailed in Table no. 1, using confirmed coronavirus infection dates as per Medhat and El Kassas (2020) and Takyi and Bentum-Ennin (2021). The COVID-19 period concludes uniformly on August 31st, 2021, facilitating consistent data processing and analysis.

Table no. 1 – Period split dates for each market

Markets	Before COVID-19	COVID-19	After COVID-19
Egypt	01/01/2018 to 13/02/2020	14/02/2020 to 31/08/2021	01/09/2021 to 31/12/2022
Kenya	01/01/2018 to 12/03/2020	13/03/2020 to 31/08/2021	
Morocco	01/01/2018 to 01/03/2020	02/03/2020 to 31/08/2021	
Nigeria	01/01/2018 to 26/02/2020	27/02/2020 to 31/08/2021	
South Africa	01/01/2018 to 04/03/2020	05/03/2020 to 31/08/2021	
Tunisia	01/01/2018 to 01/03/2020	02/03/2020 to 31/08/2021	

3.3 Methodology

3.3.1 Univariate Analysis

We commence with a univariate analysis to affirm the presence of price clustering, focusing on the frequency distribution of the final digit in stock prices. In the absence of clustering, each digit (0-9) would ideally occur with a frequency of 10%. Building on the methodologies of Ikenberry and Weston (2008), Palao and Pardo (2012), Lobão *et al.* (2019), among others, we utilize the Herfindahl-Hirshmann index (HHI). Although traditionally assessing market concentration, in our context, HHI substitutes market shares with the percentage of prices ending with specific digits. The formula is expressed as follows:

$$H = \sum_{i=1}^{B} (f_i)^2 \tag{1}$$

where f_i denotes the percentage frequency of closing stock prices within specific fractional divisions (bins), with $i = 1,2, \dots, B$. A unity HHI indicates complete clustering, while the null hypothesis suggests an HHI of 0.1, assuming uniform distribution.

To evaluate changes in clustering during a crisis, we employ the Chi-square statistic of goodness-of-fit (D), as used by Palao and Pardo (2012). The formula is given by:

$$D = \sum_{i=1}^{N} \frac{(O_i - E_i)^2}{E_i} \tag{2}$$

where O_i is the frequency of occurrence for the final digit within bin $i = 1,2, \dots, N$. and E_i is the frequency that would be observed in a scenario of uniform distribution. This statistic follows a Chi-square distribution with N-1 degrees of freedom. Elevated *D* values signify increased clustering.

To assess consistency across three samples, we calculate the ratio-based statistic $\widetilde{D}$, allowing us to identify shifts in clustering between periods preceding (D_1), during (D_2), and after (D_3) COVID-19.

$$\begin{gathered} \widetilde{D} = \left(\frac{D_2}{D_1}\right) \sim F_{N_2-1, N_1-1} \\ \widetilde{D} = \left(\frac{D_3}{D_2}\right) \sim F_{N_3-1, N_2-1} \end{gathered} \tag{3}$$

Using this statistic, we test the null hypothesis (H_2) that the three samples exhibit equal clustering levels. An elevation in the values of $\widetilde{D}$ signifies a heightened degree of price clustering within their corresponding subsets.

3.3.2 Multivariate Analysis

The multivariate analysis aims to identify factors driving price clusters across the considered markets. The dependent variable is the HHI, which quantifies price clustering while considering the tick size inherent to each stock in each market. To ensure comparability and diminish asymmetry, each independent variable will be transformed logarithmically and standardized. This entails subtracting the sample mean from the variable and dividing by the standard deviation, effectively centralizing the means at zero and standardizing the variances to unity. This procedure enables the comparison of the magnitude of the various coefficients (Ikenberry and Weston, 2008). Using this approach, we formulate the following model through Ordinary Least Squares (OLS) regression:

$$\begin{aligned} &Clustering - E(Clustering) \\ &\qquad = \alpha + \beta_1 StockPrice + \beta_2 CompSize + \beta_3 Turnover \\ &\qquad + \beta_4 Volatility + \beta_5 Iliquidity + e_i \end{aligned} \tag{4}$$

Explanatory variables align with existing literature, addressing the Price Resolution and Negotiation Hypotheses (Ball *et al.*, 1985; Harris, 1991; Aitken *et al.*, 1996; Ikenberry and Weston, 2008). Table no. 2 provides a summary of the model's variables and their expected signs according to the literature.

Table no. 2 – Description of the variables and expected signs for the independent variables coefficients

	Variables	Description		References
Dependent variable	Clustering-E (Clustering)	HHI (measure of price clustering at the last digit) minus the level of clustering expected in the null hypothesis (HHI=0.1)		Ikenberry and Weston (2008)
	Variables	**Description**	**Expected sign**	**References**
Independent variable	*Stock Price*	Average daily price of the company's shares over the sample period	+	Harris (1991); Aitken *et al.* (1996)
	Compsize	Daily average of the stock market value of the company	-	Harris (1991)
	Turnover	Average turnover of the company over the sample period	-	Ball *et al.* (1985); Ikenberry and Weston (2008)
	Volatility	Squared deviation of the time series of daily returns over the sample period	+	Harris (1991)
	Illiquidity	Arithmetic mean of the bid-ask spread ratio, centered at its midpoint, over the sample period	+	Palao and Pardo (2012)

4. RESULTS AND DISCUSSION

4.1 Univariate analysis

Table no. 3 presents the occurrence frequency of closing price last digits across the six countries, clustering test outcomes, and associated HHI values. Table no. 4 outlines clustering tests across three periods. A joint analysis of these tables follows.

Upon jointly examining Tables no. 3 and no. 4, we observe signs of price clustering across the three periods in the Egyptian sample, notably with an increased presence of digits zero and five, consistent with the Attraction Hypothesis. Statistical tests confirm this clustering across the analyzed periods. Null hypothesis H_1 is dismissed, highlighting divergences between observed and expected uniform distributions in the three periods, at a significance level of 1%. Notably, HHI values decline from the pre-COVID-19 to the COVID-19 period; however, the results suggest that this variation lacks statistical significance. Hence, we deduce that the level of price clustering remains unchanged between these two periods. In contrast, a sharp increase in HHI values occurs from the COVID-19 period to the post-COVID-19 period. The results underscore the statistical significance of this contrast, indicating a discernible shift in the degree of price clustering between these two sample intervals.

Turning to the Kenyan sample, the results also confirm the existence of price clustering across the three periods. Regardless of the period considered, roughly 30% of prices have last digits zero or five. The Kenyan sample substantiates dismissing null hypothesis H_1 and affirming the presence of a statistically meaningful distinction. Despite an increase in HHI values between the first two periods, the evaluation of the H_2 hypothesis establishes that this increment lacks statistical significance, affirming stability in price clustering levels.

Table no. 3 – Price clustering: last digit frequency – whole period

Last Digit	Egypt Frequency	%	Kenya Frequency	%	Morocco Frequency	%	Nigeria Frequency	%	South Africa Frequency	%	Tunisia Frequency	%
Panel A: Distribution of last digit of the price												
0	4961	15.81	2068	20.06	18620	53.31	17251	29.61	31126	25.39	21021	29.42
1	3120	9.94	957	9.28	1901	5.44	4622	7.93	9754	7.96	4274	5.98
2	2765	8.81	851	8.25	1322	3.78	4542	7.80	9228	7.53	4893	6.85
3	2828	9.01	857	8.31	1132	3.24	3917	6.72	9101	7.42	4644	6.50
4	2771	8.83	852	8.26	1223	3.50	3970	6.81	9418	7.68	5352	7.49
5	3339	10.64	1071	10.39	3965	11.35	7155	12.28	15566	12.70	8326	11.65
6	2676	8.53	875	8.49	1229	3.52	4338	7.45	9253	7.55	4264	5.97
7	2874	9.16	836	8.11	1201	3.44	4109	7.05	9163	7.47	5247	7.34
8	2949	9.40	918	8.90	1561	4.47	4083	7.01	9614	7.84	6283	8.79
9	3093	9.86	1026	9.95	2776	7.95	4270	7.33	10362	8.45	7158	10.02
Total	31376		10311		34930		58257		122585		71462	
% at 0 and 5		26.45		30.44		64.66		41.89		38.09		41.07
Panel B: Clustering tests and indices												
χ^2_9	1292.34		1214.54		74906.82		26281.06		35046.87		32096.48	
H$_1$ (p-value)	0.0000		0.0000		0.0000		0.0000		0.0000		0.0000	
HHI (%)	10.41		11.18		31.44		14.51		12.86		14.49	

Notes: Panel A displays both the absolute and relative price frequencies. Panel B presents the p-values for the H_1 hypothesis, along with the Herfindahl-Hirshmann index (HHI).

Table no. 4 – Price clustering: comparison between periods – before COVID-19 (I), COVID-19 (II) and after COVID-19 (III)

	Egypt I	Egypt II	Egypt III	Kenya I	Kenya II	Kenya III	Morocco I	Morocco II	Morocco III
χ^2_9	288.0	114.4	1354.7	234.8	441.5	586.5	33546.4	19279.1	22610.8
H$_1$ (p-value)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
HHI (%)	10.24	10.12	11.43	11.21	11.26	11.21	35.61	27.21	31.27
$F_{9,9}$	0.40	11.84		1.88	1.33		0.57	1.17	
H$_2$ (p-value)	0.9073	0.0005		0.1804	0.3396		0.7891	0.4081	

	Nigeria I	Nigeria II	Nigeria III	South Africa I	South Africa II	South Africa III	Tunisia I	Tunisia II	Tunisia III
χ^2_9	7500.7	10570.1	8514.1	15663.8	11338.2	8169.9	10720.5	9382.8	12736.9
H$_1$ (p-value)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
HHI (%)	13.94	15.30	14.42	13.05	13.05	12.40	13.36	14.49	16.82
$F_{9,9}$	1.41	0.81		0.72	0.72		0.88	1.36	
H$_2$ (p-value)	0.3088	0.6237		0.6810	0.6834		0.5771	0.3281	

Notes: The table presents the p-values for the H_1 and H_2 hypotheses, along with the Herfindahl-Hirshmann index (HHI). Periods I, II and III represent, respectively, the periods before COVID-19, COVID-19 and after COVID-19 (see Table no. 1 for specific dates for each country).

Analyzing the Moroccan dataset reveals a greater concentration of prices compared to the Egyptian dataset. In this sample, and regardless of the period considered, more than 50%

of prices have the last digit zero, while roughly 11% end with the digit five. These outcomes support the Attraction Hypothesis. Statistical tests convincingly refute null hypothesis H_1 across all three periods, confirming the presence of price clustering. Additionally, HHI values show a decline from the period before COVID-19 to the COVID-19 period. However, the evidence suggests that this decrease lacks statistical significance. Conversely, HHI values increased from the COVID-19 period to the period after COVID-19, indicating the inability to reject the null hypothesis H_2. Thus, no substantial disparities in the level of price clustering are discerned among the three time periods.

Analyzing the results for Nigeria, the most frequently occurring final digits are again zero and five, comprising approximately 42% of prices. Regarding statistical examinations, significant disparities between the observed distribution and the expected uniform distribution were evident across all three periods. Consequently, we can confidently reject null hypothesis H_1 due to the statistical significance of these differences. Our analysis indicates an increase in HHI values from the period before COVID-19 to the COVID-19 period, while a slight decrease in HHI values was observed from the COVID-19 period to the subsequent period. However, the test of the H_2 hypothesis revealed that these differences between the periods lack statistical significance. As a result, we can conclude that no discernible alterations in the level of price clustering were observed throughout these three periods.

In South Africa, the findings are analogous to those obtained in other markets. During the different periods, the digit zero appears in around 25% of prices, while the digit five appears around 13%. The first statistical test led to the rejection of null hypothesis H_1, given the significance of the differences between observed and expected distributions in all periods. Furthermore, the second test indicated a marginal decrease in HHI values from the pre-COVID-19 to the COVID-19 period, as well as from the COVID-19 to the post-COVID-19 period. The are unable to reject the null hypothesis H_2, thereby affirming consistent price clustering levels throughout the three periods.

Finally, the results for the Tunisian sample further support the presence of price clustering. More than 40% of closing prices end in zero or five. Analogous to findings in other samples, disparities exist between the observed distributions and anticipated uniform distributions, warranting the rejection of null hypothesis H_1. Furthermore, albeit the increase in HHI values from the pre-COVID-19 period to the COVID-19 period, the results indicate a consistent level of price clustering between these two periods. As for the COVID-19 period to the post-COVID-19 period, there was again an increase in HHI values but this increase lacks statistical significance.

In summary, the univariate analysis across all six markets underscores a consistent pattern: the last digit of stock prices does not conform to a uniform distribution, providing strong evidence of price clustering. Our findings reveal a consistent trend across the three analyzed periods within the six samples, with digits zero and five emerging as the most frequently observed. The highest level of clustering is observed in the Moroccan sample, indicated by notably high HHI values, followed by the Tunisian sample. The results validate the Attraction Hypothesis (Curcio and Goodhart, 1991), thus supporting H_1. Regarding H_2, the analysis does not reveal statistically significant disparities in clustering levels pre- or post-COVID-19 and during the COVID-19 period across the six market samples. There was only a slight increase in the level of price clustering in the Nigerian and Tunisian samples during the COVID-19 period. From this standpoint, it can be deduced that investors appear relatively less influenced by behavioral factors during periods of heightened pessimism and uncertainty, contrary to the implications of the Panic Selling Hypothesis."

4.2 Multivariate Analysis

To begin, it is essential to note that two models will be estimated for each of the six market samples across the three periods. The first model will include all explanatory variables, while the second model will address potential multicollinearity by excluding variables with correlation coefficients exceeding 0.55 with other factors (specifically, variables "CompSize" and "Volatility").

Tables no. 5A (Egypt, Kenya, and Morocco) and no. 5B (Nigeria, South Africa, and Tunisia) present the outcomes of the multivariate analysis conducted on the six countries. Tables no. 6A and no. 6B showcase the results obtained with the reduced model.

The results for Egypt in Table no. 5A evidence that during the periods prior to COVID-19 and following COVID-19, independent variables explain approximately 74% and 44% of the variance in the degree of price clustering, respectively. However, within the COVID-19 period, this proportion experiences a significant decline, dropping to around 14%. These notable disparities can be attributed to shifts in economic conditions that impact the underlying relationships. Nonetheless, in the context of the reduced model (Table no. 6A), it was observed that during the period before COVID-19 and in the period of COVID-19, there was a marginal uptick in the explanatory capability of the independent variables to 75% and 17%, respectively. However, during the period following COVID-19, a slight decrease was noted, to 43%, compared to the model encompassing all variables. The variable "Illiquidity" tends to be statistically significant and presents the expected sign, at least in the periods prior to and after COVID-19. Additionally, in the COVID-19 period, the variable "Turnover" holds statistical significance at a 10% significance level. These results persist in the reduced model, although small differences emerge. In the COVID-19 period, the "Turnover" variable becomes statistically significant at a 5% significance level within the same period. This underscores the prominence of "Illiquidity" across two periods and "Turnover" during the crisis period as the pivotal explanatory factors for price clustering within this sample, aligning consistently with the literature's expectations. In summation, the analysis suggests that the Egypt sample provides only partial confirmation of the hypothesis of price negotiation.

Regarding the results for Kenya, the adjusted R-squared coefficient for the sample periods is not notably high, but in the case of the reduced model there is an improvement in the coefficients. It is observed in Table no. 5A that in the period preceding COVID-19 only the variables "StockPrice" and "Volatility" align with the theoretical expectations. In the complete model, we observe that the variables "Turnover" and "Illiquidity" attain statistical significance at levels of 10% and 5%, respectively. However, these variables present some explanatory power in this model only in the periods before the pandemic and after the pandemic, respectively. On the other hand, within the model excluding "CompSize" and “Volatility”, the variable "Turnover" achieves statistical relevance in the two initial periods. In the periods before and after COVID-19, the variable "StockPrice" exhibit explanatory significance, as well as the variable "Illiquidity" in the last period, to a level of 1%. The variables that offer the most insightful explanation for the fluctuations in the clustering level are the "Illiquidity" variable during the post-COVID-19 period in both models, as well as the “StockPrice” and "Turnover" variables during the reduced model. Once again, our findings lead us to the conclusion that the theories scrutinized are only partially validated within the Kenyan sample.

The results for the Moroccan sample indicate that during the periods before COVID-19, COVID-19, and after COVID-19, the independent variables account for only approximately

4%, 19%, and 8% of the variance evident in price clustering, respectively. Only the variable "Illiquidity" attains statistical significance for the periods preceding COVID-19 and during COVID-19, at a 10% significance level. However, its inverse correlation with the dependent variable, render it incongruent with the study's focus. Furthermore, the variable "StockPrice" exhibits a p-value of 11% during the COVID-19 period and the post-COVID-19 period. The model excluding the variables "CompSize", and "Volatility" mirrors the results of the comprehensive model for the variable "Illiquidity". However, in the last two periods of analysis, the variable "StockPrice" attains statistical significance at a 5% significance level. Hence, it becomes evident that solely within the reduced model and during the COVID-19 and post-COVID-19 periods does the variable "StockPrice" emerge as an explanatory factor for the phenomenon of price clustering, aligning with the hypotheses posited by the literature. To sum up, our findings within the Moroccan sample do not substantiate the hypotheses of price resolution and negotiation across the three examined periods.

Table no. 5A – Determinants of price clustering: before COVID-19 (I), COVID-19 (II) and after COVID-19 (III)

	Expected sign	Egypt			Kenya			Morocco		
		(I)	(II)	(III)	(I)	(II)	(III)	(I)	(II)	(III)
Intercept		0.0177	0.0096	0.0287	0.0433	0.0257	0.0280	0.2668	0.2067	0.2429
		(0.0040)	(0.0032)	(0.0046)	(0.0230)	(0.0081)	(0.0090)	(0.0208)	(0.0205)	(0.0218)
StockPrice	+	-0.0038	-0.0023	-0.0030	0.0399	0.0098	0.0516	-0.0458	0.0784	0.0765
		(0.0094)	(0.0077)	(0.0113)	(0.0485)	(0.0263)	(0.0288)	(0.0519)	(0.0477)	(0.0468)
CompSize	-	0.0040	0.0007	0.0130	0.0069	0.0105	0.0144	0.0596	-0.0629	-0.0232
		(0.0085)	(0.0070)	(0.0108)	(0.0528)	(0.0236)	(0.0392)	(0.0444)	(0.0463)	(0.0389)
Turnover	-	-0.0045	-0.0087*	-0.0098	0.0653**	-0.0305	0.0013	-0.0388	0.0358	0.0340
		(0.0057)	(0.0048)	(0.0066)	(0.0245)	(0.0194)	(0.0248)	(0.0450)	(0.0400)	(0.0427)
Volatility	+	0.0022	0.0000	0.0013	0.0017	-0.0101	-0.0200	0.0060	0.0306	0.0219
		(0.0044)	(0.0039)	(0.0056)	(0.0478)	(0.0138)	(0.0124)	(0.0277)	(0.0332)	(0.0305)
Illiquidity	+	0.0375***	0.0054	0.0180***	-0.0157	0.0058	0.0575**	-0.0478*	-0.0715**	-0.0287
		(0.0045)	(0.0036)	(0.0053)	(0.0266)	(0.0131)	(0.0190)	(0.0276)	(0.0273)	(0.0314)
R^2		0.7862	0.2900	0.5417	0.5029	0.5416	0.6551	0.1491	0.2779	0.1833
Adjusted R^2		0.7398	0.1356	0.4421	0.2770	0.3333	0.4983	0.0427	0.1876	0.0812
F-statistic		16.9197	1.8786	5.4373	2.2258	2.5997	4.1780	1.4017	3.0785	1.7953
Prob (F-statistic)		0.0000	0.1373	0.0019	0.1249	0.0867	0.0225	0.2445	0.0192	0.1359

From the analysis conducted on the Nigerian sample it is observable in Table no. 5B that the independent variables account for approximately 36% of the variance in the level of price clustering in the period before COVID-19. In contrast, during the pandemic and post-pandemic periods, the coefficients of determination are notably higher. A similar pattern emerges when considering the reduced model (Table no. 6B), where the results are largely consistent. During the periods preceding and following COVID-19, only the variables "StockPrice", "Turnover", and "Illiquidity" exhibit signs aligned with the hypotheses of price resolution and negotiation. However, in the period of COVID-19, only the variables "StockPrice" and "Illiquidity" evidence the expected positive relationship with price clustering. The variable "Illiquidity" holds statistical significance across all three periods at a significance level of 1%, while the variable "Volatility" also exhibits explanatory capability regarding the price clustering phenomenon across the entirety of the sample, with statistical significance at a level of 5%. In the COVID-19 period, the variable "StockPrice" also maintains statistical relevance, as well as the variable "CompSize" in the post-COVID-19 period. Despite the statistical significance of the variables "Volatility" and "CompSize" within the model, the signs of their coefficients contradict the predictions from the literature. The outcomes from the reduced model reveal that in the period before COVID-19, only the variable "Turnover" lacks statistical relevance within the model. In contrast, during the COVID-19 period as well as in the post-COVID-19 period, all variables maintain statistical significance. In summary, the results indicate partial validation of the analyzed theories, with the variable "Illiquidity," followed by "StockPrice," emerging as the pivotal explanatory factors for price clustering within the two estimated models.

Table no. 5B – Determinants of price clustering: before COVID-19 (I), COVID-19 (II) and after COVID-19 (III)

	Expected sign	Nigeria (I)	Nigeria (II)	Nigeria (III)	South Africa (I)	South Africa (II)	South Africa (III)	Tunisia (I)	Tunisia (II)	Tunisia (III)
Intercept		0.1841	0.1814	0.1625	0.0432	0.0501	0.0398	0.0077	0.0930	0.01269
		(0.0217)	(0.0190)	(0.0188)	(0.0045)	(0.0036)	(0.0030)	(0.0086)	(0.0086)	(0.0105)
StockPrice	+	0.0615	0.0801*	0.0358	0.0255**	0.0363***	0.0312***	0.0387*	0.1010***	0.1131***
		(0.0477)	(0.0450)	(0.0429)	(0.0109)	(0.0131)	(0.0110)	(0.0204)	(0.0207)	(0.0211)
CompSize	-	0.0571	0.0510	0.0877**	0.0098	-0.0079	0.0058	0.0164	0.0012	0.0069
		(0.0421)	(0.0426)	(0.0436)	(0.0096)	(0.0076)	(0.0069)	(0.0165)	(0.0153)	(0.0187)
Turnover	-	-0.0410	0.0209	-0.0016	-0.0149	-0.0092	-0.0038	-0.0133	0.0190	-0.0164
		(0.0377)	(0.0346)	(0.0357)	(0.0100)	(0.0115)	(0.0105)	(0.0167)	(0.0174)	(0.0171)
Volatility	+	-0.0595**	-0.0960***	-0.1044***	-0.0075	-0.0060	-0.0063*	0.0122	-0.0163	-0.0154
		(0.0276)	(0.0219)	(0.0218)	(0.0055)	(0.0044)	(0.0036)	(0.0115)	(0.0126)	(0.0136)
Illiquidity	+	0.1125***	0.1661***	0.1290***	0.0437***	0.0362***	0.0534***	0.0262**	0.0315**	0.0135
		(0.0312)	(0.0258)	(0.0277)	(0.0086)	(0.0107)	(0.0089)	(0.0125)	(0.0141)	(0.0143)
R^2		0.4069	0.5611	0.5603	0.4966	0.6073	0.7150	0.4356	0.5468	0.6278
Adjusted R^2		0.3639	0.5293	0.5285	0.4707	0.5871	0.7003	0.3964	0.5153	0.6020
F-statistic		9.4660	17.6424	17.5860	19.1398	30.0011	48.6659	11.1153	17.3714	24.2909
Prob (F-statistic)		0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

*Notes: Standard errors presented in parenthesis. The significance levels of 10%, 5%, and 1% are denoted as *, **, and *** respectively. Periods I, II and III represent, respectively, the periods before COVID-19, COVID-19 and after COVID-19 (see Table 1 for specific dates for each country).*

Regarding the South African sample, we can observe that over 58% of the variability in the level of price clustering is explained by the independent variables used in the model during the last two periods. However, in the period before COVID-19, the independent variables explain only 47% of the variations observed in the studied phenomenon. These findings are consistent even when examining the estimated model without the "CompSize" variable (Table no. 6B). Upon examination, it becomes apparent that during the periods prior to and following the pandemic, the variables "StockPrice," "CompSize," and "Illiquidity" exhibit positive correlations with price clustering. Nonetheless, these results for the "CompSize" and "Volatility" variables diverge from the expected outcomes as suggested by Ball *et al.* (1985) and Harris (1991). Conversely, during the pandemic period, it is revealed that only the "Volatility" variable contradicts the anticipated relationship with the dependent variable in the literature. Moreover, the conclusions drawn from the reduced model align with the previously described findings, with the exception being that in the post-pandemic period, the variable "Turnover" exhibits a positive relationship with price clustering. In contrast, we have ascertained that the statistically significant variables encompass: the "StockPrice" variable, which holds a significance level of 5% in the period prior to the pandemic, 1% across the remaining periods in the comprehensive model, and consistently across all periods in the reduced model; as well as the "Illiquidity" variable, exhibiting a significance level of 1% for all periods in both analyzed models.

Table no. 6A – Determinants of price clustering (reduced model): before COVID-19 (I), COVID-19 (II) and after COVID-19 (III)

	Expected sign	Egypt (I)	Egypt (II)	Egypt (III)	Kenya (I)	Kenya (II)	Kenya (III)	Morocco (I)	Morocco (II)	Morocco (III)
Intercept		0.0177	0.0096	0.0287	0.0433	0.0257	0.0280	0.2668	0.2067	0.2429
		(0.0039)	(0.0031)	(0.0046)	(0.0212)	(0.0077)	(0.0093)	(0.0208)	(0.0206)	(0.0214)
StockPrice	+	0.001	-0.0017	0.0087	0.0469*	0.0097	0.0452***	0.0129	0.0484**	0.0698**
		(0.0045)	(0.0038)	(0.0057)	(0.0224)	(0.0106)	(0.0141)	(0.0239)	(0.0222)	(0.0266)
CompSize	-									
Turnover	-	-0.0030	-0.0084**	-0.0056	0.0658**	-0.0238*	0.0078	0.0079	0.0033	0.0228
		(0.0046)	(0.0036)	(0.0057)	(0.0222)	(0.0113)	(0.0142)	(0.0283)	(0.0283)	(0.0354)
Volatility	+	0.0026	0.0001	0.0029						
		(0.0042)	(0.0037)	(0.0054)						
Illiquidity	+	0.0370***	0.0054	0.0179	-0.0175	0.0044	0.0499**	-0.0465*	-0.0664**	-0.0252
		(0.0043)	(0.0035)	(0.0053)	(0.0221)	(0.0124)	(0.0170)	(0.0271)	(0.0270)	(0.0307)
R^2		0.7842	0.2896	0.5130	0.5016	0.5049	0.5727	0.1104	0.2382	0.1689
Adjusted R^2		0.7482	.01712	0.4318	0.3866	0.3906	0.4741	0.0469	0.1838	0.1095
F-statistic		21.7994	2.4464	6.3201	4.3613	4.4187	5.8080	1.7379	4.3771	2.8449
Prob (F-statistic)		0.0000	0.0739	0.0013	0.0248	0.0238	0.0096	0.1739	0.0091	0.0490

Table no. 6B – Determinants of price clustering (reduced model): before COVID-19 (I), COVID-19 (II) and after COVID-19 (III)

	Expected sign	Nigeria (I)	Nigeria (II)	Nigeria (III)	South Africa (I)	South Africa (II)	South Africa (III)	Tunisia (I)	Tunisia (II)	Tunisia (III)
Intercept		0.1841	0.1814	0.1625	0.0432	0.0501	0.0398	0.0777	0.0930	0.1269
		(0.0219)	(0.0190)	(0.0192)	(0.0045)	(0.0036)	(0.0030)	(0.0086)	(0.0086)	(0.0105)
StockPrice	+	0.1105***	0.1252***	0.1099***	0.0331***	0.0271***	0.0382***	0.0614***	0.0878***	0.1082***
		(0.0314)	(0.0245)	(0.0223)	(0.0079)	(0.0096)	(0.0072)	(0.0111)	(0.0122)	(0.0128)
CompSize	-									
Turnover	-	-0.0157	0.0491*	0.0469*	-0.0079	-0.0167*	0.0026	-0.0005	0.0130	-0.0176
		(0.0329)	(0.0253)	(0.0269)	(0.0073)	(0.0089)	(0.0072)	(0.0135)	(0.0151)	(0.0146)
Volatility	+	-0.0668**	-0.0966***	-0.1137***	-0.0092*	-0.0045	-.0073**			
		(0.0273)	(0.0220)	(0.0217)	(0.0052)	(0.0041)	(0.0034)			
Illiquidity	+	0.1105***	0.1696***	0.1301***	0.0439***	0.0335***	0.0562***	0.0246*	0.0294**	0.0131
		(0.0314)	(0.0257)	(0.0283)	(0.0086)	(0.0104)	(0.0082)	(0.0124)	(0.0137)	(0.0136)
R^2		0.3910	0.5520	0.5346	0.4913	0.6029	0.7129	0.4210	0.5361	0.6240
Adjusted R^2		0.3562	0.5264	0.5080	0.4705	0.5867	0.7012	0.3975	0.5173	0.6050
F-statistic		11.2371	21.5631	20.1006	23.6622	37.2045	60.8424	17.9328	28.5031	40.3094
Prob (F-statistic)		0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Notes: Standard errors presented in parenthesis. The significance levels of 10%, 5%, and 1% are denoted as *, **, and *** respectively. Periods I, II and III represent, respectively, the periods before COVID-19, COVID-19 and after COVID-19 (see Table no. 1 for specific dates for each country).

Furthermore, in the reduced model during the period preceding the pandemic, as well as in the complete model, in the periods subsequent to the pandemic, the "Volatility" variable maintains statistical relevance at a significance level of 10%. However, its relationship, contrary to the expectations of the theories under study, diminishes its significance in our analysis. The final discrepancy between the models is identified in the pandemic period within the model excluding the "CompSize" variable, where the "Turnover" variable gains statistical significance. In brief, the essential variables in elucidating fluctuations in the price clustering are "StockPrice" and "Illiquidity".

Finally, considering the Tunisian sample, we observe that the adjusted coefficient of determination exhibits notable levels of adequacy for the periods during and after the pandemic (52% and 60%, respectively). In contrast, for the period prior to the pandemic, the coefficient stands at 40%. The values derived from the reduced model mirror the outcomes of the complete model. With respect to the hypotheses examined, it was discerned that in the period before COVID-19, solely the "CompSize" variable diverges from the expected relationship with the studied phenomenon. However, in the COVID-19 period, the variables "CompSize," "Turnover," and "Volatility" do not conform to the anticipated relationship. Subsequently, during the period following COVID-19, the variables "CompSize" and "Volatility" deviate from the expected pattern. The model excluding the "CompSize" and “Volatility” variables yields congruent results for the variables included within the model. Furthermore, it is evident that the "StockPrice" variable holds explanatory power for the phenomenon of price clustering across the three periods scrutinized, in both estimated models. Similarly, the "Illiquidity" variable maintains statistical significance during the pre-pandemic and pandemic periods in both models. In conclusion, these variables emerge as the primary contributors to elucidating the variations in the phenomenon under scrutiny.

In summary, contrasting outcomes across different markets reveals varying degrees of explanatory power, with a higher degree observed in the South African sample, while encountering substantial challenges in the Moroccan sample. These variations may stem from divergent investor profiles, cultural factors, and other influences.

Examining outcomes across all time periods within each sample indicates that the constant term consistently holds statistical significance. In situations where independent variables show no variance, there is no observable price clustering, but when these variables lack variability, a pronounced level of price clustering tends to occur. This effect can be attributed to individual behavioral tendencies or psychological biases that lead individuals to exhibit a heightened attraction for specific numerical values, as argued by Ikenberry and Weston (2008).

Multiple variables contribute to elucidating the extent of price clustering across samples. The variables "Illiquidity," "StockPrice," and "Turnover" emerge as statistically significant factors supporting the Negotiation and Price Resolution hypotheses. "Illiquidity" stands out as pivotal, exhibiting statistical significance across several periods within all samples, except for Morocco, generally aligning with hypothesis H_{3e}. "StockPrice" exhibits explanatory power, except for Egypt, partially aligning with hypotheses H_{3a}. "Turnover" holds significance in clarifying fluctuations in price clustering, partially aligning with hypotheses H_{3c}. However, "CompSize" and "Volatility" consistently reject theoretical expectations, leading to the rejection of hypotheses H_{3b} and H_{3d}.

Observations suggest that disparities among coefficients between periods preceding COVID-19 and the COVID-19 period lack statistical significance, contrary to expectations of intensified clustering during economic crises. Counteracting trends, such as declines in variables like "Volatility," are observed. Similarly, differences in coefficients between the COVID-19 period and the post-COVID-19 period lack statistical relevance. The constant term shows no considerable deviation between periods, with a slight decrease during the crisis period across almost all samples.

Additionally, when applying the model to the entire period for each sample, the findings largely corroborate previous conclusions. "Illiquidity" continues to be the primary explanatory factor, except in the samples from Kenya and Morocco. "StockPrice" remains relevant in explaining the phenomenon in the Kenyan and Tunisian samples. Lastly, "Turnover" exhibits statistical significance in emphasizing the phenomenon within the South African sample.

5. CONCLUSION

Price clustering, the tendency for stock prices to concentrate around specific digits or numbers, is a non-random pattern with implications for market efficiency, trading strategies, and investor behavior. This study explores price clustering in African markets, aiming to enhance the analysis of this phenomenon and assess the impact of the COVID-19 pandemic on it. Data from six African markets were analyzed to uncover insights into the prevalence and influencing factors behind the clustering of stock price digits.

The study affirms the presence of price clustering across various periods in the analyzed markets. Univariate analysis indicates a non-uniform distribution of the last digits of stock prices, with a preference for digits zero and five. Unexpectedly, some periods and samples show a higher frequency of stock prices ending in digits one and nine, partially confirming the Attraction Hypothesis. Notably, the three analyzed periods do not exhibit significant differences, challenging expectations of heightened uncertainty and volatility during the COVID-19 period influencing investor behavior, contrary to the Panic Selling Hypothesis.

Multivariate analysis sheds light on variables significantly contributing to fluctuations in price clustering levels. "Illiquidity," "StockPrice," and "Turnover" emerge as influential factors across samples, revealing variations in how these variables explain the phenomenon over different periods. The recurring significance of the constant term suggests psychological biases and attractions to specific numbers, partially confirming the Attraction Hypothesis. The results also partially support the Negotiation and Price Resolution Hypotheses, with some variables adhering to anticipated relationships and others exhibiting contrary associations.

The tendency for prices to settle more frequently at certain levels than others carries practical implications for investors. Prior research has shown that investors can construct profitable trading strategies that exploit these clustering effects, even after accounting for the bid-ask spread (Niederhoffer, 1965; Mitchell, 2001). Niederhoffer (1965) provides specific examples of such strategies.

Consistent with univariate findings, limited consistency in coefficient variations between pre- and post-COVID-19 periods compared to the COVID-19 period indicates the economic crisis's varied impact on price clustering across markets. This highlights the complex interplay between market dynamics, investor sentiments, and the clustering phenomenon. Similar to Lobão *et al.* (2019), our research challenges the notion that economic crisis uniformly changes investor behavior, providing nuanced insights that do not strongly support the Panic Selling Hypothesis.

Our research is not free from limitations. Although our insights largely confirm existing hypotheses in a new regional context, potential omitted variables, such as regional market microstructure, institutional features, or regulatory constructs, could bias our results. Unexplained fluctuations persist, suggesting the influence of factors like investor behavior, cultural nuances, and specific market dynamics. Future research could explore alternative COVID-19 periods and include additional variables to enhance explanatory power. Specifically, market microstructure variables like bid-ask spread or measures capturing different dimensions of liquidity, such as the Amihud ratio could be included.

In summary, this paper delves into the nuanced phenomenon of price clustering in African markets, shedding light on its existence and underlying factors. The findings enrich our understanding of investor behaviors and market complexities in the financial landscape.

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