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THE EFFECT OF THE RUSSIAN-UKRAINE WAR ON PRICE CLUSTERING:

Evidence from the Moscow Stock Exchange

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Abstract

Stock markets are influenced by geopolitical events that can cause inefficiencies. Several studies have identified patterns of these inefficiencies, one of which is price clustering. Price clustering occurs when certain prices, particularly round numbers, appear more frequently than others.

This dissertation tests the presence of price clustering in the Russian stock market, from October 25th, 2021, to May 25th, 2022, with a special focus on the effect of the Russian-Ukrainian War. For that purpose, 20 stock from the MOEX index were considered, analyzing the distribution of the last digit in daily closing prices. Additionally, a linear regression was conducted to determine which factors most affected the presence of price clustering, using a dummy variable to indicate whether the daily price was part of the 'panic period' caused by the war.

The distribution analysis reveals significant evidence of price clustering, with 29% of the daily prices ending in zero, supporting the Attraction Hypothesis. Regarding the multivariable analysis, all models showed strong evidence for the Panic Trading Hypothesis. The variable 'war', representing the period right before and after the war started, was positively correlated with price clustering.

These findings suggest that political instability and panic trading can significantly impact market behavior, challenging the assumptions of the Efficient Market Hypothesis.. The relevance of these finding lies in the fact that such inefficiencies can result in significant wealth transfers and market anomalies. Therefore, identifying such inefficiencies has important implications for investor, regulators and policymakers during uncertain periods such as military events.

Sumário

O mercado financeiro é influenciado por eventos geopolíticos que podem resultar em ineficiências. Vários estudos já identificaram padrões nessas ineficiências, causadas por vieses comportamentais, sendo um desses padrões o *price clustering* (clustering de preços). O clustering de preços ocorre quando certos preços, particularmente números terminados em zero e cinco, aparecem com mais frequência do que outros.

Esta dissertação testa a presença de clustering de preços no mercado de ações da Rússia, no período entre 25 de outubro de 2021 e 25 de maio de 2022, com maior foco no efeito da guerra na Ucrânia. Com esse objetivo, foram consideradas 20 ações do índice MOEX, analisando a distribuição do último dígito nos preços de fecho diários. Além disso, foi realizada uma regressão linear para determinar quais fatores mais afetaram a presença de clustering de preços, usando uma variável dummy para indicar se o preço diário fazia parte do 'período de pânico', ou seja, o período em que a guerra mais afetou a decisão dos investidores.

A análise de distribuição revelou uma evidência significativa de clustering de preços, com 29% dos preços diários terminando em zero, não rejeitando a *Attraction Hypothesis* (Hipótese da Atração). Em relação à análise da regressão, todos os modelos mostraram fortes evidências da *Panic Trading Hypothesis* (Hipótese da Negociação em Situações de Pânico). A variável 'guerra', que representava o período imediatamente antes e depois do início da guerra, foi positivamente correlacionada com o *clustering* de preços.

Estes resultados sugerem que instabilidade política e negociações sob influência de um evento externo que resulta em incerteza podem impactar o comportamento do mercado, rejeitando a Hipótese de Mercado Eficiente. A relevância desses resultados se dá no fato dessas ineficiências resultarem em distorções relevantes no mercado. Portanto, identificar tais anomalias tem importantes implicações para investidores, reguladores e legisladores durante períodos de incerteza, como tensões militares.

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1. INTRODUCTION

As stated by Tversky and Kahneman (1974), heuristics are the decision-making based on individuals own experiences, common consensus, or quick judgments. This behavioral tool is useful for making quick decisions in everyday life. However, it can lead to severe and systematic errors caused by the mental simplification of complex processes, known as biases. Behavioral Finance studies these biases, which are relevant for explaining certain financial phenomena, challenging the premises of the Efficient Market Hypothesis that individuals are rational.

Price clustering is one of these biases that provoke market distortions. According to Aitken et al. (1996), this market anomaly is evident when certain prices, particularly round numbers, occur more frequently than others. As estimated by Bhattacharya, Holden and Jacobsen (2012), price clustering alone has caused an aggregated wealth transfer of 813 million dollars per year in the New York Stock Exchange (NYSE), confirming that this bias can cause significant market distortions.

Several authors have found evidence of price clustering in different markets. The bias was identified on real estate prices (Palmon et al., 2004), gold market (Ball et al., 1985), exchange market (Goodhart and Curcio, 1991), among other markets. However, most studies focus on the stock market. The first evidence was found in the U.S. market, by Osborne (1962). Following, several authors found price clustering in different stock markets, such as the Australian stock market (Aitken et al., 1996), China's (Mitchell and Brown, 2004), Fiji Islands (Narayan and Smyth, 2013), Netherlands (Sonnemans, 2006), the Baltics (Lobão, 2023), among others.

Several studies developed theories in order to explain the reasons for the price clustering phenomenon. The three most accepted ones are the Attraction Hypothesis (Gottlieb and Kalay, 1985), the Resolution Hypothesis (Ball, Torus, and Tshoegl, 1985) and the Negotiation Hypothesis (Harris, 1991). The first one stated that some numbers are more attractive than others, mostly the ones ending in zero and five. The second one affirm that price clustering is positively correlated with uncertainty. Finally, the third one, disclose that when the stock prices are higher, there is usually more price clustering, due to higher negotiation costs.

In addition to these three most studied determinants of price clustering, there is a fourth theory, the Panic Trading Hypothesis (Narayan and Smyth, 2013), which suggests that uncertain situations and political instability could cause price clustering. By studying Fiji's market, Narayan and Smyth (2013) found that political events can increase this bias. In the same direction, other events that lead to panic trading can also affect the market.

This dissertation analyzes the Russian stock market to test this and the other three main hypothesis, using the conflict in Ukraine as a proxy for a 'panic period'. This is probably the first study to evaluate the effect of a war in price clustering. To test these hypotheses in the Russian stock market, this study used data from 20 stocks from the MOEX index, covering the period from October 25th, 2021, to May 25th, 2022. This timeframe includes seven months, with daily prices of 127 days. For the 'panic period', it was considered the days from January 25th to May 25th, 2022, counting thirty days before the war and three months after the war began. This timeframe was chosen based on the signs that this period was the most uncertain due to political and military instability. The three months preceding the 'panic period' were considered as 'control period', in order to better caption the effect of the Russia-Ukraine conflict on the market.

The results provided evidence of three of the four tested hypothesis. First, the distribution analysis along with the z-test and chi-squared showed evidence of the Attraction Hypothesis. By analyzing the last digit of each closing price, it is possible to observe that 29% ended in zero, showing evidence that the investors have a clear preference for prices ending in zero. Second, the regressions indicated support for the Price Resolution Hypothesis. The price clustering variable was negatively correlated with liquidity (volume) and positive correlated with volatility, consistent with the hypothesis. In addition, the regressions found strong evidence for the Panic Trading Hypothesis in the studied database. In all the three models, the variable 'war' was significantly and positively correlated with price clustering, indicating that during the panic period, investors tend to cluster more compared to the control period. Finally, the regression analysis showed no signs of Negotiation Hypothesis, as the variable 'price' did not significantly affect price clustering.

These results have significant implications for investors, regulators, and policymakers, as price clustering causes notable market distortions. The evidence supporting the Attraction Hypothesis indicates that the Efficient Market Hypothesis does not fully account for market behavior, mostly when market distortions occasionally contradict its premises. Additionally, the evidence for the Panic Trading Hypothesis demonstrates that military conflicts resulting in uncertainty can cause market anomalies, which investors can potentially exploit. As stated by Niederhoffer (1965), price clustering increases the predictability of stock prices, and the bias can be included in trading strategies, affecting the profits. From the perspective of regulators and policy makers, this suggests that market transparency measures should be reinforced during crisis situations.

This dissertation is structured as follows: Section 2 presents a literature review, contextualizing for the Efficient Market Hypothesis and Behavior Finance, defining and explaining the hypotheses of price clustering, reviewing previous empirical studies, and summarizing the recent military tensions in Russia. Section 3 details the data and methodology used in this study. Additionally, Section 4 presents the empirical analysis and results. Finally, Section 5 concludes the dissertation.

2. LITERATURE REVIEW

2.1. Contextualization

2.1.1. Efficient Market Hypothesis (EMH)

Since the decade of 1950, the Modern Finance Theory has been the theoretical mainstream in the finance field. Some of its major precursor works include Markowitz's Portfolio Theory (1952), the Capital Asset Pricing Model (CAPM) developed by Sharpe (1964), and the Efficient Market Hypothesis (EMH), Fama (1970), probably one of the most important contributions and one of the pillars of modern finance.

Markowitz (1952) was one of the first researchers to defend portfolio diversification, stating that investors seek the optimization in the relationship between returns and risk. In order to defend his theory, Markowitz (1952) uses the premises that agents maximize the discounted value of future returns. In addition, according to the author, agents are always dissatisfied in terms of risk and return, meaning they will seek the portfolio with the lowest risk and the highest return, acting rationally.

Twelve years later, in 1964, "Capital asset prices: a theory of market equilibrium under conditions of risk.", by William F. Sharpe, was published. According to the CAPM model by Sharpe (1964), traditional models of investment under certainty failed to quantify the relationship between the price of an asset and its risk. Therefore, the model assumes that there is a price of risk, which is the additional expected return associated with an increase in one unit of risk. In the CAPM model, the risk of an asset can be calculated by measuring the correlation of its return with the overall market return.

Finally, in 1970, Eugine F. Fama published one of the most important studies in the Efficient Capital Markets field. Fama (1970) argued that an efficient market is the one in which all the available information is reflected on its prices, so the price of a security should reflect its intrinsic value. According to the author, there are three levels of efficiency, according to what is 'all available information'. In the weak form, the available information is only the past prices of an asset. On the other hand, the semi-strong consider information that is obviously publicly available. Finally, the strong form, investors absorb all available information. Hence, insider traders' privileged information is not a means of obtaining returns above market returns.

Therefore, these three pillars of the Modern Finance Theory have one characteristic in common: all this research considers that the agents usually are rational in their decisions, seeking for efficiency using optimal mental models. Additionally, according to Shleifer (2000), the EMH is based on three main assumptions. Under the first assumption, the market will be efficient if all its agents act rationally in response to new information and their decisions. The second condition indicates that investors in the market are not influenced by each other and trade randomly, so even if they interpret new information with bias, the market is still efficient. Finally, even if both assumptions are not satisfied, arbitrage still holds the market efficient. In this condition, the market is efficient if the arbitrage of some investors offsets the biases of irrational investors also present.

2.1.2. Behavioral Finance

Osborne (1962) claims that the stock market is a high-speed economic environment, representing a gigantic decision-making phenomenon. Thus, in a few weeks, it can reproduce a version of supply and demand that would take years to observe in any other market. For this reason, Behavior Finance deserves scientific attention, since it is a good representation of economic behavior.

According to Mullainathan and Thaler (2000), neo-classical economists used to create their models based on calculating and unemotional agents, named *Homo Economicus*, that make decisions by maximizing its results. They stated that these anti-behavioral economists defended their models simply by stating that investors really are rational in their decisions, while others argued that models that consider *unbehavioral* decisions are easier to formalize and statistically more relevant. However, the authors declared that Behavioral Economics emerged from the argument that neither of these arguments are correct. Empirical evidence shows that agents are not 100% rational, and the deviations from this full rationality are relevant and cause disturbances in the economy and in the markets. According to Shiller (2016), these disturbances result in poor allocation of capital, weakening the risk-sharing of different institutions.

As stated by Barberis and Thaler (2003), empirical evidence shows that there are significant implications arising from the systematic mistakes that agents present in their decisions. They argued that deviations from rational behavior are inherent to human nature and should be incorporated into economic analysis as a natural extension of neo-classical models. Thus, Behavioral Finance is relevant to explain some financial phenomena applying models that do not assume complete rationality. In other terms, it tries to explain how markets behave when one or more neoclassical assumptions are not satisfied, such as the assumption which agents are calculating maximizers.

2.1.3. Behavioral Biases

Individuals make decisions based on their own experiences, common consensus, or quick judgments, a process that is called heuristics. According to Tversky and Kahneman (1974), heuristics are usually helpful but can lead to severe and systematic errors caused by the mental simplification of complex processes, known as biases.

Since the first article published in the Behavioral Economics field, several authors developed works on different kinds of biases. For instance, the overconfidence bias was described by Tversky and Kahneman (1974) as agents trusting more on their estimations than they should and ignoring all the uncertainty in their decisions. According to the authors, people use their starting value as reference and insufficiently adjust their estimations, causing distortions in the market.

Another important bias is the confirmation bias, in which agents are reluctant to seek evidence that contradicts their beliefs and, when they find such evidence, they consider it with excessive skepticism. Barberis and Thaler (2003) use as an ironic example to this bias the economists that insist on defending the Efficient Market Hypothesis (EMH), even though empirical evidence shows that markets are not totally efficient.

Therefore, when researchers want to explain these systematic deviations in the market, they usually refer to this psychological evidence that explains human biases. The results of behavioral research suggest that approaches that relax traditional assumptions of perfect agent rationality can yield positive outcomes, justifying recent efforts in their development. Currently, a lot of research is aggregating behavior aspects in their models, in order to better explain the market performance, without assumptions that do not reflect reality. Hence, in order to study one of these market phenomena, this dissertation is going to focus on price clustering, a bias caused by the human tendency to distort complex calculations with simple assumptions.

2.2. Price Clustering

2.2.1. Definition and Relevance

Price Clustering is the tendency for prices to be observed more frequently in round numbers. Most definitions in the current literature state that it is more common to observe prices ending in whole numbers, zero, or half prices, the ones ending in 5 (Harris, 1991; Sopranzetti and Datar, 2002). In other words, market agents tend to settle on more salient numbers when submitting an order for buying or selling an asset. As claimed by Aitken et al. (1996), psychological experiments show that price clustering is a fundamental attribute of human behavior, to simplify decisions or simply recording measurements, when underlying value is uniformly distributed over the range of possible prices.

The first evidence of price clustering was presented by Osborne (1962). According to the author, the stock prices spend a disproportionate amount of time in some prices, provoking "congestion" in the market. Osborne (1962) documented price clustering in the closing prices of the New York Stock Exchange. Without price clustering, prices should be uniformly distributed over the range of prices. However, the author observed that prices cluster first on whole numbers, then halves, followed by quarters and odd one-eights numbers. After him, this phenomenon has been studied from different perspectives, proving to be a relevant distortion among several financial markets.

As stated by Aitken et al. (1996), price clustering is inconsistent with economic rationality and with the Efficient Market Hypothesis, since it implies that prices are not following a simple random walk process. This discrepancy highlights the importance of studying the bias, since it raises capital issues about optimal order placement strategies. In agreement with this statement, for Niederhoffer (1965), price clustering increases the predictability of stock prices, and the bias can be included in trading strategies, affecting the profits.

Price clustering can result in a degree of predictability in stock returns. The predictability of the stock market can have positive and negative effects. According to Harris (1991), the limited set of price ranges can lead to reduced time to close a deal, since negotiations may converge more rapidly. This can result in lower costs for both parties. However, the bias can also create an opportunity for some market agent, that can take advantage of the distortion and trade with the information. In other words, agents with more knowledge of the market movements can place orders to benefit from market anomalies. As observed by Aşçıoğlu et al., (2007), there is evidence of strategic trading orders one price tick higher than zero and five, to avoid buying orders that are rounded up.

Although rounding a buy or sell order of an asset might seem like a minor market distortion, empirical literature demonstrates that the effects of price clustering are relevant to the market. A study conducted by Bhattacharya, Holden and Jacobsen (2012) found evidence that price clustering alone has caused an aggregated wealth transfer of 813 million dollars per year in the New York Stock Exchange (NYSE). Thus, further research that evidence the existence and the reasons for this bias are capital, in order to minimize the negative distortions that it causes in the financial markets.

2.2.2. Price Clustering Hypothesis

Several authors developed theories in order to explain the reasons for the price clustering phenomenon. Three of these theories are widely accepted and explored in many Behavioral Finance's articles as the determinants of price clustering: the Attraction Hypothesis (Gottlieb and Kalay, 1985), the Resolution Hypothesis (Ball, Torus, and Tshoegl, 1985) and the Negotiation Hypothesis (Harris, 1991).

The Attraction Hypothesis, also known as round number syndrome, proposes that some numbers are more attractive than others to the investors. According to Goodhart and Curcio (1991), investors don´t round the undervalue to the nearest available final number. Instead, there is an attraction to round numbers, such as the ones ending in zero, five, and quarters (¼ and ¾), in this order, because they are psychologically more appealing to investors, for being easier to recall.

The Price Resolution Hypothesis states that price clustering is positively correlated with uncertainty. Investors tend to submit round orders in scenarios where they are uncertain about the underlying value of a security. This uncertainty is a result of incomplete information, leading investors to cluster prices in certain numbers, in order to minimize search costs. Therefore, according to Lobão (2023), price clustering is expected to have a negative correlation with liquidity and positive correlation with volatility, that can be represented by volume of trade and the volatility of the stock, respectively.

The Negotiation Hypothesis is an economic theory, such as the Resolution Hypothesis. However, differently from the Resolution Hypothesis, the Negotiation Hypothesis states that the inverters' preference for round numbers occurs in order to minimize the negotiation costs. According to Harris (1991), price clustering limits the number of different bids and offers that can be made, allowing negotiations to converge more quickly. Therefore, when the stock prices are higher, there is usually more price clustering, due to higher negotiation costs.

In addition to these three most studied determinants of price clustering, recently an important hypothesis has been suggested, the Panic Trading Hypothesis. By studying Fiji's stock market, Narayan and Smyth (2013) suggested that political instability could be a cause for price clustering. As reported by the authors, the uncertainty caused by political instability results in lower trading confidence and can result in investors setting a quick round price. In the same direction, a military event can result in "panic trading", which leads investors to agree in round numbers.

2.2.3. Previous Empirical Evidence

As pointed by Aitken et al. (1996), behavioral biases are becoming more frequent with the increase in trading activities across markets. This phenomenon leads to the tendency of prices to cluster in certain numbers. Several authors tested the presence of price clustering in different markets, usually testing the main drivers for these biases, based on the hypothesis presented in the last section. Clustering has been identified in real estate prices (Palmon et al., 2004), gold market (Ball et al., 1985), exchange market (Goodhart and Curcio, 1991), among other markets.

However, the market in which the current literature found more evidence of price clustering is the stock market. In line with Aitken et al. (1996), this reflects a global tendency where price clustering commonly occurs in stock markets The first study to identify the bias in the stock market was conducted by Osborne (1962). The author observed that prices didn't follow a uniform distribution over admissible prices, finding evidence of price clustering in the American Stock Exchange.

Following, several authors tested stock markets for the presence of price clustering. There is evidence of the bias in the Australian stock market (Aitken et al., 1996), China's (Mitchell and Brown, 2004), Fiji Islands (Narayan and Smyth, 2013), Netherlands (Sonnemans, 2006), the Baltics (Lobão, 2023), among others. As stated by Narayan and Smyth (2013), there are few studies for stock markets in developing countries. Therefore, by examining the Russian market, this project seeks to address this gap by investigating a relevant stock market in a developing country.

2.3. Russia's Geopolitical Situation

Since 2022, the conflict between Russia and Ukraine has been the center of international political attention. It was a result of almost eight years of military tension, involving the dispute for the areas of Crimea and Donbass. On February 21st, 2022, Russia recognized the areas of Donetsk and Luhansk as independent and invaded these regions, an act that was seen as a war declaration. However, only three days later, on February 24th, 2022, the conflict in Ukraine officially started, when Russia's government decided to start a full-scale invasion in Ukraine.

In the subsequent months, the United States and the European Union began to apply several economic sanctions against Russia. As stated by Bougatef and Nejah (2024), the sanctions applied by Russia's most important trading partners had a tremendous impact on the country's economy. The result of these sanctions was a drawback in Russia's most important sources of income, such as nickel, fertilizers, energy and wood.

The effects of the war have already been identified in several financial markets. Lo et al. (2022) examined 73 countries to demonstrate that financial markets around the world reacted significantly to the shock caused by the war, resulting in increased volatility. On the same direction, Izzeldin et al. (2023) found evidence that stock markets responded more rapidly to the Russian invasion than to other shocks, such as Covid-19 and the 2008 financial crisis. It is possible to suggest from both studies that this event could amplify price clustering since volatility and rapid responses usually positively influence behavior biases.

In addition to increased volatility and rapid market response, several studies found evidence of the negative correlation between the conflict in Ukraine and stock market. Bongou and Yatié (2022) studied the daily stock of 94 countries from January 22nd, 2022, to March 24th, 2022, to prove a negative and significant effect of the military conflict on world's stock markets. The authors also found evidence of a weaker performance in countries bordering Russia and Ukraine, as well as the UN countries that demanded as end to Russia invasion, since the risk of the conflict scaling for these countries was higher.

On the same direction, another research more specifically analyzed the effect of the Russia's declaration of its recognition of two independent states in Ukraine on February 21st, 2022 (Ahmed et al., 2022). The authors found evidence of a negative abnormal return in the 3 days before and after the reference date, highlighting a higher negative effect on February 21st, 2022. In a country level analysis, the research found heterogeneous reactions in the stock market from different European countries. For instance, while stocks in the Nederland's reported a significantly negative reaction, companies in UK experienced a positive and significant abnormal return on the event date.

In a more general analysis, Berkman et al. (2011) used a database of 447 international political crises, as a proxy for perceived disaster probability, finding consistent evidence that changes in crisis index have a large impact on the market's returns and volatility. Similarly, Lehkonen and Heimonen (2015), studying 49 emerging markets, reported an inverse relationship between political risk and stock market returns.

Political crises have a negative effect on the market, and can lead to abnormal behaviors of market agents, and this can lead to behavior biases. As first reported by Narayan and Smyth (2013), political instability can also have a positive impact on price clustering. For these reasons, Russia's recent events can be used as a framework to test the relationship between the political instability caused by a war scenario, and the bias price clustering. Similarly, some studies already identified sings that the Russia-Ukraine War resulted in market anomalies.

According to Bougatef and Nejah (2024), this event caused the formation of herding behavior in the Russian stock market, especially during market downturns.

This military event played and is playing a significant role in shaping the country's political landscape, reflecting a broader era of political volatility with important implications for Russia's economic and financial arenas. Therefore, this dissertation uses the conflict between Russia and Ukraine as a proxy for political instability in Russia, to test the Panic Trading Hypothesis introduced by Narayan and Smyth (2013).

3. DATA AND METHODOLOGY

3.1. Data

This research uses data from the Russian stock market, more specifically the stocks included in the MOEX index. For that purpose, the software Refinit Workspace was used to extract the data. The MOEX index is the most relevant stock index in the country and tracks the performance of the top 50 most valuable and liquidity stocks in the Moscow Stock Exchange.

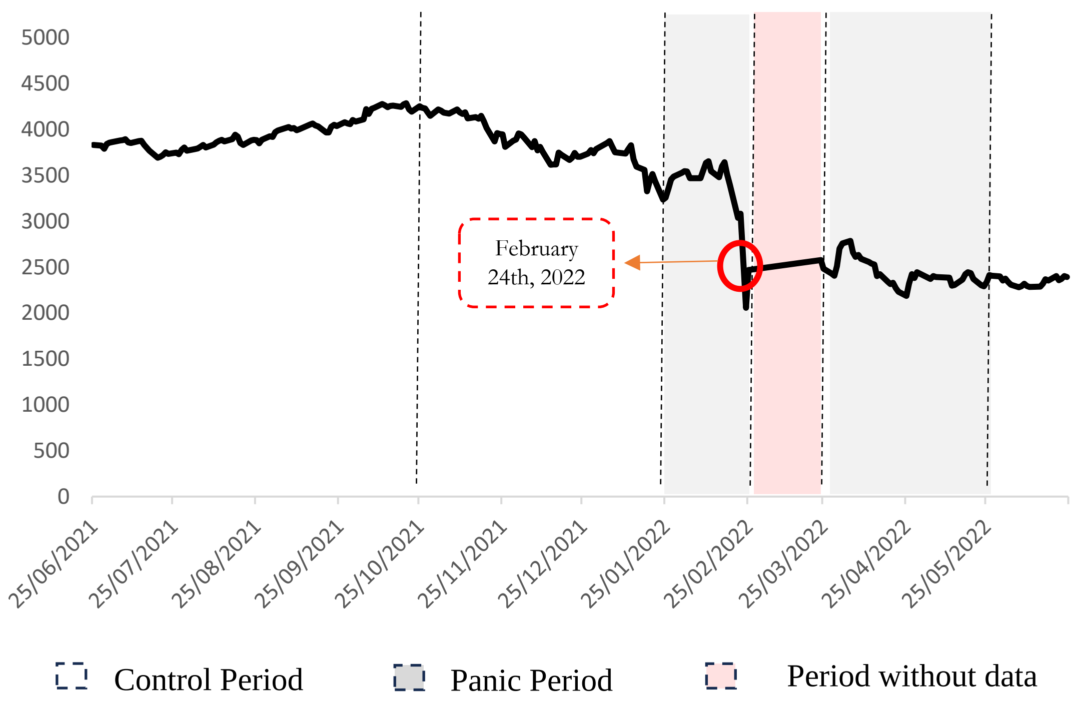
In this research, the daily prices of 20 stocks from the MOEX index were considered, since the other 30 stocks have the last digit ending only in 5 and 0, or only in even numbers. To test for price clustering, the ending digit has to vary from 0 to 9, and for that reason only 20 stocks were considered. Table 1 shows the 20 stocks that were included in the empirical study.

TABLE 1 – List of Stocks Analyzed

Ticker	Company
AFKS.MM	AFK SISTEMA PAO
AFLT.MM	AEROFLOT-ROSSIYSKIYE AVIALINII PAO
ALRS.MM	AK ALROSA PAO
CBOM.MM	MOSKOVSKIY KREDITNYI BANK PAO
FLOT.MM	SOVKOMFLOT PAO
GAZP.MM	GAZPROM PAO
HYDR.MM	FGK RUSGIDRO PAO
MOEX.MM	MOSKOVSKAYA BIRZHA MMVB-RTS PAO
MTLR.MM	MECHEL PAO
PHOR.MM	PHOSAGRO PAO
PIKK.MM	PIK SPETSIALIZIROVANNYI ZASTROYSHCHIK PAO
POLY.MM	POLYMETAL INTERNATIONAL PLC PK
RTKM.MM	ROSTELEKOM PAO
SBER.MM	SBERBANK ROSSII PAO
SBER_p.MM	SBERBANK ROSSII PAO
SELG.MM	SELIGDAR PAO
SGZH.MM	GK SEGEZHA PAO
TATN.MM	TATNEFT' PAO
TATN_p.MM	TATNEFT' PAO
UPRO.MM	YUNIPRO PAO

The database used in this research consists of 2,527 observations. The analysis covers the period from October 25th, 2021, to May 25th 2022, covering seven months and resulting in daily prices of 127 days. One limitation of this research is the lack of data or incomplete information on stocks between February 26th and March 23rd, 2022 (immediately following the start of the conflict). Consequently, this 26-day period was excluded from the analysis.

Figure 1 –The reaction of the MOEX index return to the conflict



To test the Panic Trading Hypothesis (Narayan and Smyth, 2013), this study considered as 'panic period' the days from January 25th to May 25th, 2022, covering 64 days of stock prices. This period was chosen because the conflict began on February 24, 2022, and it was considered as the time when the conflict had the most significant impact on market behavior, approximately one month before and three months later. As illustrated in Figure 1, the stock market in these months was very unstable, showing uncertainty and instability and, consequently, being a good proxy for the 'panic period'.

For the "non-panic" period, the study considered the three months preceding the panic period, from October 25, 2021, to January 24, 2022, covering 63 days of stock prices. Figure 1 illustrate that, in this period, the market return curve is flatter, showing a more stable period compared to the preceding months.

For this dissertation, a seven-month period was analyzed, in order to better capture the effect of the war. A shorter period might result in biased perceptions, due to a small sample size, while a longer period could include days when the market was not as affected by the war as those chosen for the 'panic period'.

In their study on herd behavior, Bougatef and Nejah (2024) separated their sample into pre-invasion and post-invasion periods. This research divided the data set slightly differently. It was considered that the month before the invasion was more chaotic and uncertain than a few months after the war, because of the tension and unpredictability that preceded the event, as illustrated by the volatility of the MOEX index in Figure 1. For that reason, the month immediately preceding the invasion was also included in the 'panic period'.

Other studies used the same criteria to investigate the effect of the war in Ukraine in stock markets. Bongou and Yatié (2022) studied 94 countries to prove the negative and significant effect of the Russia-Ukraine conflict on world's stock markets. For that purpose, they did not consider only the period after the war began, they also considered the month right after the invasion. The authors found that the reaction of global stock markets was weaker in the weeks following the invasion.

Table 2 presents the summary statistics of the model's variables. The table indicates that there are 2,527 observations for each variable, suggesting a balanced dataset. Two variables in the model are dummy variables: 'pc', representing price clustering, and 'war', indicating whether the observation falls within the 'panic' period. The other variables exhibit the price, volume of negotiations, volatility and tick size of the stocks analyzed in the period described above.

TABLE 2 - Summary Statistics

Variable	Observations	Mean	SD	Min	Max	Skewness	Kurtosis
pc	2527	0.29	0.46	0.00	1.00	0.91	-1.17
price	2527	526.44	1354.47	0.62	8908.00	3.94	14.79
volume	2527	46646.79	135343.60	22.89	2970826.00	9.24	140.57
volatility	2527	0.05	0.06	0.01	0.74	5.29	40.44
ticksize	2527	2.00	0.90	0.00	4.00	0.00	0.12
war	2527	0.50	0.50	0.00	1.00	-0.01	-2.00

Notes:

pc	Dummy for price clustering (1 if the closing price ends in zero)
price	Closing price of stock i in day t
volume	Volume of negotiation of stock i in day t
volatility	Difference between the max and min price normalized by the closing price of stock i in day t
ticksize	Ticksize of stock i in day t
war	Dummy for panic period (1 if day i is within January 25th and May 25th, 2022)

The summary statistics reveal important characteristics of the dataset analyzed. On average, 29,3% (mean 0.293) of the asset prices end in zero (dummy 1), showing a tendency of the dataset to display price clustering, since the expected mean for this variable is 0.1. The average price of the assets is approximately 526.44, but with a high standard deviation of 1,354.4, reflecting substantial variability. This variability is emphasized by the price distribution's skewness (3.937) and kurtosis (14.786), indicating the presence of extreme high prices (outliers) and a long right tail.

Trading volume also shows significant variability, with an average of 46,646.79 and a standard deviation of 135,343.6. The volume distribution is highly skewed to the right (9.239) and has a high kurtosis (140.571), suggesting extreme high outliers. This can indicate that, in specific days, agents traded more frequently, probably due to panic situations. Volatility has a mean of 0.052 and is moderately variable (SD of 0.059). The stock's tick size varies from 0 to 4, a specific characteristic of the Russian stock market, suggesting a potential need to account this variable in the price clustering regression. During the analyzed period, 50.1% of the observations (mean 0.501) occurred during the war, with a symmetric distribution, suggesting that the databased was almost equally divided into stock prices during the panic period and stock prices during the control period.

3.2. Methodology

The empirical part of this research is divided into two parts: first, the examination of the frequency of the last digit of the stock prices to test the price clustering hypothesis, second the regression analysis to test which factors most affect the presence of the bias.

In the first part, the Attraction Hypothesis (Goodhart and Curcio, 1991) was considered to test if some numbers are more attractive than others for the investor. For that, the last digit of the daily price of each stock was observed, to test the presence of price clustering. To reject the presence of price clustering, each digit should be observed around 10% of the time. The chi-squared test was used to check whether the frequencies (number of values) in each category are statistically different from the expected 10%. Finally, the z-test check if each digit individually has a different frequency than the expected.

In the second part, in order to determine which factors influence the presence of the bias, a regression analysis was performed. Equation 1 above defines the regression:

Equation 1

$$PC_{i,t} = \alpha + \beta_1 Price_{i,t} + \beta_2 Volume_{i,t} + \beta_3 Volatility_{i,t} + \beta_4 TickSize_{i,t} + \beta_5 War_{i,t} + \varepsilon_{i,t}$$

where

$PC_{i,t}$ is a dummy variable, that is 1 when the last digit of the price of the stock *i* in day *t* ends in zero, and zero otherwise.

$Price_{i,t}$ is the closing price of the stock *i* in day *t*

$Volume_{i,t}$ is the number of stocks traded *i* in day *t* (in thousands)

$Volatility_{i,t}$ is the difference between the maximum price of stock *i* in day *t* and the minimum price of stock *i* in day *t*, divided by the closing price of stock *i* in day *t*. This variable was used as a proxy of the volatility of the stock *i* in day *t*.

$TickSize_{,t}$ is the tick size of stock *i* in day *t*.

$War_{i,t}$ is a dummy variable, that is 1 for stock *I* if the day *t* is included in the "panic" period described above, and zero otherwise.

The variable 'price' was included in the model to test the Negotiation Hypothesis (Harris, 1991), which suggests that higher negotiation prices lead to higher negotiation costs, making price clustering more likely. In addition, the Resolution Hypothesis (Ball, Torus, and Tshoegl, 1985) states that price clustering is positively correlated with uncertainty. According to Lobão (2023), this hypothesis implies that price clustering should have a negative correlation with liquidity and a positive correlation with volatility. Therefore, the variables 'volume' and 'volatility' were included in the regression.

The control variable 'tick size' was included in the regression. The tick size of the stocks in the database ranges from zero to four. This variable was selected to mitigate the influence of these variations on the results. Additionally, the other variables also serve as control variables, as previous studies have shown they can impact price clustering. By isolating the effect of these four variables, we can more accurately test whether the conflict in Ukraine affects price clustering.

Finally, the variable 'war' represents the period when the Russia-Ukraine military clearly affected the stock market. It is a dummy variable set to 1 for the days considered the 'panic period', defined as one month before the conflict began and three months after 24th of

February 2022. It is set to 0 for the control period, which is the three months preceding the 'panic period. The coefficient of this variables analyses the Panic Trading Hypothesis, which examines whether political and military instability have a positive effect on price clustering. Thus, if the variable's coefficient is positive and significant, it can be concluded that the instability caused by the Russia-Ukraine conflict impacts the market behavior by increasing price clustering.

4. EMPIRICAL ANALYSIS

4.1. Preliminary Data Analysis

Table 3 reports the distribution of the last digit of the stocks analyzed in each day observed.

TABLE 3 - Distribution of Last Digit of Closing Price

Last Digit	Absolute Frequency	Relative Frequency	Z-stat	P-value	
0	740	29.30%	17.27	0.00	***
1	211	8.30%	-2.09	0.04	**
2	216	8.50%	-1.84	0.07	*
3	154	6.10%	-5.10	0.00	***
4	186	7.40%	-3.28	0.00	***
5	228	9.00%	-1.21	0.23	
6	184	7.30%	-3.42	0.00	***
7	159	6.30%	-4.81	0.00	***
8	206	8.20%	-2.23	0.03	**
9	243	9.60%	-0.48	0.63	
Total	**2527**	**100%**			

Notes: ***p<0.1; **p<0.05; ***p<0.01**

Chi-Squared Test

Chi-Squared Statistics 1,072.9

p-value 0.00000

The table shows clear evidence of an unbalanced distribution, since almost one third (29.3%) of the closing prices observed end in zero, a much higher number than the expected 10%. This proportion shows a clear sign of price clustering, since the investors tend to prefer trading stocks ending in zero.

The chi-squared test exhibited very low p-value (next to 0.00000), indicating that the difference between the observed distribution of the last digits of prices and the expected distribution is extremely significant. Additionally, the p-value from the z-stat test indicates that the frequency of the last digit zero, three, four, six, and seven are far from the expected. In this case, the digit zero with more observations that expected, and the others with less. This strongly suggests the presence of price clustering in the data sample, especially in digit zero. It is also possible to state that the chi-squared test demonstrates evidence of attraction hypothesis in the dataset, since prices ending in zero seems to be more attractive than others.

By analyzing the 'panic period' and 'control period' separately, it is possible to observe signs of Panic Trading Hypothesis in the sample. As shown in Table 4 and 5, even though there is evidence of price clustering in both periods, the frequency of the digit zero in the panic period is 34% against 24% in the 'control period'. Therefore, it indicates that when individuals face uncertain events, they tend to cluster more frequently.

TABLE 4 - Distribution of Last Digit of Closing Price (Panic Period)

Last Digit	Absolute Frequency	Relative Frequency	Z-stat	P-value	
0	434	34.25%	14.71	0.00	***
1	96	7.58%	-2.15	0.03	**
2	101	7.97%	-1.79	0.07	*
3	67	5.29%	-4.46	0.00	***
4	76	6.00%	-3.71	0.00	***
5	116	9.16%	-0.72	0.47	
6	81	6.39%	-3.31	0.00	***
7	76	6.00%	-3.71	0.00	***
8	105	8.29%	-1.50	0.13	
9	115	9.08%	-0.79	0.43	
Total	**1267**	**100%**			
Notes:	***p<0.1;**	****p<0.05;**	*****p<0.01**		

TABLE 5 - Distribution of Last Digit of Closing Price (Control Period)

Last Digit	Absolute Frequency	Relative Frequency	Z-stat	P-value	
0	306	24.29%	9.51	0.00	***
1	115	9.13%	-0.74	0.46	
2	115	9.13%	-0.74	0.46	
3	87	6.90%	-2.79	0.01	***
4	110	8.73%	-1.09	0.27	
5	112	8.89%	-0.95	0.34	
6	103	8.17%	-1.59	0.11	
7	83	6.59%	-3.10	0.00	***
8	101	8.02%	-1.74	0.08	
9	128	10.16%	0.13	0.89	
Total	**1260**	**100%**			
Notes:	***p<0.1;**	****p<0.05;**	*****p<0.01**		

This result is aligned with findings from similar studies. Harris (1991), Aitken (1996), Brown and Mitchell (2008), Sonnemans (2006), Lobão (2023), and Narayan and Smyth (2013) are among the researchers who have discovered evidence of price clustering in different stock markets, including the US, Australia, China, Germany, Indonesia, Malaysia, Pakistan, and Fiji. However, unlike Harris (1991) and Aitken (1996), this research does not find evidence of price clustering around the number five. Stock prices ending in three and seven appear to be less favored ones, as they have the lowest frequency of closing prices.

4.2. Regression Results

The second phase of this study aims to examine the factors that impact price clustering in the Russian stock market. For that purpose, a regression analysis was conducted, as outlined in Section 2.2 Methodology. The results of this regression analysis are presented in Table 6:

TABLE 6- Determinants of Price Clustering

	Dependent Variable: pc					
Independent Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
price	-0.00001	-0.00001	-0.00001	-0.00001	-0.00001	-0.00001
	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)
volume	-0.00000	-0.00000	-0.00000*	-0.00000*	-0.00000**	-0.00000*
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
volatility	-	-	0.803***	0.616***	0.817***	0.626***
	-	-	(0.155)	(0.160)	(0.157)	(0.163)
ticksize	-	-	-	-	0.008	0.005
	-	-	-	-	(0.015)	(0.015)
war	-	0.099***	-	0.080***	-	0.079***
	-	(0.018)	-	(0.019)	-	(0.019)
AIC	3197.4	3169.1	3172.5	3156.3	3174.2	3158.1
BIC	3220.7	3198.2	3201.7	3191.3	3209.2	3199
Observations	2,527	2,527	2,527	2,527	2,527	2,527
Adjusted R2	0.0003	0.012	0.011	0.017	0.010	0.017

Notes:	***p<0.1; **p<0.05; ***p<0.01**
pc	Dummy for price clustering (1 if the closing price ends in zero)
price	Closing price of stock i in day t
volume	Volume of negotiation of stock i in day t
volatility	Difference between the max and min price normalized by the closing price of stock i in day t
ticksize	Ticksize of stock i in day t
war	Dummy for panic period (January 25th to May 25th, 2022). 1 if day t is considered panic period

Table 4 presents six regressions, each using different variables. The models that best explain the factors that influence price clustering are the ones including the variable 'war'. The AIC and BIC tests indicate that models 4 and 6 best fit our data, suggesting that the variable 'War' is significant for the model. Among these models, model 4 is preferred, indicating that the variable 'tick size' does not make the model more accurate. Thus, the focus of this results analysis in going to be Model 4, that includes all the relevant variables and exclude the one that have no relevant effect on price clustering.

In the three models where the variable 'War' was included, it is positive and significant in a 1% significance level. This evidence shows that the variable is positively correlated with price clustering, meaning that in periods when the war had a greater impact on the market, people tend to have this bias. In addition, these results are aligned with the Panic Trading Hypothesis, proposed by Narayan and Smyth (2013), which states that political instability induces price clustering. These results indicates that, as argued by Narayan and Smyth (2013), the uncertainty caused by political instability results in lower trading confidence and can result in invertors setting a quick round price. On the same direction as Bougatef and Nejah (2024), the regression analysis prove that the Russia-Ukraine conflict have positive effect on behavior biases such as price clustering and herd behavior.

The findings presented in Table 4 also indicate signs supporting the Price Resolution hypothesis, which suggests that price clustering is expected to have a negative correlation with liquidity (volume) and positive correlation with volatility. In model 4, the volume variable is negatively significant at 10%, while the volatility variable is positive and significant at 1%. These results support the hypothesis proposed by Ball et al., (1985), and are aligned with other studies such as Aitken et al. (1996), Ohta (2006) and Hu et al., (2017), that also found evidence of positive and significant relation between stock prices volatility and price clustering.

Finally, these results reject the Negotiation Hypothesis. The variable 'price' does not have a significant impact in price clustering in none of the models since it is not significant at 10%. These outcomes diverge from other studies in the field. Lobão (2023), Lobão (2024) and Harris (1991) found evidence that higher price level was associated with a statistically significant increase in the likelihood of price clustering in some securities analyzed, thus supporting the Negotiation Hypothesis.

In conclusion, the distribution and regression analysis support three of the four hypothesis tested with the stocks from the MOEX index. The Attraction Hypothesis is clearly evident with 29% of the sample's closing prices end in zero. Following, the variable 'war' is positive and significant in all models that it is included in, indicating strong evidence of Panic Trading Hypothesis. Third, there are also signs of the Price Resolution Hypothesis, as volatility and trading volume appear to have a positive and negative relationship with price clustering, respectively. Finally, there is no evidence of Negotiation Hypothesis since the variable 'price' does not show a significant relationship with price clustering.

5. CONCLUSION

According to the Efficient Market Hypothesis (Fama, 1970), stock prices are expected to reflect all available information and follow a uniform distribution. However, as noted by Barberis and Thaler (2003), systematic mistakes by investors can result in market anomalies or biases. One of these biases is price clustering, where investors tend to prefer certain numbers over others. Additionally, Narayan and Smyth (2013) suggest that investors are more prone to these systematic mistakes during panic situations.

Therefore, to test these hypotheses, this dissertation aimed to evaluate the efficiency of the Russian stock market from October 25th, 2021, to May 25th, 2022, by examining the market for price clustering. For that, 20 stocks from the MOEX index were analyzed. Additionally, four hypotheses were tested, with a focus on the Panic Trading Hypothesis, in order to determine whether the conflict in Ukraine impacted investor behavior during that period.

First, the univariate analysis showed evidence of price closing in the dataset, since 29% of the daily prices in the analyzed period ended in zero. The chi-squared and z-test strongly suggested the presence of price clustering. It is also possible to state that the chi-squared test demonstrates evidence of Attraction Hypothesis, since some prices seems to be more attractive than others.

Following, the regression analysis provided strong evidence for the Panic Trading Hypothesis. The variable 'war' was positively significant at a 1% level in all tested models, indicating that during a panic period, investors tended to cluster more, showing signs of irrationality. In addition, the variable 'volume' was negatively correlated with price clustering and significant at a 10% level, while the variable 'volatility' was positively significant at a 1% level. These results are aligned with the Price Resolution Hypothesis (Ball, Torus, and Tshoegl, 1985), which states that price clustering is positively correlated with uncertainty. Finally, the database showed no evidence supporting the Negotiation Hypothesis, diverging from other studies such as Harris (1991) and Lobão (2023).

These results have important implications for the functioning of financial markets. The identification of the Panic Trading Hypothesis effect indicates that stock markets are less efficient and more predictable during periods of military and geopolitical tension, allowing the development of investments strategies capable of generating abnormal returns. As stated by Niederhoffer (1965), price clustering increases the predictability of stock prices, and the bias can be included in trading strategies, affecting the profits. According to Aşçıoğlu et al., (2007), some investors strategic order one price tick higher than zero and five, to avoid buying orders that are rounded up. From a micro perspective, it shows that investor tend to be more irrational and rely more on heuristics during uncertain events. Additionally, the results are relevant for regulators and policymakers, as they suggest that market transparency measures should be reinforced during crisis situations.

For future studies, it is important to analyze the impact of events that result in uncertainty in developed countries, as most studies testing the Panic Trading Hypothesis have focused on extreme events in developing country. For instance, political instability from events like U.S. elections could affect investor rationality, leading to price clustering. Testing such events would help determine if regular events in developed countries can also be significant factors for price clustering, or if only extreme events, such as military conflicts and extreme political events, have this effect.

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