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Psychological Price Barriers in Shariah-Compliant Stocks: Evidence from Five Emerging Markets

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Biographical Note

Sara Garcês was born in Braga, Portugal, on February 20th, 2002. In 2023, she completed her bachelor's degree in Economics at Universidade do Minho, where she developed a strong interest in financial markets and economic analysis. That same year, she joined the Master's in Finance at Faculdade de Economia of Universidade do Porto (FEP), where she is currently studying.

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Abstract

Contrary to common belief, financial markets are not guided solely by numerical data and rational analysis. Instead, they are a reflection of human behavior and its psychological biases. Round numbers have been widely studied as potential psychological barriers, affecting various asset classes and global financial markets. While there is considerable evidence that this phenomenon affects returns and variance, especially in stock indices, the literature remains limited regarding individual stock prices, particularly in markets that follow *Shariah* law.

This study tests psychological barriers in Islamic markets ruled by ethical and religious principles. Based on robust methodologies applied in similar studies, our research is the first, to our knowledge, to investigate this market anomaly in Islamic stocks. Our sample includes the three largest market capitalization stocks from five Islamic markets: Saudi Arabia (S&P Saudi Arabia Shariah), Malaysia (FTSE Bursa Malaysia EMAS Shariah Index), Qatar (QE Al Rayan Islamic Index), Pakistan (KMI 30) and Turkey (S&P BMI Turkey Shariah Index), considering a time window from 2014 to 2024. The countries were chosen based on two criteria: (i) a predominantly Muslim population and (ii) the existence of robust financial markets with national Islamic indices.

Regarding the methodology, the analysis includes uniformity and barrier tests, and the study of conditional effects on returns and variances. The results reveal that psychological barrier effects can vary depending on the type of test applied. Although the evidence is not fully systematic, barrier signs are detected in most markets. Additionally, the impact of barriers seems stronger on volatility than on average returns. Consequently, investment strategies based on psychological barriers should be approached with particular caution in these markets.

Key Words: psychological barriers, round numbers, islamic finance, behavioral finance

JEL-Codes: G14, G15, G41, Z12

Resumo

Ao contrário da crença comum, os mercados financeiros não são guiados apenas por dados numéricos e análises racionais. Na verdade, eles são um reflexo do comportamento humano e dos seus vieses psicológicos. Os números redondos têm sido amplamente estudados como potenciais barreiras psicológicas, com efeitos em diversas classes de ativos e mercados financeiros mundiais. Embora haja evidências consideráveis de que este fenómeno afete os retornos e a variância, especialmente em índices de ações, a literatura permanece limitada em relação aos preços das ações individuais, particularmente em mercados que seguem a lei *Shariah*.

Este estudo testa barreiras psicológicas em mercados islâmicos regidos por princípios éticos e religiosos. Com base em metodologias robustas aplicadas em estudos semelhantes, a nossa investigação é a primeira, tanto quanto sabemos, a examinar esta anomalia em ações islâmicas. A nossa amostra inclui as 3 ações de maior capitalização de cinco mercados islâmicos: Arábia Saudita (S&P Saudi Arabia Shariah), Malásia (FTSE Bursa Malaysia EMAS Shariah Index), Qatar (QE Al Rayan Islamic Index), Paquistão (KMI 30) e Turquia (S&P BMI Turkey Shariah Index), considerando uma janela temporal de 2014 a 2024. Os países foram escolhidos com base em dois critérios: (i) população predominantemente muçulmana e a (ii) existência de mercados financeiros robustos com índices islâmicos nacionais.

Relativamente à metodologia, foram aplicados testes de uniformidade, testes de barreiras e análises de efeitos condicionais sobre os retornos e a variância. Os resultados obtidos revelam que os efeitos associados às barreiras psicológicas variam consoante o tipo de teste aplicado. Embora a evidência de barreiras não seja sistemática, são poucos os mercados em que não se observa qualquer indício das mesmas. Além disso, o efeito das barreiras parece influenciar mais a volatilidade do que os retornos médios. Consequentemente, as estratégias de investimento baseadas em barreiras psicológicas devem ser abordadas com especial cuidado nestes mercados.

Palavras-Chave: barreiras psicológicas, números redondos, finanças islâmicas, finanças comportamentais

Códigos-JEL: G14, G15, G41, Z12

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1. Introduction

Around the world, investors often present irrational behaviors when trading in stock markets, particularly hesitating as prices approach round numbers, such as 100 or 1000 (Donaldson and Kim, 1993). These numbers can serve as psychological barriers, preventing investors from trading when prices are near them and acting as resistance or support levels when approached from above or below. Despite lacking intrinsic economic significance, psychological barriers have been widely documented in financial markets (Bahng, 2003; Cyree et al.,1999; Donaldson and Kim, 1993; Woodhouse et al., 2016). Their impact is so significant that economic agents are often skeptical about crossing these levels during market upturns or downturns (Cyree et al., 1999). This phenomenon challenges the principles of traditional finance since, in efficient markets, price changes should reflect new information and follow a random walk (Fama, 1970). In such markets, no specific price level should hold any intrinsic significance. Consequently, the most plausible explanations seem to be related to behavioral biases (Woodhouse et al., 2016).

The literature on psychological barriers is vast, covering a wide range of asset classes, financial markets, and regions worldwide (Aggarwal and Lucey, 2007; Dorfleitner and Klein, 2009; Lobão and Lopes, 2024). However, the studies are conducted in relatively conventional markets, in the sense that none of their financial systems is based on ethical and religious principles, such as Islamic financial markets. The Islamic finance industry has grown rapidly over the past decade, significantly impacting the global economic environment. The industry growth in 2023 was around 11%, reaching values of $4.9 trillion in assets, with projections of $7.5 trillion by 2028. This progress was driven by strategic markets, such as Saudi Arabia, Malaysia, Indonesia, the United Arab Emirates (UAE), and Iran; innovative initiatives such as *sukuk*[1] linked to ESG (Environmental, Social and Governance) practices and the advancement of Islamic fintech. Additionally, this industry has demonstrated resilience during periods of crisis, such as during the economic shocks of 2022, demonstrating its stability and potential to attract global investors (ICD and LSEG, 2024). Despite its growing importance, Islamic markets remain relatively unexplored in the literature, particularly "market behaviors of Islamic stock indexes are largely ignored" and the way "emotions, irrational behavior and biases drive share prices" (Hassan et al., 2021, p.1283).

[1] Sukuk are Islamic financial instruments similar to bonds, but structured to comply with Islamic law by avoiding interest payments, which are prohibited under *Sharia* law.

In light of this, the present study intends to bridge the existing gap in the literature and for the first time, to the best of our knowledge, analyze whether countries ruled by Islamic financial principles, including the prohibition of practices like speculation (*gharar*) and interest rates (*riba*), are prone to the formation of psychological barriers. For this purpose, this research will implement five psychological barrier detection methods. These tests will be applied to stocks from five Islamic market indices: Saudi Arabia (S&P Saudi Arabia Shariah), Malaysia (FTSE Bursa Malaysia EMAS Shariah Index), Qatar (QE Al Rayan Islamic Index), Pakistan (KMI 30), and Turkey (S&P BMI Turkey Shariah Index). The selection of countries was based on two factors: (i) the high percentage of Muslim population and (ii) the existence of robust financial markets with national Islamic indices compatible with *Shariah* law. Moreover, according to the Islamic Finance Development Indicator (IFDI) 2024, the most developed countries in Islamic finance are Malaysia, Saudi Arabia, the United Arab Emirates, Indonesia, and Pakistan. Remarkably, three of these countries, Malaysia, Saudi Arabia, and Pakistan, are included in our empirical sample, confirming the strategic importance of these markets in the global Islamic financial system (ICD and LSEG, 2024).

Concerning the methodology approach, we will follow the methodology proposed by Aggarwal and Lucey (2007). First, we will perform a uniformity test assuming that the M-values follow a uniform distribution without psychological barriers. M-values are the last two digits in the integer portion of a certain price. Afterwards, we will run two types of tests, the barrier proximity, to assess the tails of the M-values' distribution, and a hump shape test to visualize the entire distribution shape. Finally, we will implement the conditional effects tests that evaluate potential changes in conditional returns and variances of single stocks around barriers.

The evidence does not point to a consistent pattern of psychological barriers across the Islamic markets analyzed, mainly because the results vary depending on the type of test applied. While the presence of barriers is not systematic, they are observed in most markets through at least one of the methodologies employed. In particular, the results for the conditional variance equation indicate that round numbers seem to influence stock price volatility more than they influence returns. The results obtained do not contradict the Market Efficiency Hypothesis, particularly in its weak form, since no systematic abnormal returns were observed after crossing psychological barriers. However, their impact on volatility suggests that these points exert some psychological influence on economic agents, which may indicate local behaviors of limited rationality, compatible with the view of quasi-efficient markets.

Proceeding from this chapter, this dissertation is structured as follows. The next chapter will address the literature review, indicating what psychological barriers are, how they are observed around the world, and their underlying causes. We then explain the fundamentals of Islamic Finance and, finally, review the evidence on Islamic investor behavior. The third chapter presents the methodological aspects, including the data description and the methods applied to examine the existence of barriers. The fourth chapter includes the results obtained and their respective analysis. Lastly, the fifth chapter contains the conclusion.

2. Literature Review

The present literature on psychological barriers in Islamic Financial markets is divided into four subchapters: (2.1.) Psychological barriers worldwide; (2.2.) Causes for Psychological barriers, including overconfidence, anchoring, herding, odd-ending prices, and aspiration levels; (2.3.) Islamic Finance and (2.4.) Islamic investor behavior.

2.1. Psychological barriers worldwide

The studies on psychological barriers began in the early 1990s in the stock and exchange markets. Donaldson and Kim (1993) were pioneers in introducing the concept of psychological barriers in the field of finance through the study of the Dow Jones Industrial Average (DJIA). Specifically, the authors compared the behavior of the DJIA with the Wilshire Associates 5000 (WA) index. Their findings revealed that the DJIA exhibited notable reactions, particularly increased volatility, when prices crossed 100-point thresholds. This indicated a "bandwagon effect", in which investors' decisions seemed to follow market trends. On the other hand, this pattern was not observed in a less popular index, such as WA, suggesting that DJIA's popularity could have contributed to the development of psychological barriers.

These discoveries inspired several global studies on this phenomenon. For instance, Koedijk and Stork (1994) found evidence that round-number price levels, multiples of 100, were crossed less frequently than statistically expected across five major stock markets. This result suggests that psychological barriers are not just a sampling bias. Results varied by country, with the Brussels (Belgium), S&P 500 (U.S.), and FAZ General (Germany) indices showing strong evidence of psychological barriers. Nikkei 225 (Japan) also exhibited psychological barriers with significantly non-zero parameters. Even so, the effects were too small, and in the case of the FTSE-100 (UK), the indication of psychological barriers was not consistent across the sub-periods analyzed.

The DJIA has been widely studied in the context of psychological barriers, likely due to its popularity, making it more prone to this bias. Cyree et al. (1999) included this index in their analysis alongside the S&P 500, FTSE 100, TSE (Canada), CAC 40 (France), Hang Seng (Hong Kong), and Nikkei 225 (Japan). Their findings suggested the presence of psychological barriers in most indices, with barrier crossings significantly affecting both the mean returns and variances. The conditional effects test showed that crossing the barrier in an upward movement had a positive impact on returns. At the same time, variance tended to increase as the barrier was being approached and fall after it was crossed. However, these variance effects were inconsistent across all markets: the DJIA and Nikkei presented clear patterns, whereas the CAC 40 saw increased variance after downward movements.

Expanding the geographical scope, Bahng (2003) studied emerging Asian markets, such as South Korea, Taiwan, Hong Kong, Thailand, Malaysia, Indonesia, and Singapore, and detected inconsistent barrier patterns. Taiwan presented the strongest evidence of psychological barriers, with prices concentrating at the 1000 threshold and forming a hump shape around its multiples. Thailand showed partial signs of barriers, while Indonesia and Hong Kong exhibited inverse patterns, with concentration near the barriers. On the other hand, the remaining markets presented no evidence of barriers.

More recently, in the European context, Kalaichelvan and Jie (2012) analyzed psychological barriers in five indices, FTSE-100, CAC 40, DAX 30, ATX, and SMI. The results revealed the significant presence of barriers only in the SMI index, where prices clustered around 1000 points. However, the remaining indices did not indicate abnormal behavior or psychological resistance at the round levels. Furthermore, Woodhouse et al. (2016) investigated the NASDAQ index and identified that it tends to "pause" or move more slowly near round numbers, such as multiples of 100, arguing that these numbers can act as psychological barriers. When comparing real index behavior with randomized simulations, the authors concluded that this pattern did not happen by chance: average returns tend to decrease as the index nears the barrier, followed by shifts in returns after crossing it, indicating hesitation followed by reaction, consistent with known cognitive biases. Lobão and Pereira (2017) analyzed the main stock market indices of Greece, Italy, Portugal, and Spain and concluded that psychological barriers exist in the Greek market, but are only vaguely visible in the Iberian markets, whereas in Italy, they are non-existent.

Taken as a whole, the literature does not point to a homogeneous pattern of psychological barriers across global markets. Instead, such barriers have been identified in developed and emerging market contexts and at different barrier levels. However, the vast majority of existing studies consider stock indices. Within the studies of psychological barriers using stock prices, Cai et al. (2007) analyze the behavior of class A and B share prices on the Shanghai and Shenzhen stock exchanges. In the A-share market, composed of domestic investors, prices tend to be concentrated in the digits 0, 5, and especially 8, considered auspicious; while the digits 4 and 7, associated with bad luck, are avoided. The same digits 0, 5, and 8 turned out to be significant resistance points. In contrast, in the B-share market, composed of foreign investors, these patterns were weak or absent. The results suggest that Chinese culture has a significant impact on clustering and price resistance, especially among domestic investors.

Dorfleitner and Klein (2009) analyzed four European indices and eight German stocks and found evidence of price concentration around round numbers. Particularly, at the 1000s level in the case of indices and at the lower 10s or 1s levels in stocks. However, the results varied between assets and tests: not all showed clear patterns, and the effects on returns and volumes were inconclusive. Only a few assets showed greater volatility near the barriers. The authors attribute this inconsistency to the different characteristics of each asset, supporting the idea that psychological barriers are contextual rather than a universal phenomenon.

Shifting focus to frontier markets, i.e., smaller economies that are less developed than emerging markets but have structured financial systems, Berk et al. (2017) studied individual stocks in the MSCI Frontier100 index and found evidence of psychological barriers. Moreover, these effects were stronger in stocks with low liquidity and countries with less individualistic cultures, suggesting that investors in these markets are more susceptible to group behavior. Expanding this discussion, Lobão and Lopes (2024) analyzed the existence of psychological barriers in the Estonian, Latvian, and Lithuanian markets, which are also frontier markets, across the main stock indices (OMX Tallinn, OMX Riga, and OMX Vilnius) and the ten most liquid stocks in the OMX Baltic 10 index. The results reveal more robust evidence of psychological barriers in the indices, especially in the OMX Tallinn, whereas individual stocks showed little evidence of positional effects, but showed significant changes in volatility when crossing barriers (transgressive effects), with Telia Lietuva standing out.

Given the mixed evidence regarding the existence of psychological barriers worldwide, important questions arise: *What are the underlying reasons or causes for those barriers to occur? Are there specific characteristics of investors that make them more prone to them?*

2.2. Causes for Psychological Barriers

The natural human tendency is to simplify complex decisions as much as possible and find familiar patterns to justify intuition when situations become more difficult. Notwithstanding, individuals are influenced by psychological biases that hinder the interpretation of information, which can lead to flawed judgments and suboptimal decision-making. To capture how this tendency influences age measurement and registration, Yule (1927) analyzed the frequency of distribution of the final digits from 0 to 9 in registrations of age data and discovered that people record their age with simpler and familiar numbers (e.g., 0 or 8). Following those discoveries, Kendall and Smith (1938) defended that the agents' numerical choices are not random. The authors used a "randomizing machine" to generate a random sequence of numbers between 0 and 9. Participants reported observing more even numbers and a few specific odd numbers, such as 1, 3, 9, meaning that the bias was related to human perception and not the machine itself.

In financial markets, investors also prefer numbers that have a cultural and cognitive significance for them. The "modern decimal system" reinforces this preference, since numbers such as 10, 100, or 1000 are easier to use as a reference. Psychological experiments show investors use heuristics, such as anchoring and herding, to simplify their choices. Especially during periods of greater uncertainty, investors are likelier to imitate others; consequently, prices tend to cluster around a certain price level, usually a round number. This can contribute to psychological barriers, as it creates conditions for certain numbers to become reference points, incentivizing investors to avoid crossing them (Mitchell, 2001).

2.2.1. Anchoring

Anchoring refers to investors' tendency to rely heavily on a past prediction to make future projections, and subsequent "adjustments are typically insufficient" and "biased toward the initial values". The initial estimates serve as an anchor from which they have difficulty dissociating when making assessments of future evaluations (Tversky and Kahneman, 1974, p.1128).

The connection between psychological barriers and anchoring was discovered by Westerhoff (2003) through the development of a behavioral model applied to foreign exchange markets where the fundamental value is anchored to the nearest round number. Investors adjusted their anchors over time. As exchange rates fluctuated around the perceived (i.e., psychologically anchored) fundamental value, the market was constantly misaligned with real fundamentals. Therefore, the only way to eliminate the pattern of biased anchors would be to break the psychological barriers between anchors.

At a later stage, Andersen (2007) studied anchoring in financial markets, namely in the Dow Jones and CAC 40 indices. The author developed a trading algorithm based on the operation of biological engines, which use positive feedback loops to build momentum and move in a specific direction. This algorithm was designed to simulate how investors respond to price fluctuations, particularly by predicting when they are likely to anchor their decisions to past prices. The study found that anchoring bias can create arbitrage opportunities, especially for market-neutral portfolio strategies that exploit mispricing without relying on the general market trend.

Expanding on these discoveries, Campbell and Sharpe (2009) defend that although individuals are not completely rational and often rely on anchors, their investment decisions are commonly influenced by estimates provided by analysts. However, professional forecasters often rely on past data to make their estimations. For instance, when they predict economic indicators such as retail sales and inflation, the estimates are too close to the values registered in the previous month instead of reflecting the new information.

2.2.2. Herding

The concept of herding refers to the intrinsic characteristic of individuals to copy the behavior of other agents, abandoning their information to follow the decision made by the group (Banerjee, 1992). Such behavior can heavily influence investors' decisions and lead to clustering, which is the concentration of prices around a specific level. As a result, the power of psychological barriers is reinforced by encouraging economic agents to act in line with market trends rather than relying on fundamentals (Mitchell, 2001).

The environment in which the decisions are made considerably impacts the manifestation of biases. For instance, uncertain environments might potentiate herding behavior and lead managers to follow other firms' managers' decisions to reduce the risk. According to Lieberman (2006, p.366), "firms might imitate to avoid falling behind their rivals, or because they believe that others' actions convey information". During the technological bubble at the end of 1990, agents were incentivized to invest in technological companies, persuaded by analysts' optimistic forecasts and stock prices' increase. As more and more investors entered the market, influenced by each other's decisions, there was an excessive allocation of resources to technological start-ups regardless of their profitability. This culminated in the overvaluation of those companies, leading to a bubble that burst after the failure of many of those firms in 2000 (Lieberman, 2006).

Dorfleitner and Klein (2009) documented similar dynamics in European stock markets, which characterized the phenomenon as a "bandwagon effect". When the price indices crossed a certain level associated with a psychological barrier, such as round numbers, they tended to move sharply away from that level. The underlying reason was that, as investors saw other agents buying, they were incentivized to follow the same decision, creating a positive feedback trend in the market.

Additionally, the role information ability plays in this bias manifestation should not be disregarded. Investors frequently face the challenge of dealing with incomplete information, as access to data is not available to all of them in the same way. This hardens the searching process in decisions to buy or sell stocks. Without full access to all the information, investors are incentivized to simplify this process and buy "attention-grabbing stocks", which present higher price movements or with more coverage in the news (Barber and Odean, 2008). Financial literacy emerges as a potential mitigator of herding behavior, as investors with higher financial knowledge tend to be less influenced by others. In situations where agents present a loss of historical record, financial literacy can reduce herding by promoting more rational and independent decisions. At the same time, it can amplify the confidence of overconfident investors in their skills, leading them to make even more independent choices (Sabir et al., 2019).

2.2.3. Odd ending price

The concept of odd pricing was first studied in the retail sector by Holdershaw and Gendall (1997), through 840 advertisements where 87% of the prices analyzed were odd, mainly prices that ended with 9. The reason behind it was that retailers believed this type of pricing had a greater capacity to stimulate consumption as it made prices appear lower. Prices ending with "odd" numbers, as $9.99, were more common because consumers perceived these prices as significantly cheaper than the closest rounded number, $10. This effect is reinforced by the tendency to focus more on the first digits of a price, since they are more salient and easier to remember.

Extending this analysis, Sonnemans (2006) investigated the frequency of price clustering around round numbers in the Dutch market from 1990 to 2001, focusing on changes before and after the euro's introduction. The study found that, with the transition to the euro, investors gradually shifted their reference points from round guilder prices (old currency) to round prices in euros. This indicates that using round numbers as a reference point has remained, even after a currency change.

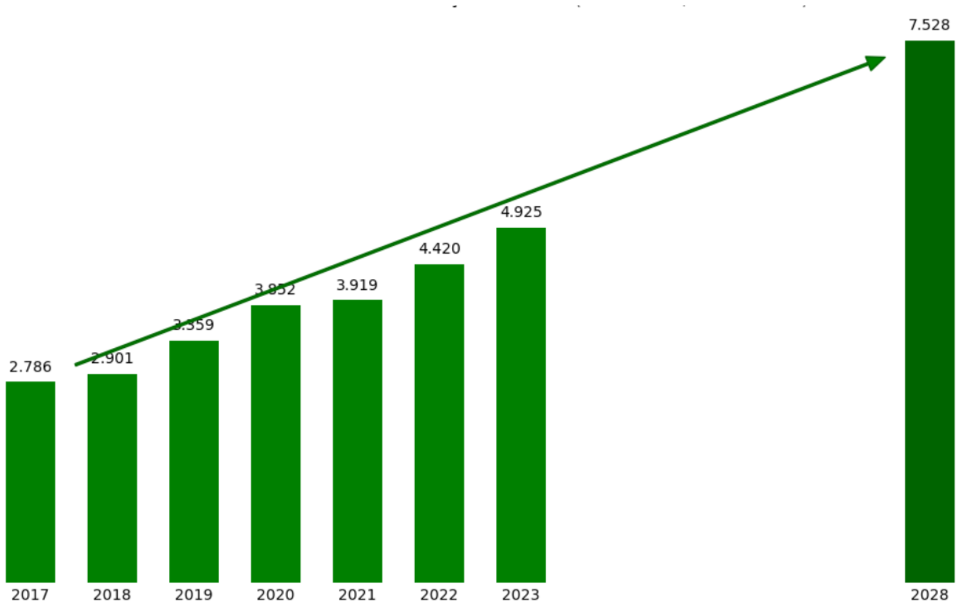
2.2.4. Aspiration levels

As the name suggests, aspiration levels are thresholds that an investor aims or expects to reach when deciding to buy or sell. When making such decisions, investors typically rely on subjective reference points tied to varying degrees of satisfaction. Additionally, these levels tend to be dynamic and adjusted according to the investor's previous experiences or difficulty in achieving the desired outcome (Simon, 1955).

In his investigation of the Dutch market, Sonnemans (2006) detected this behavior after the implementation of the euro. Despite the currency change, investors initially maintained their price targets based on the old currency (guilders), which affected their selling decisions. Over time, the focus gradually shifted to euros, yet the preference for round numbers as a psychological benchmark persisted. Although a behavior change was expected after the currency change, it was not instantaneous, which suggests that aspiration levels maintained their strong influence on market behavior.

Given that most studies on psychological barriers have focused on conventional financial markets, largely oriented by profit maximization and standard regulations, it becomes relevant to investigate whether such behavioral patterns manifest differently in alternative financial environments. One particularly distinct context is Islamic financial markets, which are based on moral principles that extend beyond profit maximization. From an academic perspective, they provide an opportunity to expand the discussion of behavioral biases worldwide; while, from a practical perspective, their sustained assets' growth and promising projections enhance their relevance for investors and policymakers (ICD and LSEG, 2024).

Figure 1. Islamic finance assets growth from 2017 to 2023, with a projection for 2028 (in USD billion)



Source: Islamic Finance Development Report 2024 (ICD and LSEG, 2024)

2.3. Islamic Finance

Islamic finance incorporates ethical and religious principles into its financial systems, governed by *shariah* law[2], whose main focus is to ensure the fairness and well-being of the current and future generations. "Wealth has to be used in such a way that it ensures success in this world and the world hereafter" (Ayub, 2009, p.23). These aims can be divided into two layers: primary and secondary. The primary objectives that underlie

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[2] *Shariah* Law is the religious law of Islam based on the Quran, Sunnah, and Islamic jurisprudence. It is believed to represent the divine will and regulates religious, social, and commercial aspects, ensuring that practices, including financial ones, follow the ethical principles of Islam.

shariah include respect for religion, life, family unity, property, intellect, and honor. These principles lead to the creation of secondary pillars that focus on ensuring an equitable justice system, promoting social security, empathy, mutual help, maintaining peace and security, and promoting moral values (Ayub, 2009).

Understanding how money is perceived helps to clarify the intuition behind some of the principles inherent to this financial system. Money by itself has no intrinsic value; its usefulness lies in being a tool for transacting products and services, which are real activities with underlying value. In this sense, it should not be possible to generate money through money, so Islamic contracts should be based on real assets and comply with the *shariah* law, which prohibits trading debt contracts to make *riba* profit. The term *riba* in Arabic can be translated to elevation, in other words, an increase in wealth that is not based on a productive activity (Ayub, 2009).

It may seem that Islamic finance provides an ideal form of financing as it is a risk-free rate. However, the prohibition of *riba* does not imply the absence of compensation for capital gains. One of the *shariah* laws is that "Reward, returns or benefits must always accompany liability or risk", this means that investment returns must be fairly earned and not just the result of the time value of money, which is the basis of the prohibition of *riba* (Obaidullah, 2005, p.11). Thus, the return on capital can and does have associated risks. Nonetheless, it is determined ex-post and must be based on the performance of the underlying real asset to ensure that the available financing is directed to productive and fair activities.

All ideals are interconnected at some level, since the principle of fairness is also the basis of the prohibition of *gharar* (excessive risk), which occurs when the trading conditions underlying contracts are unclear. It is a matter of the morality of the parties involved in the contract, since they must reduce the information asymmetry as much as possible. If *gharar* is proved to exist, the contract should be cancelled. Accordingly, contractual relationships must be clear without potential sources of ambiguity arising from information asymmetry between the parties that may lead to the loss of one of them based on the mutual participation model of *mudarabah*. When there are opportunities for profit with associated risks, they must be shared by stakeholders fairly. Economic transactions should not cause harm to either party. Therefore, Islamic financial services should not be invested in activities that are not considered *halal* (compatible with *shariah*), such as activities linked to addictions, for example, alcohol, gambling, and tobacco (Obaidullah, 2005).

Finally, Islamic finance is based on the principle of ownership, which focuses on the rule "do not sell what you do not possess" (Ayub, 2009, p.137). This implies that it is mandatory to own the real asset to establish a commitment with the counterparty, preventing activities such as short-selling, where investors earn by speculating on potential drops in the asset price. These types of transactions are perceived as volatile and unfair, where one of the parties would be harmed to the detriment of the other.

2.4. Islamic Investor Behavior

One might think that psychological barriers, entrenched in universal behavioral tendencies, would manifest similarly across all financial markets. However, investors' economic, social, and cultural characteristics can vary significantly worldwide, including their predispositions to certain biases. For instance, cultures with lower levels of long-term orientation are more prone to the disposition effect; investors tend to be less conservative, accepting instant gratification, making them more prone to loss aversion biases. Contrarily, long-term-oriented countries are less inclined to sell assets during periods with higher volatility, as their focus is on the long-term performance of the investment (Breitmayer et al., 2019).

In this sense, when analyzing the phenomenon of psychological barriers in Islamic markets, it is important to consider their specific characteristics and Islamic investors' behavior. Rashid et al. (2014) found that, in Malaysia, while emotional factors can influence investors' decisions, macroeconomic variables, such as interest and exchange rates, exert a more significant impact. Similarly, Aloui et al. (2016) showed that investor sentiment significantly affects both Islamic and conventional stock returns in the U.S., particularly during periods of negative sentiment and in mid-cap firms, suggesting that *shariah* principles did not significantly affect that relation.

Furthermore, religion and understanding Islamic financial principles are crucial determinants of investment behavior. According to Yusuff and Mansor (2016), religiosity and Islamic financial literacy heavily influence the decision-making process of Muslim investors in Malaysia when selecting Islamic unit trust funds. Investors with higher Islamic financial knowledge and stronger religious commitment tend to choose funds that comply with *Shariah* principles. Moreover, Islamic religious events, such as the Hajj pilgrimage, Ramadan, and Eid al-Fitr, positively influence investor sentiment. Those occasions can improve optimism and confidence among investors, increasing the market activity (Jaziri and Abdelhedi, 2018).

In line with this, Danila et al. (2021) studied the impact of market sentiment shocks on the volatility of Islamic stock indices in five ASEAN countries: Indonesia, Malaysia, Thailand, the Philippines, and Singapore. All markets registered periods of high and low volatility; however, only Malaysia, Thailand, and Singapore exhibited a stronger reaction to negative shocks. In Indonesia and Malaysia, both Muslim-majority countries with more mature Islamic financial systems, the market sentiment had a stronger influence on index returns. This suggests that, despite being ruled by Islamic principles, investor behavior in these markets can still be emotionally driven, similar to conventional markets.

The behavior of economic agents is shaped by both access to information and their ability to interpret it. For Islamic investors, this calls for attention to the dual importance of informational transparency and *Shariah*-compliant financial literacy. Arisanti and Oktavendi (2020) showed that limited disclosure regarding corporate *Shariah* governance practices in Indonesia contributes to herding behavior, as investors tend to follow others when information is scarce or unclear. Nonetheless, herding behavior does not manifest uniformly across all market conditions. Stavroyiannis and Babalos (2017), in their study of stocks in the Dow Jones Islamic Index, identified significant anti-herding behavior during periods of financial turbulence. In such contexts, Islamic investors appeared more likely to adopt independent and rational strategies, potentially reflecting the conservative and disciplined nature encouraged by Islamic financial principles.

While some studies reveal signs of rational and independent behavior among Islamic investors, others highlight significant herding tendencies, particularly during positive market periods. Chaffai and Medhioub (2018), analyzing the Gulf Cooperation Council (GCC), found strong evidence of herding in growth phases, demonstrating that rising prices lead investors to follow others, perceiving such movements as signals of informed behavior. Similarly, Mnif et al. (2020) observed pronounced herding in Islamic equity markets like the Dow Jones Islamic Market (DJIM), while the *Sukuk* market displayed greater stability, attributed to its structural transparency and asset-backed nature, which may reduce irrational behavior. Bougatef and Nejah (2022) further demonstrated how external shocks, such as the COVID-19 pandemic, amplified herding behavior among Islamic investors in Malaysia due to heightened uncertainty and fear. Likewise, Ah Mand et al. (2021) found that herding was more prevalent in *Shariah*-compliant stocks, during both upward and downward market conditions, with a particularly non-linear pattern during growth periods. Contrarily, in conventional stocks, the evidence of herding was practically nonexistent, even during downturns.

Additional studies explore how other psychological biases reinforce these dynamics. Din et al. (2021) reported that self-attribution, illusion of control, and information availability amplify herding in Pakistan; however, *Shariah* literacy helped mitigate some of those biases. Shah et al. (2018) highlighted that biases like overconfidence, anchoring, and availability lead to suboptimal decisions and reduced perceptions of market efficiency. Cheema and Nartea (2018) argued that even structured investment strategies, like momentum, can foster overconfidence and incentivize trend-following behavior in both Islamic and conventional markets.

Finally, Chaffai and Medhioub (2020) noted that during market expansions, Muslim investors in Islamic markets of the GCC, including Saudi Arabia, Kuwait, United Arab Emirates, Qatar, Bahrein, and Omã, often rely on anchoring heuristics, such as using the 52-week high as a reference point, and even analysts tend to base estimates on historical norms reinforcing biased expectations. The overall literature suggests that despite the principle-based differences between Islamic and conventional systems, investors tend to behave similarly under informational or emotional pressure.

3. Methodological Aspects

This section covers the main methodological aspects of our study, laying the foundation for the investigation of psychological barriers in Islamic stock prices. In this sense, we will begin by presenting the database used, detailing its composition and relevance for the analysis.

From there, we move on to the empirical approach, which begins with the analysis of stock prices' distribution, testing whether they follow a uniform pattern or show signs of concentration in certain values. Subsequently, we applied two specific tests to identify the presence of psychological barriers around round numbers, investigating their robustness and impact on the market. Finally, we examine the effects of these barriers on returns and price volatility, assessing if the proximity to these levels significantly influences market dynamics.

3.1. Data

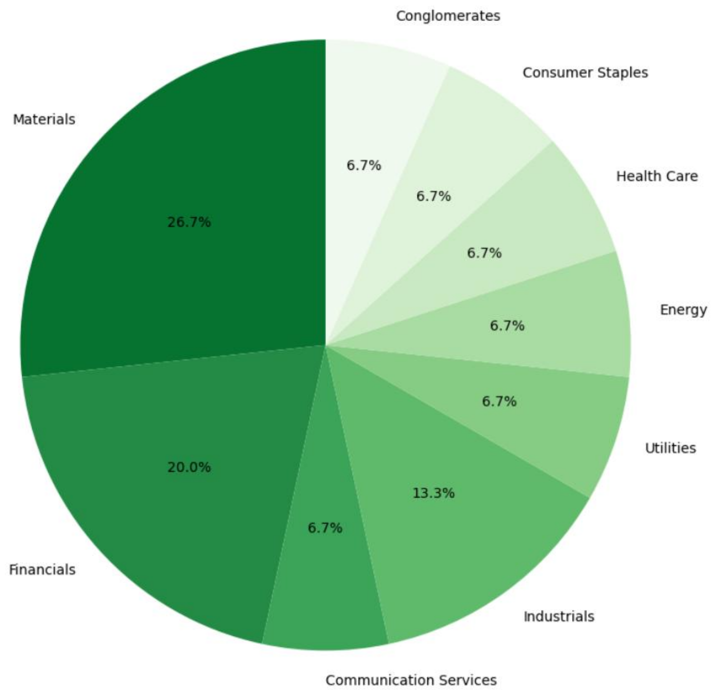
In this investigation, we assess the existence of psychological barriers in single stock prices of Islamic stock indices that follow the principles of *Shariah* law. The selection of countries was based on two factors: (i) the high percentage of Muslim population and (ii) robust financial markets with national Islamic indices compatible with *Shariah* law.

Accordingly, the chosen countries and their respective indices were: Saudi Arabia (S&P Saudi Arabia Shariah), Malaysia (FTSE Bursa Malaysia EMAS Shariah Index), Qatar (QE Al Rayan Islamic Index), Pakistan (KMI 30), and Turkey (S&P BMI Turkey Shariah Index). In terms of the projected percentages of Muslim population in those countries for 2020–2050: Saudi Arabia (92.7%), Malaysia (66.1%), Qatar (65.2%), Pakistan (96.5%), and Turkey (98.0%) (Pew Research Center, 2022). The sample period covers 10 years, following similar approaches from international studies. For Pakistan, Turkey, and Malaysia, the analysis includes the period from October 10, 2014, to October 10, 2024. In the case of Qatar and Saudi Arabia, from October 12, 2014, to October 10, 2024.

Even though most psychological barrier studies use international stock indices, these instruments are not directly tradable, which may limit their ability to accurately reflect investor behavior. On the other hand, individual stocks being directly traded on stock markets offer a more accurate perspective of investor behavior. With this in mind, we selected three stocks from Refinitiv Datastream with the highest market capitalization on each Islamic index to guarantee representativeness of these markets. Furthermore, to ensure full compliance with *Shariah* principles throughout the full sample period, we excluded any stocks that were not continuously included in the indices from 2014 to 2024.

In terms of sectoral distribution, the Islamic stocks in our sample are mostly concentrated in a few key industries. As shown in Figure 2, the majority of the companies operate in the financial, industrial, and materials sectors[3], reflecting the traditional composition of *Shariah*-compliant indices, which often exclude companies operating in conventional banking, alcohol, gambling, and other non-compliant sectors.

Figure 2. Sector Composition of Islamic Stocks



Source: Own elaboration

[3] Sectors were grouped according to the Global Industry Classification Standard (GICS), based on the core business activities of Islamic stocks. Cement producers and chemical manufacturers are classified under "Materials"; Islamic banks under "Financials"; electricity providers under "Utilities"; oil refining under "Energy"; and diversified holdings such as *Koç Holding AS* under "Conglomerates". "Industrials" includes infrastructure and aviation; "Communication Services" refers to telecommunications; "Health Care" refers to hospital operators; and "Consumer Staples" covers essential retail businesses.

Table 1 presents descriptive statistics for the stocks included in our study. The return series for all stocks deviate from the assumption of normality, as indicated by the significant levels of skewness and excess kurtosis, a common feature of financial time series, that reflects asymmetries and fat tails in the distributions. Although average daily returns are generally low, as expected, they tend to be positive across most stocks, with only a few exceptions (e.g., *Saudi Basic Industries*, *Qatar Industries,* and *Masraf Al Rayan*). In terms of stocks' volatility, *Attock Refinery Ltd* and *Turk Hava Yollari AO* exhibit higher standard deviations, indicating a greater degree of risk.

Most of the Islamic stocks also show positive skewness, characterized by a longer right tail in the return distribution, which is associated with more extreme positive returns compared to negative ones. The exceptions include stocks such as *Gamuda Bhd* and *Qatar Industries*, with negative skewness, revealing some degree of heterogeneity within our sample. Overall, the high kurtosis values confirm the occurrence of extreme returns, highlighting the non-normal distribution of the daily Islamic stock prices.

Table 1 – Database of Islamic stocks

Stock Index	Stock	N	Return Series				Level Series	
			Mean	SD	Skew	Kurtosis	Minimum Price	Maximum Price
S&P Saudi Arabia Shariah	Saudi Basic Industries Corporation SJSC	2497	-0.000082	0.015588	0.081189	10.080382	60.88	139.00
	Al Rajhi Banking and Investment Corporation SJSC	2497	0.000566	0.014593	0.133337	7.635638	18.43	114.75
	Saudi Telecom Company SJSC	2497	0.000270	0.014205	0.601350	9.325915	20.48	54.23
FTSE Bursa Malasyia EMAS Shariah Index	Gamuda Bhd	2449	0.000469	0.019714	-1.715638	26.727860	1.87	8.28
	IHH Healthcare Bhd	2449	0.000256	0.012416	0.485379	10.789209	4.47	7.26
	Tenaga Nasional Bhd	2449	0.000152	0.011397	0.688311	10.782187	7.89	15.04
KMI 30 Pakistan	Attock Refinery Ltd	2475	0.000603	0.027295	0.174945	6.527422	59.32	418.88
	Cherat Cement Company Ltd	2475	0.000845	0.025094	0.279389	7.830381	22.39	192.73
	D.G. Khan Cement Company Ltd	2475	0.000291	0.024055	0.212321	13.869118	39.44	245.37
QE Al Rayan Islamic Index	Qatar Islamic Bank QPSC	2494	0.000367	0.015004	0.136876	9.548257	7.73	27.50
	Qatar Industries	2494	-0.000011	0.015985	-0.157660	7.901204	6.50	20.20
	Masraf Al Rayan QPSC	2494	-0.000216	0.014708	0.053166	11.058396	1.90	5.82
SP BMI Turkey Shariah Index	Koç Holding AS	2508	0.001458	0.021487	0.027751	5.874557	8.26	263.75
	BIM Birlesik Magazalar AS	2508	0.001501	0.019750	0.161579	6.165497	16.27	620.33
	Turk Hava Yollari AO	2508	0.001817	0.025536	0.141326	5.120612	4.63	330.00

3.2. Methodology

Over the years, research on psychological barriers in financial markets has evolved considerably. However, the methodologies used have converged towards standardized approaches. The first steps in this area were taken by Donaldson and Kim (1993), who proposed a uniformity test to analyze the distribution of the M-values of an asset. The central idea was that, if stock prices were randomly distributed, their final digits should exhibit a certain regularity. Accordingly, deviations from this pattern could indicate the existence of psychological barriers, although this alone would not be sufficient to prove their influence.

To improve the investigation, the same authors developed two complementary tests: the barrier proximity and the barrier hump, which examine whether the concentration of prices close to round numbers significantly interferes with market behavior. In the subsequent years, Cyree et al. (1999) broadened this debate by introducing a conditional effect test, which evaluates how overcoming a barrier impacts both returns and assets' volatility. While several studies have adapted these methodologies, the influential research is still based on these three fundamental approaches. Therefore, our investigation follows the line of Aggarwal and Lucey (2007) study, as its methodological structure brings together the most widely adopted strategies in studies on psychological barriers, allowing a robust analysis aligned with the main academic evidence.

3.2.1. Definition of Barrier Levels

Adopting the classification used by Dorfleitner and Klein (2009), barrier level l will be interpreted as the number of zeroes a barrier presents. Complementing the analysis with the techniques used by Brock et al. (1992), the *band technique* will be applied to define an interval around the potential barriers. The main purpose of using this technique is to accurately capture investor behavior when approaching a potential barrier. Investors tend to become more or less active as they are close to reaching a support or resistance level. For instance, considering the price level of 100 euros, it would be expected that when prices reach levels close to that number (e.g., 95 euros or 105 euros, or even 98 or 102), investors change their behavior.

In this sense, we will define multiples of 1, 10, 100, and 1000 with intervals with an absolute length of 2%, 5%, 10%, and 25% of the corresponding power of ten as barriers.

Accordingly, there will be four possible barrier bands:

- Barrier level l=3 (1000s) 980-20; 950-50; 900-100; 750-250
- Barrier level l=2 (100s) 98-02; 95-05; 90-10; 75-25
- Barrier level l=1 (10s) 9.8-0.2; 9.5-0.5; 9.0-1.0; 7.5-2.5
- Barrier level l=0 (1s) 0.98-0.02; 0.95-0.05; 0.90-0.1; 0.75-0.25

For each stock in the Islamic indices, we select different barrier levels to study potential psychological barriers and ensure that the suitable ones are used. The intuition behind this decision is that different stocks have different price intervals. For instance, a share price of 800 euros will most likely not be relevant at the barrier levels of 10s or 1s; however, it could be more significant at 100s or even 1000s levels.

3.2.2. M-Values

The M-values were introduced by Donaldson and Kim (1993) as the potential price levels where psychological barriers may manifest, and they are defined by the final digits of price indices. The DJIA presented a lower frequency of closing prices when the last two digits (M-values) approached 00, suggesting a resistance to surpassing these thresholds. This phenomenon is interpreted as the effect of psychological barriers, particularly at round-number levels, such as multiples of 100 (i.e., 300, 400, …, 3400, 3500, …).

$$k \; X \; 100, k = 1,2, \ldots \qquad (3.1a)$$

It is important to notice that, as stated by De Ceuster et al. (1998), M-values defined for US markets might not be the same in other world indices. A fixed number for M-values could be too limiting in the context of psychological barriers, as it would ignore the existence of barriers at other price levels, such as 10, 20, 100, 200, etc. This limitation becomes increasingly significant at higher price levels, where the absolute difference between round numbers expands but their relative psychological impact may diminish, thereby complicating the identification of consistent threshold effects across global markets.

Therefore, the existence of barriers at other levels ..., 10, 20, ..., 100, 200, ..., 1000, 2000 should be considered, ... i.e. at:

$$k\ X\ 10^{l}, k = 1,2, \dots, 9; l = \cdots, -1, 0, 1, \dots \quad (3.1b)$$

and also at the levels …, 10, 11, …, 100, 110, …, 1000, 1100, …, i.e. generally at:

$$k\ X\ 10^{l}, k = 10, 11, \dots, 99; l = \cdots, -1, 0, 1, \dots \quad (3.1c)$$

The M-values used in this work can be defined considering these barriers.

$$M_k = \left[P_t * \frac{100}{k}\right] mod\ 100, \quad k = 0.01, 0.1, 1, 10, 100, 1000 \quad (3.2)$$

Considering that $\left[P_t * \frac{100}{k}\right]$ represents the integer part of $P_t * \frac{100}{k}$ and that $mod\ 100$ is the reduction modul of 100.

To clarify, if P_t =2359.47 then M1 equals 47, M10 is 94, M100 is 59 and M1000 is 35. At each level, psychological barriers are expected to occur when the M-value reaches 00. Each level of analysis is only relevant within a specific price range; for instance, M1000 will only be considered for price levels whose integer part has 4 digits (e.g., 7294), M100 for 3 digits (e.g., 552), M10 for 2 digits (e.g., 89.22), etc. Accordingly, a barrier level 2 (M100) would not be applicable for a price level, such as 98.99, as it falls below the required scale. The lower boundary in terms of barrier levels is the tick size of each market.

The possible M-values to be studied for each stock are based on the price ranges observed during the analysis period. Furthermore, to ensure the reliability of the statistical tests applied to the M-values, we also estimated the lag-1 autocorrelation at each potential barrier level. This step was motivated by the findings of Dorfleitner and Klein (2009), who emphasize that extremely high autocorrelation levels in the M-values, especially in higher barrier levels, could cause deviations in results and lead to misleading interpretations.

Although autocorrelation can arise due to psychological barriers, since investors may react similarly around salient price thresholds, it is important not to misinterpret one effect with the other. As noted by Dorfleitner and Klein (2009), very high barrier levels tend to show higher autocorrelation simply due to the data structure itself: broader price intervals reduce variability in M-values, leading to repetitive statistical patterns. These patterns may resemble behavioral phenomena, but are technical artifacts. To avoid this confusion, we excluded from our analysis barrier levels with excessively high autocorrelation.

Considering this reasoning, Table 2 presents the estimated autocorrelation coefficients for each stock and barrier level considered. These estimations were used to guide the selection of the barrier levels that would be meaningful for each stock. As expected, higher barrier levels exhibit stronger autocorrelation, reinforcing the methodological decision to focus on the lower levels. Therefore, barrier level 2 will not be considered for Saudi Arabian or Pakistani stocks. This level will only be examined for specific Turkish stocks, such as *Koç Holding AS*, *BIM Birlesik Magazalar,* and *Turk Hava Yollari.*

Additionally, barriers at level 0 will be tested across all stocks in the sample. Barrier level 1, however, does not apply to *Masraf Al Rayan* (Qatar), *IHH Healthcare*, and *Gamuda* (Malaysia), as their price levels fall below the minimum scale required to examine barriers at the tens level.

Table 2 – Estimated autocorrelation of M-values (closing prices)

	M1 (l=0)		M10 (l=1)		M100 (l=2)	
	AC	**p-value**	**AC**	**p-value**	**AC**	**p-value**
Saudi Arabia						
Saudi Basic Industries Corporation SJSC	0.138	0.060*	0.248	0.000***	0.788	0.001***
Al Rajhi Banking and Investment Corporation SJSC	0.141	0.001***	0.336	0.000***	0.821	0.000***
Saudi Telecom Company SJSC	0.109	0.000***	0.233	0.000***	-	-
Malaysia						
Gamuda Bhd	0.245	0.002***	-	-	-	-
IHH Healthcare Bhd	0.233	0.000***	-	-	-	-
Tenaga Nasional Bhd	0.321	0.000***	0.501	0.000***	-	-
Pakistan						
Attock Refinery Ltd	0.137	0.000***	0.284	0.000***	0.783	0.002***
Cherat Cement Company Ltd	0.107	0.000***	0.272	0.000***	0.891	0.001***
D.G. Khan Cement Company Ltd	0.127	0.000***	0.288	0.000***	0.932	0.000***
Qatar						
Qatar Islamic Bank QPSC	0.216	0.000***	0.363	0.000***	-	-
Qatar Industries	0.294	0.001***	0.390	0.000***	-	-
Masraf Al Rayan QPSC	0.335	0.000***	-	-	-	-
Turkey						
Koç Holding AS	0.205	0.000***	0.344	0.001***	0.496	0.003***
BIM Birlesik Magazalar AS	0.073	0.000***	0.136	0.000***	0.394	0.000***
Turk Hava Yollari AO	0.216	0.000***	0.284	0.000***	0.440	0.000***

Table 2 presents the estimated autocorrelation of the M-values, where AC refers to the lag-1 autocorrelation for the M-values at all possible barrier levels of each stock. As it is observable, autocorrelation levels increase as the barrier levels reach higher values for all stocks. Significance at the 10%, 5%, and 1% levels is represented by *, **, and ***.

3.2.3. Uniformity Test

The uniformity test was introduced by Ley and Varian (1994) to examine whether the final digits of the Dow Jones index values appear with equal frequency, as expected in a random market. Using a chi-square test, they found that the digit distribution is not uniform. However, they proved that such patterns can arise by chance, even in an efficient market modeled as a random walk. De Ceuster et al. (1998) argued that, over time, as the index grows, the spacing between round-number levels also increases. This leads the digit frequency of numbers to be naturally non-uniform, even without psychological barriers. As a result, we cannot conclude the existence of barriers solely based on this test.

Later, Aggarwal and Lucey (2007) applied these tests to gold markets using the Kolmogorov-Smirnov Z-statistic test. In this sense, following the authors' proposed methodology, the underlying hypothesis will be:

- H_0: uniformity
- H_1: non-uniformity.

The rejection of H_0 suggests a non-uniform distribution; the stock indices closing prices are not randomly distributed, which serves as an initial indicator for the presence of psychological barriers.

3.2.4. Barrier Tests

Barrier tests, firstly applied by Donaldson and Kim (1993), allow the detection of consistent deviations in M-values from uniform distributions near psychological barriers. Those tests include two types of tests, barrier proximity and barrier hump tests, to examine whether the frequency of closing prices near barriers significantly deviates from what would be expected under a random distribution.

3.2.4.1. Barrier Proximity Test

The application of this test consists of a linear regression, whose dependent variable f(M) measures the frequency that stock prices closes with its last two digits (M-values), minus

1 percentage point, and D_{ij} is a dummy variable assuming a value equal to 1 whenever the stock price approaches a barrier and 0 otherwise.

As proposed by Donaldson and Kim (1993), the chosen model (3.4) was the following:

$$f(M) = \alpha + \beta D_{ij} + \varepsilon \tag{3.4}$$

Despite the dummy variable being too strict, assuming the value 1 if M=00 and 0 if not, there will be 3 dummies studied for each potential barrier level.

The dummies studied for the 1-level, 10-level, and 100-level are:

- D98-02 = 1 if M ≥ 98 or M ≤ 02, = 0 otherwise
- D95-05 = 1 if M ≥ 95 or M ≤ 05, = 0 otherwise
- D90-10 = 1 if M ≥ 90 or M ≤ 10, = 0 otherwise
- D75-25= 1 if M ≥ 75 or M ≤ 25, = 0 otherwise

If there is a deviation in frequency between M-values that lie inside or outside the barrier, the β coefficient must be statistically significant and different from zero. A negative β implies that prices are avoiding a certain level, which is translated in the model by a lower frequency within an interval around a round number.

3.2.4.2. Barrier Hump Test

The Barrier Hump Test increments the analysis by examining the whole shape of the M-values distribution. Contrarily to the Barrier Proximity Test, which focuses solely on the immediate area around round numbers. Despite their different purposes, the two tests are complementary and provide a more complete picture of price behavior around potential psychological barriers.

Aggarwal and Lucey (2007) follow the methodology proposed by Donaldson and Kim (1993), who argue that it is insufficient to assume a uniform distribution as the null hypothesis of uniformity in the absence of psychological barriers. It is also necessary to define an alternative hypothesis that characterizes how the distribution would behave if barriers were present. Inspired by the investigation of Bertola and Caballero (1992), who examined exchange rate dynamics within target zones under forward-looking expectations, the authors assume that a hump-shape distribution is an appropriate representation of how prices might cluster around psychological barriers.

This test will be applied through the following (3.5) quadratic regression:

$$f(M) = \alpha + \gamma M + \delta M^2 + \varepsilon \tag{3.5}$$

Where M=00,01, …, 99.

If investors anticipate that the price is getting closer to a psychological barrier, there might be a concentration of transactions near, but not exactly at, the barrier. This implies the formation of a hump in the price distribution with an abnormal concentration of prices around a specific level. According to Donaldson and Kim (1993), the null hypothesis of no psychological barriers implies that the δ coefficient assumes the value of zero. In contrast, under the alternative hypothesis, a negative and statistically significant δ indicates a hump-shape distribution of prices.

3.2.5. Conditional Effects Tests

As previously mentioned, Ley and Varian (1994) defended that rejecting the uniformity of M-values distribution was not a sufficient condition to confirm the existence of psychological barriers. Building on this idea, Cyree et al. (1999) instead of only focusing on the price distribution, analyzed the behavior of returns around these barriers, considering the mean and variance of returns using 10 days before and after the barrier was crossed.

In more recent studies, Aggarwal and Lucey (2007) implemented the same GARCH[4] approach to analyze gold markets, reducing the period under observation to 5 days, since wider intervals could capture factors not necessarily caused by psychological barriers. The main purpose was to assess whether the impact on price changes would vary depending on whether the barrier was being approached on an upward or downward movement.

[4] GARCH refers to an acronym for Generalized AutoRegressive Conditional Heteroskedasticity.

This process begins by estimating a simple linear regression equation with indicator variables (dummies) to capture the impact of upward and downward movements in the face of barriers. According to the OLS (ordinary least squares) model, the equation (3.6) obtained would be as follows:

$$R_t = \beta_1 + \beta_2 BD_t + \beta_3 AD_t + \beta_4 BU_t + \beta_5 AU_t + \varepsilon_t \tag{3.6}$$

The dummy variables will assume the value 1 in the specified days and 0 otherwise:

- $\boldsymbol{BD_t}$ **(Before Downward):** captures the 5 trading sessions before the price crosses the barrier in a downward movement.
- $\boldsymbol{AD_t}$ **(After Downward):** captures the 5 trading sessions after the price crosses the barrier in a downward movement.
- $\boldsymbol{BU_t}$ **(Before Upward):** captures the 5 trading sessions before the price crosses the barrier in an upward movement.
- $\boldsymbol{AU_t}$ **(After Upward):** captures the 5 trading sessions after the price crosses the barrier in an upward movement.

The problem with this approach is that distributional shifts associated with barriers invalidate the underlying assumptions of OLS, such as constant variance of error terms (homoscedasticity) and the independence of residuals (no autocorrelation) across the sample (Cyree et al., 1999). Consequently, to overcome the OLS limitations and fully capture the barrier effects, the mean equation (3.6) will be regressed again using the GARCH model that assumes that:

$$\varepsilon_t \sim N\,(0, V_t) \tag{3.7}$$

Where V_t refers to the conditional variance that can change over time.

Here, the coefficients associated with betas reveal the impact of crossing a barrier on the average returns, which can vary depending on whether this crossing occurs in an upward or downward movement.

Subsequently, the volatility of the variance around the barriers (heteroscedasticity) will be analyzed through the GARCH equation, which indicates how indicator variables can influence volatility. Additionally, the equation (3.8) includes a moving average parameter and a GARCH parameter.

$$V_t = \alpha_1 + \alpha_2 BD_t + \alpha_3 AD_t + \alpha_4 BU_t + \alpha_5 AU_t + \alpha_6 V_{t-1} + \alpha_7 \varepsilon_{t-1}^2 + \eta_t \quad (3.8)$$

In markets where psychological barriers do not affect prices, the explanatory variable's coefficients assume the value of zero, so returns and volatility do not show significant changes before or after crossing a barrier. If any of those coefficients is significant and non-zero, this suggests that the psychological barrier has a real effect on volatility or returns or both. After estimating the model, it was necessary to compare the coefficients of the explanatory variables. For this purpose, a Wald test was applied to assess if there were statistically significant differences in returns and volatility before and after crossing a barrier in an upward or downward movement.

As previously done by Cyree et al. (1999) and Aggarwal and Lucey (2007), the four null hypotheses tested will be:

H_1: There is no difference in the conditional mean return before and after a downward crossing of a barrier.

H_2: There is no difference in the conditional mean return before and after an upward crossing of a barrier.

H_3: There is no difference in conditional variance before and after a downward crossing of a barrier.

H_4: There is no difference in the conditional variance before and after an upward crossing of a barrier.

4. Empirical Results

This section contains the empirical findings of the tests described in the previous section. The analysis focuses on detecting the presence of psychological barriers in individual stock prices across five Islamic markets. For each test, the main findings are reported for the full sample period, and results are discussed at the country and company levels.

4.1. Uniformity Test

Across all five markets, Saudi Arabian, Malaysian, Pakistani, Qatari, and Turkish stocks present consistent non-uniformity patterns at the 1% significance for all barrier levels tested, indicating that the stocks considered do not exhibit equally distributed M-values. Nonetheless, there are some exceptions: individual stocks such as *BIM Birlesik Magazalar AS*(Turkey) and *Saudi Telecom Company SJSC* (Saudi Arabia) only reject the null hypothesis of uniformity at barrier level 0, at the 10% significance level.

Additionally, it is possible to observe a pattern in Table 3, where higher levels of barriers present stronger deviations from uniformity distribution. For instance, the highest M-value considered (M100) for Turkey presents the most significant deviation from a uniform distribution. This pattern was also observed by De Ceuster et al. (1998); the higher the price series, the wider the intervals between potential barriers. Therefore, the theoretical distribution of digits and their frequency of occurrence is no longer uniform.

Our results are also aligned with Dorfleitner and Klein (2009) discoveries, who found significant deviations from uniformity, particularly for larger barrier levels in European indices and German stocks. However, while their evidence was more heterogeneous across assets, especially at lower barrier levels, our results suggest a more consistent non-uniformity pattern across Islamic markets. Nonetheless, as previously mentioned in section 3.2.3, non-uniformity only indicates that prices are not randomly distributed; it does not necessarily imply the existence of psychological barriers.

Table 3 – Z test for uniformity of digits

	M1 (l=0)		M10 (l=1)		M100 (l=2)	
	Z-stat	p-value	Z-stat	p-value	Z-stat	p-value
Saudi Arabia						
Saudi Basic Industries Corporation SJSC	7.723	0.000***	9.553	0.000***	-	-
Al Rajhi Banking and Investment Corporation SJSC	3.381	0.000***	6.451	0.000***	-	-
Saudi Telecom Company SJSC	1.235	0.093*	4.283	0.000***	-	-
Malaysia						
Gamuda Bhd	2.779	0.000***	-	-	-	-
IHH Healthcare Bhd	3.869	0.000***	-	-	-	-
Tenaga Nasional Bhd	2.424	0.000***	8.041	0.000***	-	-
Pakistan						
Attock Refinery Ltd	6.105	0.000***	7.127	0.000***	-	-
Cherat Cement Company Ltd	5.102	0.000***	6.069	0.000***	-	-
D.G. Khan Cement Company Ltd	4.115	0.000***	5.987	0.000***	-	-
Qatar						
Qatar Islamic Bank QPSC	3.901	0.000***	6.399	0.000***	-	-
Qatar Industries	2.876	0.000***	12.702	0.000***	-	-
Masraf Al Rayan QPSC	3.246	0.000***	-	-	-	-
Turkey						
Koç Holding AS	2.242	0.000***	2.823	0.000***	20.864	0.000***
BIM Birlesik Magazalar AS	1.853	0.064*	5.819	0.000***	11.605	0.000***
Turk Hava Yollari AO	2.855	0.000***	3.139	0.000***	12.924	0.000***

Table 3 presents the results of a Kolmogorov-Smirnov test for uniformity. In this sense, the Z-stat refers to the test statistic value, while the p-value indicates the statistic marginal significance. H0: uniformity, H1: non-uniformity. Significance at the 10%, 5%, and 1% levels is represented by *, **, and ***.

4.2. Barrier Tests

4.2.1. Barrier Proximity Test

Tables 4 to 8 present the results of the barrier proximity tests performed on the five Islamic markets, considering all the barrier intervals mentioned in sections 3.2.1. and 3.2.4.1. The results of these tests provide evidence regarding the presence of psychological barriers in some of the Islamic stocks analyzed. Considering a barrier at the exact point of the zero module, evidence in Table 4 shows that, at the barrier level 0, a few Saudi Arabian, Turkish, and Qatari companies present statistically significant results. However, since the corresponding β coefficients are positive, this does not support the existence of barriers, as it implies no reduction in M-values' frequency near barrier points.

As we start to enlarge the barrier intervals, indications of lower frequencies around barriers begin to emerge. Considering the 98–02 range, in Table 5, for barrier level 0, *Masraf Al Rayan* rejects the null hypothesis at a 10% significance level. Regarding barrier level 1, *Saudi Telecom* (Saudi Arabia) and *Turk Hava Yollari* (Turkey) present indications of barriers at 1% and 5% significance levels, respectively.

As we further widen the intervals around barriers, to 95-05 ranges, the results presented in Table 6 exhibit a similar pattern. *Masraf Al Rayan QPSC* and *Saudi Telecom* continue to reject the null hypothesis for barrier levels 0 and 1, respectively, at a 1% significance level. However, no other Qatari or Saudi Arabian stock replicates this behavior, which could make the evidence rather isolated than potentially indicative of the broader Qatari and Saudi Arabian markets. In comparison, the findings in Turkey become more heterogeneous with *Turk Hava Yollari,* no longer exhibiting signs of barriers, whereas *BIM Birlesik Magazalar* rejects the null hypothesis at level 2 with a 5% significance level.

Expanding the barrier interval even further, considering the 90–10 range, evidence becomes slightly more diffuse. New patterns of barriers emerge for Saudi Arabian stocks (e.g., *Al Rajhi Banking* and *Investment Corporation* and *Saudi Telecom*) for barrier level 1, at 10% and 1% significance levels, respectively. For Qatar, *Masraf Al Rayan* remains the only Qatari stock exhibiting a negative and statistically significant β coefficient for barrier level 0. Whereas in Turkey, the only stock with evidence of barriers is *BIM Birlesik Magazalar* at the barrier level 2 considering a 1% significance level.

Lastly, Table 8 presents the results for the broadest barrier range, where the rejection of the no-barrier hypothesis appears less consistent and more dispersed. While previous evidence was concentrated in Qatari and Saudi Arabian stocks, the 75–25 interval suggests new patterns emerging in other markets. Specifically, in Malaysia, *IHH Healthcare* rejects the null hypothesis at level 1, for 10%, whereas in Turkey, *BIM Birlesik Magazalar* no longer presents evidence of barriers.

Ultimately, the evidence appears dispersed, with no consistent pattern across the different barrier intervals and within each Islamic market. Apart from a few Qatari and Saudi Arabian stocks, which reject the null hypothesis of no barriers under the first proximity scenarios at barrier levels 0 and 1, the remaining stocks indicate no clear evidence of psychological barriers around round numbers throughout the full sample period. In addition, R^2 values remain relatively low, consistent with previous studies using indices, suggesting that while barriers may exist for certain stocks, they do not constitute a systematic phenomenon across all markets and price levels.

Table 4 – Barrier proximity test: strict barrier

	M1 (l=0)			M10 (l=1)			M100 (l=2)		
	β	p-value	R^2	β	p-value	R^2	β	p-value	R^2
Saudi Arabia									
Saudi Basic Industries Corporation SJSC	0.1459	0.000***	0.416	0.0117	0.000***	0.439	-	-	-
Al Rajhi Banking and Investment Corporation SJSC	0.0582	0.000***	0.229	0.0023	0.401	0.007	-	-	-
Saudi Telecom Company SJSC	0.0085	0.023**	0.052	0.0001	0.978	0.000	-	-	-
Malaysia									
Gamuda Bhd	-0.0068	0.213	0.016	-	-	-	-	-	-
IHH Healthcare Bhd	0.0206	0.962	0.000	-	-	-	-	-	-
Tenaga Nasional Bhd	0.0035	0.684	0.002	0.0110	0.114	0.025	-	-	-
Pakistan									
Attock Refinery Ltd	0.0017	0.501	0.005	-0.0032	0.534	0.004	-	-	-
Cherat Cement Company Ltd	0.0070	0.002***	0.091	-0.0002	0.976	0.000	-	-	-
D.G. Khan Cement Company Ltd	0.0013	0.490	0.005	0.0067	0.264	0.013	-	-	-
Qatar									
Qatar Islamic Bank QPSC	0.0352	0.000***	0.171	-0.0001	0.979	0.000	-	-	-
Qatar Industries	0.0349	0.000***	0.196	0.0071	0.228	0.015	-	-	-
Masraf Al Rayan QPSC	0.0025	0.526	0.004	-	-	-	-	-	-
Turkey									
Koç Holding AS	0.0096	0.000***	0.122	0.0044	0.157	0.020	-0.0030	0.802	0.001
BIM Birlesik Magazalar AS	0.0000	0.988	0.000	0.0060	0.163	0.019	-0.0089	0.458	0.005
Turk Hava Yollari AO	0.0475	0.000***	0.358	-0.0024	0.514	0.004	-0.0077	0.569	0.003

Table 4 presents the regression $f(M)=\alpha+\beta D+\varepsilon$ results, where f(M) indicates the frequency of M values, D is a dummy variable that assumes the value 1 whenever M=00 and 0 otherwise. Refer to section 3.2.4.1 for details. Significance at the 10%, 5%, and 1% levels is represented by *, **, and ***.

Table 5 – Barrier proximity test: 98-02 barrier

	M1 (l=0)			M10 (l=1)			M100 (l=2)		
	β	p-value	R^2	β	p-value	R^2	β	p-value	R^2
Saudi Arabia									
Saudi Basic Industries Corporation SJSC	0.0244	0.018**	0.055	0.0034	0.095*	0.028	-	-	-
Al Rajhi Banking and Investment Corporation SJSC	0.0063	0.258	0.013	-0.0016	0.488	0.005	-	-	-
Saudi Telecom Company SJSC	-0.0008	0.665	0.002	-0.0048	0.002***	0.097	-	-	-
Malaysia									
Gamuda Bhd	-0.0014	0.571	0.003	-	-	-	-	-	-
IHH Healthcare Bhd	-0.1246	0.527	0.004	-	-	-	-	-	-
Tenaga Nasional Bhd	0.0024	0.547	0.004	0.0089	0.002***	0.094	-	-	-
Pakistan									
Attock Refinery Ltd	-0.0002	0.839	0.000	0.0006	0.524	0.004	-	-	-
Cherat Cement Company Ltd	0.0015	0.148	0.021	-0.0008	0.402	0.007	-	-	-
D.G. Khan Cement Company Ltd	-0.0006	0.448	0.005	-0.0003	0.745	0.001	-	-	-
Qatar									
Qatar Islamic Bank QPSC	0.0059	0.129	0.023	0.0179	0.000***	0.309	-	-	-
Qatar Industries	0.0074	0.041**	0.042	0.0072	0.014**	0.059	-	-	-
Masraf Al Rayan QPSC	-0.0029	0.095*	0.028	-	-	-	-	-	-
Turkey									
Koç Holding AS	0.0011	0.408	0.007	0.0036	0.157	0.021	-0.0035	0.713	0.001
BIM Birlesik Magazalar AS	-0.0005	0.634	0.002	0.0037	0.056**	0.036	-0.0086	0.118	0.025
Turk Hava Yollari AO	0.0071	0.051**	0.038	-0.0037	0.028**	0.048	-0.0065	0.291	0.011

Table 5 presents the results of a regression $f(M)=\alpha+\beta D+\varepsilon$, where $f(M)$ stands for the frequency of appearance of the M values, D is a dummy variable that takes the value 1 when the M-value is in the 98-02 interval and 0 otherwise. Refer to section 3.2.4.1 for details. Significance at the 10%, 5%, and 1% levels is represented by *, **, and ***.

Table 6 – Barrier proximity test: 95-05 barrier

	M1 (l=0)			M10 (l=1)			M100 (l=2)		
	β	p-value	R^2	β	p-value	R^2	β	p-value	R^2
Saudi Arabia									
Saudi Basic Industries Corporation SJSC	0.0079	0.277	0.012	0.0001	0.949	0.000	-	-	-
Al Rajhi Banking and Investment Corporation SJSC	-0.0003	0.943	0.000	-0.0017	0.267	0.011	-	-	-
Saudi Telecom Company SJSC	-0.0005	0.664	0.002	-0.0041	0.001***	0.139	-	-	-
Malaysia									
Gamuda Bhd	0.0000	0.990	0.000	-	-	-	-	-	-
IHH Healthcare Bhd	-0.1814	0.185	0.018	-	-	-	-	-	-
Tenaga Nasional Bhd	0.0026	0.333	0.009	0.0094	0.000***	0.193	-	-	-
Pakistan									
Attock Refinery Ltd	-0.0003	0.674	0.002	-0.0001	0.983	0.000	-	-	-
Cherat Cement Company Ltd	0.0003	0.715	0.001	-0.0010	0.146	0.021	-	-	-
D.G. Khan Cement Company Ltd	0.0003	0.514	0.004	0.0010	0.875	0.002	-	-	-
Qatar									
Qatar Islamic Bank QPSC	0.0019	0.485	0.005	0.0146	0.000***	0.421	-	-	-
Qatar Industries	0.0048	0.052**	0.038	0.0071	0.000***	0.120	-	-	-
Masraf Al Rayan QPSC	-0.0037	0.002***	0.094	-	-	-	-	-	-
Turkey									
Koç Holding AS	0.0002	0.782	0.001	0.0037	0.009***	0.068	-0.0032	0.622	0.003
BIM Birlesik Magazalar AS	0.0000	0.917	0.000	0.0041	0.002***	0.203	-0.0089	0.025**	0.051
Turk Hava Yollari AO	0.0024	0.345	0.009	-0.0012	0.182	0.018	-0.0029	0.367	0.008

Table 6 presents the results of a regression $f(M)=\alpha+\beta D+\varepsilon$, where $f(M)$ stands for the frequency of appearance of the M values, D is a dummy variable that takes the value 1 when the M-value is in the 95-05 interval and 0 otherwise. Refer to section 3.2.4.1 for details. Significance at the 10%, 5%, and 1% levels is represented by *, **, and ***.

Table 7 – Barrier proximity test: 90-10 barrier

	M1 (l=0)			M10 (l=1)			M100 (l=2)		
	β	p-value	R²	β	p-value	R²	β	p-value	R²
Saudi Arabia									
Saudi Basic Industries Corporation SJSC	0.0051	0.368	0.008	0.0008	0.445	0.005	-	-	-
Al Rajhi Banking and Investment Corporation SJSC	0.0011	0.733	0.001	-0.0021	0.091*	0.028	-	-	-
Saudi Telecom Company SJSC	-0.0008	0.367	0.008	-0.0038	0.000***	0.208	-	-	-
Malaysia									
Gamuda Bhd	-0.0003	0.818	0.001	-	-	-	-	-	-
IHH Healthcare Bhd	-0.1194	0.288	0.012	-	-	-	-	-	-
Tenaga Nasional Bhd	0.0023	0.267	0.013	0.0089	0.000***	0.285	-	-	-
Pakistan									
Attock Refinery Ltd	0.0001	0.876	0.000	-0.0002	0.753	0.001	-	-	-
Cherat Cement Company Ltd	0.0009	0.088*	0.029	-0.0007	0.169	0.019	-	-	-
D.G. Khan Cement Company Ltd	0.0004	0.321	0.010	0.0007	0.199	0.016	-	-	-
Qatar									
Qatar Islamic Bank QPSC	0.0017	0.419	0.007	0.0117	0.000***	0.462	-	-	-
Qatar Industries	0.0043	0.024**	0.051	0.0066	0.000***	0.177	-	-	-
Masraf Al Rayan QPSC	-0.0039	0.000***	0.177	-	-	-	-	-	-
Turkey									
Koç Holding AS	0.0011	0.110	0.026	0.0032	0.000***	0.183	-0.0002	0.963	0.000
BIM Birlesik Magazalar AS	-0.0002	0.696	0.001	0.0047	0.000***	0.203	-0.0101	0.001***	0.113
Turk Hava Yollari AO	0.0015	0.446	0.006	-0.0012	0.182	0.018	-0.0029	0.367	0.008

Table 7 presents the results of a regression $f(M)=\alpha+\beta D+\varepsilon$, where f(M) stands for the frequency of appearance of the M values, D is a dummy variable that takes the value 1 when the M-value is in the 90-10 interval and 0 otherwise. Refer to section 3.2.4.1 for details. Significance at the 10%, 5%, and 1% levels is represented by *, **, and ***.

Table 8 – Barrier proximity test: 75-25 barrier

	M1 (l=0)			M10 (l=1)			M100 (l=2)		
	β	p-value	R²	β	p-value	R²	β	p-value	R²
Saudi Arabia									
Saudi Basic Industries Corporation SJSC	0.0027	0.541	0.004	0.0012	0.162	0.019	-	-	-
Al Rajhi Banking and Investment Corporation SJSC	0.0006	0.798	0.001	-0.0044	0.000***	0.200	-	-	-
Saudi Telecom Company SJSC	-0.0001	0.916	0.000	-0.0023	0.001***	0.114	-	-	-
Malaysia									
Gamuda Bhd	0.0002	0.887	0.001	-	-	-	-	-	-
IHH Healthcare Bhd	-0.1608	0.059**	0.036	-	-	-	-	-	-
Tenaga Nasional Bhd	0.0015	0.393	0.007	0.0046	0.001***	0.110	-	-	-
Pakistan									
Attock Refinery Ltd	0.0009	0.091*	0.028	-0.0003	0.561	0.004	-	-	-
Cherat Cement Company Ltd	0.0003	0.552	0.004	-0.0007	0.118	0.025	-	-	-
D.G. Khan Cement Company Ltd	0.0001	0.604	0.003	-0.0002	0.662	0.002	-	-	-
Qatar									
Qatar Islamic Bank QPSC	0.0007	0.694	0.002	0.0044	0.001***	0.099	-	-	-
Qatar Industries	0.0022	0.163	0.019	0.0045	0.000***	0.124	-	-	-
Masraf Al Rayan QPSC	-0.0034	0.000***	0.201	-	-	-	-	-	-
Turkey									
Koç Holding AS	0.0016	0.004***	0.082	0.0007	0.252	0.013	0.0116	0.001***	0.101
BIM Birlesik Magazalar AS	-0.0007	0.149	0.021	0.0061	0.000***	0.498	-0.0035	0.147	0.022
Turk Hava Yollari AO	0.0009	0.539	0.004	-0.0006	0.386	0.008	0.0069	0.009***	0.067

Table 8 presents the results of a regression f(M)=α+βD+ε, where f(M) stands for the frequency of appearance of the M values, D is a dummy variable that takes the value 1 when the M-value is in the 72-25 interval and 0 otherwise. Refer to section 3.2.4.1 for details. Significance at the 10%, 5%, and 1% levels is represented by *, **, and ***.

4.2.2. Barrier Hump Test

Table 9 presents the results for the barrier hump test; whose main purpose is to assess the M-values' distribution shape. In the existence of psychological barriers, this distribution is expected to form a hump, associated with a correspondent negative and statistically significant δ coefficient. The results obtained provide limited evidence regarding the presence of psychological barriers across the Islamic stocks analyzed. In most cases, the quadratic coefficient is not statistically significant, and its value is either zero or very close to zero. On the other hand, signals of hump-shaped distributions are observed at barrier level 0 for *IHH Healthcare Bhd* (Malaysia) and *Masraf Al Rayan* (Qatar), at 10% and 1% significance levels, respectively. For barrier level 1, *Al Rajhi Banking and Investment Corporation*, *Saudi Telecom* (Saudi Arabia), and *Cherat Cement Company* (Pakistan) reject the null hypothesis at 1% significance level. Finally, for barrier level 2, *BIM Birlesik Magazalar* (Turkey) presents indications of barriers at 5% significance level.

While some stocks within each Islamic market exhibit signs of psychological hesitation near barrier levels, the general evidence remains insufficient to confirm their existence. Similarly, Aggarwal and Lucey (2007) also find mixed evidence of barriers, indicating that these effects may be localized and not necessarily persistent across the distribution.

Taken together, the results obtained for Barrier Proximity Test corroborate the Barrier Hump Test ones. Nevertheless, the slight deviations between the two can be explained by their methodological differences. The first approach measures the frequency of observations immediately close to the barrier, being sensitive even to subtle and localized deviations. On the other hand, the second one requires a more structured pattern in M-values (i.e., with price concentration before the barrier and dilution afterwards) to identify the "hump-shape" in distribution. Accordingly, the avoidance of a round number can occur around a psychological level without necessarily forming asymmetric or statistically strong pattern that meets the criteria of the Hump Test. Therefore, certain forms of investor hesitation may be detected by the Proximity Test but remain undetected by the Hump Test. This seems to be the case of *Turk Hava Yollari AO*, for which the Proximity Test identified negative and statistically significant signs of barriers in the 98–02 range, but not across wider intervals or under the Hump specification. This outcome may indicate a localized psychological effect without the consistency or strength necessary to generate a clearer shift in market participants' collective behavior.

Table 9 – Barrier hump test

	M1 (l=0)			M10 (l=1)			M100 (l=2)		
	δ	p-value	R^2	δ	p-value	R^2	δ	p-value	R^2
Saudi Arabia									
Saudi Basic Industries Corporation SJSC	0.000003	0.405	0.017	0.000001	0.184	0.018	-	-	-
Al Rajhi Banking and Investment Corporation SJSC	0.000001	0.928	0.007	-0.000003	0.000***	0.219	-	-	-
Saudi Telecom Company SJSC	0.000000	0.589	0.004	-0.000002	0.000***	0.352	-	-	-
Malaysia									
Gamuda Bhd	-0.000004	0.984	0.013	-	-	-	-	-	-
IHH Healthcare Bhd	-0.000098	0.078**	0.097	-	-	-	-	-	-
Tenaga Nasional Bhd	0.000001	0.210	0.016	0.000005	0.000***	0.399	-	-	-
Pakistan									
Attock Refinery Ltd	0.000000	0.585	0.003	-0.000001	0.618	0.012	-	-	-
Cherat Cement Company Ltd	0.000001	0.324	0.010	-0.000001	0.044**	0.111	-	-	-
D.G. Khan Cement Company Ltd	-0.000003	0.459	0.031	0.000004	0.997	0.046	-	-	-
Qatar									
Qatar Islamic Bank QPSC	0.000000	0.668	0.017	0.000006	0.000***	0.366	-	-	-
Qatar Industries	0.000002	0.085*	0.034	0.000004	0.000***	0.553	-	-	-
Masraf Al Rayan QPSC	-0.000003	0.000***	0.322	-	-	-	-	-	-
Turkey									
Koç Holding AS	0.000001	0.009***	0.084	0.000001	0.013***	0.088	0.000001	0.109	0.020
BIM Birlesik Magazalar AS	-0.000000	0.403	0.009	0.000004	0.000***	0.565	-0.000005	0.021**	0.178
Turk Hava Yollari AO	0.000001	0.563	0.011	-0.000001	0.102	0.113	0.000003	0.089*	0.075

Table 9 shows the results of a regression $f(M) = \alpha+\gamma M+\delta M^2+\varepsilon$, where f(M), the frequency of appearance of each M-value, is regressed on M, the M-value itself, and M^2, its square. Significance at the 10%, 5%, and 1% levels is represented by *, **, and ***.

4.3. Conditional Effects Tests

In the presence of psychological barriers, we would expect the dynamics of individual stock returns to exhibit abnormal patterns around these levels. The conditional effects approach is useful to understand whether prices cross barriers in a downward movement, which could indicate a support level, or in an upward movement, suggesting a resistance level. In these tests, we will use one potential barrier level for each stock, selected as the likeliest to represent a psychological barrier based on the outcomes from the previous tests.

Table 10 shows the results for the conditional mean return equation. In most cases, there are no clear signs of stock return changes before and after crossing a barrier, as most of the estimated coefficients are not statistically significant. The only exception is the negative mean return indicator before a downward movement (β_2) for Saudi Arabian stocks. This indicates that prices tend to decline gradually in the days leading up to a downward crossing of a psychological barrier. A potential explanation could be that investors may become more pessimistic as the price approaches a round-number perceived as a support level. Nonetheless, *Saudi Basic Industries*, *Al Rajhi Banking*, and *Saudi Telecom Company* are only statistically significant at 10%.

While most coefficients in the conditional mean return equation are not statistically significant, this does not invalidate the existence of psychological barriers. These effects may not systematically influence the average returns but can still induce higher uncertainty and price fluctuations, which are more accurately captured by the conditional variance equation within the GARCH model.

Table 10 – GARCH analysis: mean equation

		β_1	β_2	β_3	β_4	β_5
Saudi Arabia						
Saudi Basic Industries Corporation SJSC	*Coeficient*	0.00014	-0.00076	0.00034	-0.00063	0.00013
	p-value	0.168	0.082*	0.151	0.118	0.197
Al Rajhi Banking and Investment Corporation SJSC	*Coeficient*	0.00012	-0.00081	0.00055	0.00045	0.00063
	p-value	0.491	0.065*	0.376	0.587	0.103
Saudi Telecom Company SJSC	*Coeficient*	-0.00021	-0.00074	0.00301	0.00042	0.00081
	p-value	0.643	0.079*	0.518	0.830	0.744
Malaysia						
Gamuda Bhd	*Coeficient*	-0.00031	0.00401	-0.00046	0.00052	0.00102
	p-value	0.518	0.313	0.720	0.473	0.667
IHH Healthcare Bhd	*Coefficient*	-0.00001	0.00071	-0.00403	0.00041	0.00654
	p-value	0.341	0.265	0.736	0.185	0.850
Tenaga Nasional Bhd	*Coefficient*	0.00007	0.00053	0.00028	-0.00011	0.00021
	p-value	0.658	0.838	0.160	0.162	0.465
Pakistan						
Attock Refinery Ltd	*Coefficient*	0.00088	0.00029	-0.00037	0.00031	-0.00009
	p-value	0.505	0.966	0.272	0.878	0.295
Cherat Cement Company Ltd	*Coefficient*	0.00011	0.00756	-0.00421	-0.00706	0.00510
	p-value	0.252	0.110	0.561	0.303	0.497
D.G. Khan Cement Company Ltd	*Coefficient*	-0.00012	0.00084	0.00096	-0.00622	0.00820
	p-value	0.215	0.531	0.352	0.394	0.281
Qatar						
Qatar Islamic Bank QPSC	*Coefficient*	0.00061	0.00891	-0.00210	0.00065	-0.00301
	p-value	0.708	0.386	0.112	0.694	0.243
Qatar Industries	*Coefficient*	0.00032	-0.00146	-0.00082	-0.00234	0.00056
	p-value	0.334	0.361	0.736	0.105	0.780
Masraf Al Rayan QPSC	*Coefficient*	0.00081	-0.00006	-0.00061	-0.00089	-0.00014
	p-value	0.523	0.731	0.579	0.890	0.369
Turkey						
Koç Holding AS	*Coefficient*	0.00011	0.00051	-0.00093	0.00064	-0.00603
	p-value	0.877	0.582	0.191	0.645	0.253
BIM Birlesik Magazalar AS	*Coefficient*	0.00026	-0.00043	0.00041	0.00062	-0.00071
	p-value	0.317	0.194	0.818	0.466	0.595
Turk Hava Yollari AO	*Coefficient*	-0.00042	0.00039	-0.00087	0.00071	0.00091
	p-value	0.667	0.882	0.741	0.703	0.709

Table 10 indicates the results of the mean equation of the following GARCH estimation $R_t = \beta_1 + \beta_2 BD_t + \beta_3 AD_t + \beta_4 BU_t + \beta_5 AU_t + \varepsilon_t$; $\varepsilon_t \sim (0, V_t)$; $V_t = \alpha_1 + \alpha_2 BD_t + \alpha_3 AD_t + \alpha_4 BU_t + \alpha_5 AU_t + \alpha_6 V_{t-1} + \alpha_7 \varepsilon_{t-1}^2 + \eta_t$. BD, AD, BU, and AU represent the dummy variables. BD assumes the value 1 in the 5 trading sessions before crossing a barrier on a downward movement and zero otherwise, whereas AD is for the 5 trading sessions after the same event. BU is for the 5 trading sessions before crossing a barrier from below, while AU is 1 in the 5 trading sessions after the same upward crossing. V_{t-1} expresses the moving average parameter, and ε_{t-1}^2 stands for the GARCH parameter. Barriers at l=0 are tested in Qatar and Malaysia; at l=1 in Saudi Arabia and Pakistan, whereas barriers at l=2 are tested in Turkey. Significance at the 10%, 5%, and 1% levels is represented by *, **, and ***.

The results for the conditional variance equation, presented in Table 11, reveal stronger effects of barriers on volatility than on the mean returns. The GARCH terms are positive and statistically significant at 1%, indicating persistence of volatility in daily stock returns and justifying our choice to use the GARCH model. Specifically, the constant term (α_1) is positive and statistically significant at 1% for all stocks. Additionally, the GARCH moving average parameter (α_6) is significant for all stocks, revealing considerable GARCH effects around the barriers. The coefficients associated with the lagged quadratic residuals (α_7) are also significant at 1% in all cases, suggesting that conditional variances increase with higher residuals from the previous period.

Concerning the variance indicators, the results are considerably stronger when compared to the return indicators; nevertheless, we cannot detect a consistent pattern among all markets. The variance coefficient before a downward movement (α_2) is positive and statistically significant for stocks in Saudi Arabia (e.g., *Qatar Islamic Bank*) and Qatar (e.g., *Masraf Al Rayan QPSC*), which could indicate an increase in volatility when investors anticipate a negative market movement. This interpretation is aligned with the findings of Campbell and Hentschel (1992), who defended that volatility is asymmetric and penalizes losses more than gains. Consequently, negative market movements, such as bad news, could amplify volatility. Despite that, this was not observable for stocks in Malaysia, Turkey, and Pakistan; the coefficients recorded in this indicator were mostly negative. In addition, the majority of stocks in Saudi Arabia and Qatar recorded negative values for the variance indicator after crossing the barrier in a downward movement (α_3). In this sense, the results support the idea that Saudi Arabian and Qatari stocks not only show higher levels of volatility before crossing the barrier from above, but these markets seem to calm down after the barrier is crossed.

Regarding the remaining countries, Malaysia presents negative variance indicators after crossing a barrier on an upward movement (α_5). A potential interpretation could be that after the surpassing of a psychological threshold, volatility decreases, reflecting a lower level of investors' uncertainty after prices cross a resistance level. On the other hand, Pakistan and Turkey presented stocks with negative variance indicators before an upward movement (α_4). This outcome indicates that, in these markets, there is a tendency for volatility to diminish immediately before stock prices increase through a barrier, which could reflect a period of greater market stability or investor confidence. At first glance, this pattern might seem counterintuitive when compared to the broader trend, i.e., higher volatility typically observed before crossing a barrier and lower volatility afterward; however, the focus should be on whether the existence of psychological barriers affects volatility, rather than the specific direction of the impact. As mentioned by Cyree et al. (1999), psychological barriers can have a significant impact on volatility, even if the direction of that effect is not consistent across all cases. Furthermore, the authors acknowledge that alternative scenarios may arise in which the usual patterns become ambiguous, particularly when other market forces outweigh the influence of technical trading pressure.

Similarly, our results point out that although barriers may exert a stronger impact on volatility than on returns, there is still no generalized behavior across the different Islamic markets analyzed. In each case, volatility responds differently to crossing barrier levels, supporting the argument that the timing and direction of volatility shifts depend on the context and particularities of each Islamic market.

Table 11 – GARCH analysis: variance equation

		α_1	α_2	α_3	α_4	α_5	α_6	α_7
Saudi Arabia								
Saudi Basic Industries Corporation SJSC	*Coefficient*	0.00001	0.00084	-0.00092	0.00010	0.00062	0.79941	0.02155
	p-value	0.000***	0.001***	0.000***	0.000***	0.450	0.000***	0.000***
Al Rajhi Banking and Investment Corporation SJSC	*Coefficient*	0.00009	0.00023	-0.00010	-0.00001	0.00003	0.56712	0.20976
	p-value	0.000***	0.002***	0.001***	0.023***	0.101	0.000***	0.002***
Saudi Telecom Company SJSC	*Coefficient*	0.00008	0.00073	-0.00022	0.00008	0.00030	0.66733	0.09414
	p-value	0.000***	0.001***	0.000***	0.234	0.029**	0.000***	0.000***
Malaysia								
Gamuda Bhd	*Coefficient*	0.00003	0.00002	-0.00008	0.00005	-0.00009	0.72445	0.10208
	p-value	0.000***	0.001***	0.204	0.095*	0.001***	0.000***	0.000***
IHH Healthcare Bhd	*Coefficient*	0.00004	-0.00015	0.00003	0.00009	-0.00007	0.86630	0.02340
	p-value	0.000***	0.009***	0.312	0.094*	0.000***	0.001***	0.000***
Tenaga Nasional Bhd	*Coefficient*	0.00005	-0.00003	0.00074	0.00007	-0.00001	0.80168	0.07489
	p-value	0.000***	0.006***	0.064*	0.239	0.000***	0.000***	0.001***
Pakistan								
Attock Refinery Ltd	*Coefficient*	0.00006	-0.00011	0.00084	-0.00029	0.00009	0.59522	0.23533
	p-value	0.000***	0.000***	0.358	0.001***	0.003***	0.000***	0.000***
Cherat Cement Company Ltd	*Coefficient*	0.00002	-0.00003	0.00013	-0.00012	0.00001	0.83449	0.06234
	p-value	0.000***	0.001***	0.123	0.000***	0.009***	0.001***	0.000***
D.G. Khan Cement Company Ltd	*Coefficient*	0.00001	0.00002	-0.00008	-0.00134	0.00039	0.56150	0.08794
	p-value	0.000***	0.000***	0.006***	0.003***	0.320	0.000***	0.000***
Qatar								
Qatar Islamic Bank QPSC	*Coefficient*	0.00000	0.00001	-0.00030	0.00008	0.00031	0.72807	0.00806
	p-value	0.002***	0.000***	0.005***	0.400	0.349	0.000***	0.000***
Qatar Industries	*Coefficient*	0.00002	0.00039	-0.00001	0.00014	0.00001	0.77749	0.00519
	p-value	0.000***	0.000***	0.003***	0.049**	0.382	0.000***	0.000***
Masraf Al Rayan QPSC	*Coefficient*	0.00001	0.00005	-0.00045	0.00002	0.00091	0.67505	0.00478
	p-value	0.000***	0.001***	0.000***	0.110	0.090*	0.000***	0.000***
Turkey								
Koç Holding AS	*Coefficient*	0.00000	-0.00006	0.00017	-0.00005	0.00003	0.75592	0.00165
	p-value	0.000***	0.000***	0.034**	0.000***	0.335	0.000***	0.000***
BIM Birlesik Magazalar AS	*Coefficient*	0.00001	0.00018	0.00003	-0.00019	-0.00001	0.55406	0.00584
	p-value	0.000***	0.000***	0.012***	0.001***	0.009***	0.000***	0.000***
Turk Hava Yollari AO	*Coefficient*	0.00001	-0.00001	0.00030	0.00009	0.00011	0.73078	0.00360
	p-value	0.000***	0.000***	0.001***	0.000***	0.203	0.000***	0.000***

Table 11 indicates the results of the variance equation of a GARCH estimation of the form $R_t = \beta_1 + \beta_2 BD_t + \beta_3 AD_t + \beta_4 BU_t + \beta_5 AU_t + \varepsilon_t$; $\varepsilon_t \sim (0, V_t)$; $V_t = \alpha_1 + \alpha_2 BD_t + \alpha_3 AD_t + \alpha_4 BU_t + \alpha_5 AU_t + \alpha_6 V_{t-1} + \alpha_7 \varepsilon^2_{t-1} + \eta_t$. BD, AD, BU, and AU represent the dummy variables. BD assumes the value 1 in the 5 trading sessions before crossing a barrier on a downward movement and zero otherwise, whereas AD is for the 5 trading sessions after the same event. BU is for the 5 trading sessions before crossing a barrier from below, while AU is 1 in the 5 trading sessions after the same upward crossing. V_{t-1} expresses the moving average parameter, and ε_{t-1}^2 stands for the GARCH parameter. Barriers at l=0 are tested in Qatar and Malaysia; at l=1 in Saudi Arabia and Pakistan, whereas barriers at l=2 are tested in Turkey. Significance at the 10%, 5%, and 1% levels is represented by *, **, and ***.

Finally, Table 12 presents the tests conducted on the four psychological barrier hypotheses to assess the existence of such barriers in stock prices. These are parameter restriction tests, designed to evaluate whether the mean and variance of returns change at specific moments. Specifically, before and after prices cross psychologically relevant levels, such as round numbers. When psychological barriers are present, it is common for price returns and volatility to behave differently around that level. For instance, before the price crosses the barrier, investors may become more uncertain, leading to constrained returns and increased volatility. After the crossing, these pressures are expected to ease: the market "relaxes", returns normalize, and volatility tends to decline. These tests aim to verify whether there is statistical evidence supporting changes in behavioral patterns.

The results obtained are in line with our previous analysis. Except for Saudi Arabian stocks, no consistent evidence was found that average returns are significantly affected by barrier crossings. Hypothesis H_1 tested whether conditional mean returns differed before and after a downward crossing. This hypothesis was rejected for only two stocks, and even then, only at the 10% significance level. Hypothesis H_2, which examined changes in mean return following upward crossings, showed even weaker evidence.

In terms of price volatility analyzed through the third and fourth tests, H_3 and, H_4, the results present a stronger influence of psychological barriers. The third test looked at whether conditional variance, i.e., the volatility of returns, would change significantly after a price decrease through the barrier. Here, the difference was statistically significant for 5 stocks out of a total of 15, at a 10% significance level. Additionally, it is possible to detect a trend in the data, before the price falls and crosses the barrier, volatility levels are higher; however, after the fall, these levels are reduced. The interpretation behind these findings suggests that investors may be more fearful before the barrier is crossed, but afterwards, the market calms down. On the other hand, when analyzing upward crossings of psychological barriers, the relationship with volatility remains present; however, there is no consistent pattern among stocks. The hypothesis that there is no difference in volatility before and after crossing the barrier was rejected in 4 out of the 15 stocks, at a 10% significance level.

Our results are consistent with those of Cai et al. (2007), Dorfleitner & Klein (2009), and Lobão and Lopes (2024) for Chinese, German, and Baltic single stocks, respectively. The authors also defend that psychological barriers, whether shaped by cultural preferences, round-number salience, or technical significance, do not generate predictable or consistent excess returns. However, they may temporarily affect volatility, particularly near prominent thresholds. Moreover, these volatility effects tend to be asymmetric and market-specific.

These discoveries also align with Aggarwal and Lucey's (2007) investigation, where the authors observed significant changes in the variance of gold prices after crossing psychological thresholds, particularly after downward movements. Since variance serves as a proxy for risk, such shifts in volatility could challenge the traditional risk–return relationship. Specifically, perceived risk changes without corresponding movements in returns could indicate a distortion in this relationship near psychological barriers. Accordingly, our results suggest that investor behavior around psychological barriers may introduce biases into the pricing of individual stocks by affecting the perceived risk even when expected returns remain unchanged.

Table 12 – Barrier hypothesis test

		H_1	H_2	H_3	H_4
Saudi Arabia					
Saudi Basic Industries Corporation SJSC	χ^2	2.874	0.177	2.583	0.387
	p-value	0.090*	0.674	0.108	0.534
Al Rajhi Banking and Investment Corporation SJSC	χ^2	3.355	0.171	2.839	1.621
	p-value	0.067*	0.679	0.092*	0.203
Saudi Telecom Company SJSC	χ^2	2.304	1.335	3.380	0.352
	p-value	0.129	0.248	0.066*	0.553
Malaysia					
Gamuda Bhd	χ^2	0.881	0.953	3.192	1.052
	p-value	0.348	0.329	0.074*	0.305
IHH Healthcare Bhd	χ^2	1.386	0.172	0.080	1.335
	p-value	0.239	0.678	0.777	0.248
Tenaga Nasional Bhd	χ^2	0.147	0.064	0.269	3.483
	p-value	0.701	0.801	0.604	0.062*
Pakistan					
Attock Refinery Ltd	χ^2	2.317	0.510	0.546	23.928
	p-value	0.128	0.475	0.460	0.000***
Cherat Cement Company Ltd	χ^2	0.074	0.017	2.613	0.841
	p-value	0.786	0.897	0.106	0.359
D.G. Khan Cement Company Ltd	χ^2	0.548	0.848	3.005	0.814
	p-value	0.459	0.357	0.083*	0.367
Qatar					
Qatar Islamic Bank QPSC	χ^2	0.324	0.003	3.623	2.022
	p-value	0.569	0.957	0.057*	0.155
Qatar Industries	χ^2	0.000	0.000	0.101	0.038
	p-value	0.996	0.995	0.751	0.846
Masraf Al Rayan QPSC	χ^2	0.185	0.019	0.297	0.201
	p-value	0.667	0.889	0.586	0.654
Turkey					
Koç Holding AS	χ^2	0.311	0.527	0.015	2.771
	p-value	0.577	0.468	0.902	0.096*
BIM Birlesik Magazalar AS	χ^2	0.197	0.000	0.007	2.822
	p-value	0.657	0.985	0.934	0.093*
Turk Hava Yollari AO	χ^2	0.524	2.145	0.328	0.000
	p-value	0.469	0.143	0.567	0.985

Table 12 presents the results for a $\chi 2$ test of four different null hypotheses. The hypotheses considered are the following: H1: There is no difference in the conditional mean return before and after a downward crossing of a barrier; H2: There is no difference in the conditional mean return before and after an upward crossing of a barrier. H3: There is no difference in conditional variance before and after a downward crossing of a barrier; H4: There is no difference in the conditional variance before and after an upward crossing of a barrier. Significance at the 10%, 5%, and 1% levels is represented by *, **, and ***.

5. Conclusion

Over the years, psychological barriers have been increasingly capturing the attention of market participants, probably due to their notorious impact on financial markets across different asset classes and markets. In parallel, Islamic Finance has been growing and attracting the curiosity of investors, defending the idea that financial systems should be based on ethical and religious principles. This growing interest is not only attributable to the expansion of global assets but also to its alignment with global trends in ethical, sustainable, and inclusive finance (ICD and LSEG, 2024). To address such important aspects for financial markets, this dissertation analyzed the presence of psychological barriers in Islamic financial markets that follow the principles of *shariah* law. By applying methodologies widely used in the literature, we have discovered new evidence about the existence of psychological barriers in single stock prices of Saudi Arabia, Malaysia, Pakistan, Qatar, and Turkey, considering a time interval of 10 years (2014-2024).

The evidence suggests that the impact of psychological barriers on individual stocks is less pronounced and more heterogeneous than reported in studies focused on stock indices. While some signs of barriers were observed in certain Islamic markets, these effects varied across the tests applied and within the same market, lacking a consistent pattern. This divergence from earlier findings based on market indices (e.g., Bahng, 2003; Donaldson & Kim, 1993; Woodhouse et al., 2016) may appear contradictory. However, as noted by Dorfleitner and Klein (2009), such anomalies can be partly explained by their tendency to fade after publication. Once these price distortions are publicly known, investors are incentivized to exploit them in their investment strategies. As a result, the markets tend to adjust, leading to the gradual disappearance of the anomaly over time.

In terms of the tests performed, the initial ones rejected the null hypothesis of uniform distribution for all stock prices analyzed. Furthermore, the barrier tests revealed indications of barriers in stocks in Qatar and Pakistan; however, these effects were heterogeneous across the whole market. When we examined the conditional effects test, no systematic influence was found on stock returns after crossing psychological barriers. However, the scenario was different when analyzing volatility. The conditional effects test for the variance equation revealed that 9 out of the 15 stocks considered seem to have their volatility influenced by the crossing of barriers.

Overall, our results indicate that there seems to be occasional evidence of barriers in individual stocks; however, the effects were isolated and varied depending on the type of test applied. Consequently, we do not extrapolate the results for the whole market and recognize the localized and potentially specific nature of such effects. These findings are consistent with prior literature in single stocks (e.g., Cai et. al, 2007; Dortfliener and Klein, 2009; Lobão and Lopes, 2024).

In this sense, our main result was that the effects of barriers on volatility are significant for most of the stocks analyzed, and this can have implications for the risk-return traditional models. Theoretically, there should be a positive relationship between risk and associated return (Fama, 1970). However, the barrier hypothesis test shows that in most stocks, there were significant changes in price volatility before and after barrier-crossing periods. What would be expected is that these changes in variance, which is a proxy for risk, would be accompanied by corresponding changes in expected returns. However, this was only observed in 2 stocks.

These findings do not contradict the Efficiency Market Hypothesis (EMH) in its weak form; instead, they reveal behavioral limitations in the analyzed markets, where prices adjust rapidly without predictable returns, but with risk variations (volatility) that are not fully compensated by returns. Thus, investors who use round numbers as an investment strategy do not find consistent statistical support for systematic gains in these markets. However, the evidence regarding volatility suggests that these levels may signal zones of temporary instability, useful for risk management strategies or volatility pricing.

Finally, despite the meaningful insights provided by this research, we recognize that our study has some limitations that could be explored in future investigations. Firstly, the sample of countries analyzed is relatively narrow and may not fully reflect the behavior of Islamic markets as a whole. Therefore, future analyses could consider a larger number of Islamic markets. Another point worth considering is the methodological limitation. Although we have incorporated complementary approaches, the methodology is strongly based on models used by previous studies. The application of alternative methods could offer a more comprehensive understanding of the phenomenon. On the other hand, the comparison between Islamic and conventional stocks could be enriching for the literature. Theoretically, one could think that *shariah* principles (e.g., *gahar*) could attenuate barriers; however, our results do not allow us to test such a hypothesis. In this sense, it would be interesting to investigate whether psychological barriers are more or less evident in Islamic or conventional markets.

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