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Post-COVID-19 technology adoption and noise trading: elucidation of investors' sentiments across cultures

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Abstract

Purpose – Despite its devastating nature, the COVID-19 pandemic has also catalyzed a substantial surge in the adoption and integration of technological tools within economies, exerting a profound influence on the dissemination of information among participants in stock markets. Consequently, this present study delves into the ramifications of post-pandemic dynamics on stock market behavior. It also examines the relationship between investors' sentiments, underlying behavioral drivers and their collective impact on global stock markets.

Design/methodology/approach – Drawing upon data spanning from 2012 to 2023 and encompassing major world indices classified by Morgan Stanley Capital International's (MSCI) market and regional taxonomy, this study employs a threshold regression model. This model effectively distinguishes the thresholds within these influential factors. To evaluate the statistical significance of variances across these thresholds, a Wald coefficient analysis was applied.

Findings – The empirical results highlighted the substantive role that investors' sentiments and behavioral determinants play in shaping the predictability of returns on a global scale. However, their influence on developed economies and the continents of America appears comparatively lower compared with the Asia–Pacific markets. Similarly, the regions characterized by a more pronounced influence of behavioral factors seem to reduce their reliance on these factors in the post-pandemic landscape and vice versa. Interestingly, the post COVID-19 technological advancements also appear to exert a lesser impact on developed nations.

Originality/value – This study pioneers the investigation of these contextual dissimilarities, thereby charting new avenues for subsequent research studies. These insights shed valuable light on the contextualized nexus between technology, societal dynamics, behavioral biases and their collective impact on stock markets. Furthermore, the study's revelations offer a unique vantage point for addressing market inefficiencies by pinpointing the pivotal factors driving such behavioral patterns.

Keywords COVID-19, Technology, Sentiments, Biases, Financial decisions, Stock market

Paper type Research paper

The present study employs a supervised implementation of AI-assisted tools for the refinement of any linguistic errors.

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1. Introduction

One of the most important aspects of studying finance has always comprehended human behavior in financial decision-making. The dynamics of human behavior, which have historically been linked to sophisticated, socially conscious, and logical behavior in society, have been profoundly changed by the recent evidence attributed to the exponential growth of technology (Rasheed, Rasheed, & Khalid, 2024; Stivers & Stirk, 2001). The increase in technology has brought an increasing number of noise traders, whose erratic behavior presents an anomaly that needs to be investigated. The adoption of technology has changed the activities, structures, and accessibility of information in the stock market as well as its overall connectivity. This has also led to paradoxically increasing uncertainty, making economic development unsustainable in terms of public and ecological aspects (Cleary, 2017; Rasheed, Zahid, & Sadiq, 2022). Therefore, a detailed analysis of stock market activity is also necessary to tackle this sustainability issue.

Capital markets are a vital source of capital for corporate growth among modern capitalist economies; a stock market brings together buyers and sellers of financial assets. In addition, stock markets also support several economic activities, such as facilitating capital inflows both domestically and internationally and lowering unemployment through boosting business and economic activity (Levine & Zervos, 1996; Samuel, 1996). Moreover, stock market trends are essential in establishing economic trends, which in turn influence business climate. Increases in share prices are a sign of a positive investment environment, which promotes long-term economic growth (Jaswani, 2008; Ofek & Richardson, 2003). The stock market also offers an opportunity for saving investments and returns that are proportionate to the risks involved in individual investors. In the stock market, investor yields include price fluctuations as well as yearly profit shares distributed as dividends. For this reason, research on the behavior of global investors and stock markets is still very much relevant and essential for academics, investors, and decision-makers.

Boudoukh, Richardson, and Whitelaw (1994) reviewed the underlying reason for the existence of stock return predictability and abridged theoretical clarifications for the behavior of the capital market. According to conventional financial theory, the stock market behaves rationally, with stock prices moving in a random walk. Real-world observations, however, show that stock prices and returns are quite predictable. According to the traditional literature, this idea is called into question by the existence of market frictions that prevent investors from acquiring entire information. Despite significant developments in technology to reduce information asymmetry, information overload and hoarding are still a worry among traditionalist (Bernales, Valenzuela, & Zer, 2022; He, Feng, & Feng, 2023; Jansen, Nikiforov, & Lee, 2020). According to an alternative viewpoint, this return predictability or deviation is attributed to shifts in risk variables linked to stock prices and economic risk premiums (Conrad & Kaul, 1988; Fama & French, 1988; Xue & Zhang, 2017). Nevertheless, this point of view also finds it difficult to explain anomalies, bubbles, and financial market disasters. These viewpoints fall short of addressing the difficulty posed by the presence of irrational noise agents. This brings up the behavioral aspect, which claims

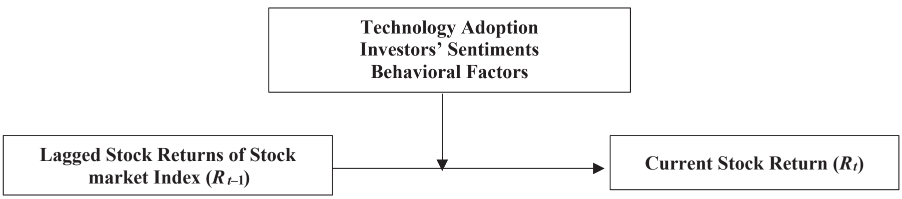

Figure 1. Theoretical framework

Source(s): Figure by authors

that investors are irrational by nature and that cognitive and behavioral variables are the source of stock prediction. When market players either overreact or underreact to available information that is frequently unrelated, return predictability occurs (Rasheed, Gul, Hashmi, & Mumtaz, 2021; Xue & Zhang, 2017). This view posits that investor behavior is greatly impacted by biassed information due to a variety of biases, prejudices, heuristics, and framing strategies (Dhingra, Yadav, Saini, & Mittal, 2024; Hussain, Sadiq, Rasheed, & Amin, 2022; Rasheed, Gul, Akhtar, & Tariq, 2020; Tversky & Kahneman, 1974; Waweru, Munyoki, & Uliana, 2008).

The behavioral financial approach of the stock market, which has its roots in prospect theory and socionomic theory by Kahneman and Tversky (1979) and Prechter (2016), postulates that different sources of information elicit different responses from financial stakeholders. Veronesi (1999) discovered that investors tend to overreact to negative news during market expansions, but they tend to respond less during market collapses. The market's predictability is derived and aided by this insufficient or unwarranted reaction by the investors to the underlying informational flow (Bondt & Thaler, 1985; Thaler, 2015). In stock markets, herding behavior—which results from interactions that distribute irrationality throughout the population—increases predictability and can cause market crashes and bubbles (Amini, Gebka, Hudson, & Keasey, 2013; Baur, Dimpfl, & Jung, 2012; Chen, Hsieh, & Huang, 2018; Dhingra *et al.*, 2024; Lewellen, 2002). Therefore, the motivation of this study is to determine how investors behave and how emotions influence stock market autocorrelation. This paper provides a thorough framework for comprehending stock market behavior by incorporating cognitive biases as a substantial underlying driver for stock market forecasting. Furthermore, in light of the increased dependence on technology methods of information exchange since the COVID-19 epidemic, the study also examines the hypothesis that improved access to information results in more effective international markets. By using MSCI classification, the research chooses one market from each category and region to offer contextualized explanations for this phenomenon, adding theoretical value and helping different stakeholders understand how technology functions in different regional and economic contexts, improving our comprehension of actual stock market behavior. The findings suggest that post-COVID technology adoption appears to have a reversed influence between Asian and American regions and a reduced influence on developed stock markets. Moreover, after the pandemic, the countries with a larger reliance on behavioral biases relied less on behavioral characteristics that produced market predictability, and vice versa. The results for investor sentiment show that return predictability is relatively rare in Western and American markets, but it is strongly correlated with market predictability in Middle Eastern markets. Finally, it is discovered that investor sentiments around the globe are primarily driven by behavioral factors, also having a substantially higher impact in the Asia Pacific. Overall, the markets worldwide are greatly impacted by biases, heuristics and framing. In conclusion, the investigation proved that, despite advances in technology and knowledge, human irrationality and bias-driven behavior continue to be major contributors to stock market inefficiency.

2. Literature review

The existence of irrational noise traders in financial markets presents ongoing difficulties to the idea of market efficiency. Noise trading is often associated with higher-than-expected volume and volatility of trading activity in the stock markets (Willman, Fenton-O'Creevy, Nicholson, & Soane, 2006). Therefore, investors who respond to insufficient or irrelevant information for their financial decisions are known as noise traders. This causes them to make irrational and poor decisions, deviating the overall markets from the conventional model of stock efficiency. The empirical evidence on the topic also appears to contradict the assertions made by proponents of classical finance theory that stock markets in developed economies would be efficient and reasonable. According to Lo and MacKinlay (2011), the support for market efficiency is insufficient and predictability exists in stock markets, which provides substantial evidence in favor of the theory of market inefficiency. Since stock returns, even in leading nations and economies, seem to be autocorrelated and predictable, modern financial academics view market efficiency as an antiquated concept that cannot explain real-world behavior (Amini *et al.*, 2013; Lehtinen & Kuorikoski, 2007).

Stock return autocorrelation is a subject of active research globally. The literature indicates that stock yields exhibit positive autocorrelation (Conrad & Kaul, 1988; Poterba & Summers, 1988). MacKinlay (1997) finds significant autocorrelation among various US marketplaces. According to Kim, Shamsuddin, and Lim (2011) analysis of the Dow Jones Industrial Average index from 1900 to 2009, this autocorrelation helps to anticipate stock return volatility. Hudson (2010) established that even in times of low correlation, the significance of autocorrelation persists, which makes stock prices predictable. The study by Kinnunen (2013) looks into Russian markets and finds that one of the most important factors in stock return prediction is autocorrelation. According to the majority of the reported literature, market predictability is reflected in the correlation between stock prices across the global stock markets (Amini *et al.*, 2013; Rasheed *et al.*, 2021; Xue & Zhang, 2017).

It is expected that return predictability will be higher and more meaningful in developing nations where market frictions and other barriers are even higher. In earlier explorations, significant return connection was discovered in developing markets by employing linear regression models (Amini *et al.*, 2013; Khan & Ahmad, 2017; Khilji & Nabi, 1993). Similarly, a comparative analysis of return autocorrelation in industrialized and unindustrialized nations by Harvey (1995) concluded that return autocorrelation and predictability are higher in emerging nations.

On the other hand, Boudoukh *et al.* (1994) provided a summary of several theories explaining the predictability of stock returns, such as risk factors associated with shifting economic dynamics and market frictions. These arguments, however, leave various aspects unaddressed like noisy traders, market bubbles, crashes, and other oddities in capital markets. This results in the evolution and acceptance of the behavioral explanation of stock markets as the most valid explanation. This model recognizes the irrational presumptions of conventional models and views investors as regular people as opposed to rational beings (Lehtinen & Kuorikoski, 2007; Rasheed, Rafique, Zahid, & Akhtar, 2018). This method emphasizes that not all investments are necessarily rational by arguing that autocorrelation originates from psychosomatic components. Based on historical evidence, investors' overreactions or underreactions to easily accessible and frequently irrelevant news might result in significant returns (Dhingra *et al.*, 2024; Rasheed *et al.*, 2021; Xue & Zhang, 2017). This behavioral explanation is used in the current study to investigate whether stock predictability exists in global stock markets based on MSCI categorization, which varies in terms of development and demographic orientation.

2.1 Technology adoption and return predictability

The conventional view in financial theory is that equities have a random walk-in future value and that market activity is efficient. Nonetheless, there is a good deal of predictability between stock prices and returns in the actual world. Research frequently relates this predictability to market frictions that prevent investors from getting all the information they need to make informed decisions. The expectation was that technological developments would remove these frictions by reducing informational frictions, but investors are now facing a serious problem with information overload and information hoarding (Ali, Wilson, & Husnain, 2022; Bernales *et al.*, 2022; Guerron-Quintana, Hirano, & Jinnai, 2023; Jansen *et al.*, 2020).

According to Stivers and Stirk (2001), technology—which was once thought to be a product of science and reason—is producing a paradox whereby it increases irrationality and produces miraculous results, which goes against the grain of conventional financial theory. Technology is making the stock market environment more unstable and unsustainable rather than improving market efficiency (Cleary, 2017). Due to information overload brought on by the plethora of available data, investors are now forced to rely on unreliable sources and make irrational financial decisions based on their feelings and behavioral patterns.

Technology has significantly changed communication channels by enabling the quick interchange of ideas and information. This interactive strategy has been embraced by stock markets, where brokers engage in regular communication with investors and financial specialists use interactions with executives and brokers to influence the market. These social interactions are important because they improve the degree of consistency and fluctuation in stock returns, particularly in collectivist settings where social influence and behavioral characteristics are likely to have a bigger impact (Dhingra *et al.*, 2024; Rasheed *et al.*, 2018, 2021).

Instantaneous engagement among investors has been made possible by the advancement of technical communication tools, leading to an abundance of often irrelevant information on platforms such as Facebook, Twitter, and WhatsApp. The trend of exponential increase in technology and internet adoption was further accelerated by the COVID-19 pandemic. According to the report, the adoption and application of technology will spread throughout the world's investor community and influence changes in the stock market. Behaviorists contend that greater interaction can result in biased behavior, noise trading, and illogical market behavior, whereas traditionalists may anticipate a decrease in market friction and information asymmetry.

In light of these technological developments and acceleration in their adoption post-COVID-19 pandemic, the study suggests comparing pre- and post-COVID activities at stock exchanges across the globe to observe and validate how markets are acting. This methodology seeks to comprehend the true effects of current technical developments on market dynamics, taking into account the possibility of both efficiency gains and behavioral biases in a dynamic financial environment.

2.2 Market sentiments and predictability

The study also seeks to explain real-world stock return behavior by drawing a link between investor sentiment and the general social mood in society. The collective conduct of the crowd toward the financial market is referred to as "investors or market sentiments" (Brown & Cliff, 2004; Chan, Durand, Khuu, & Smales, 2017; Rasheed, 2021), and in this study, we examine this shared conduct via the prism of "socionomic theory".

Socionomic theory is centered on the study of societal behavior and how it influences actions and behavioral consequences. It was first presented by Prechter in the early 1970s (Nofsinger, 2005). According to this idea, financial economics is unable to separate entire structures for investigation, in contrast to physical sciences and therefore treated as a collective social system interacting and influenced by various social aspects. Lo (2002) further goes on to say that the fiscal system is not a physical system; rather, it is a social system. Prechter (2016) asserts that social attitudes under this perspective are neither conscious nor reasonable. According to the socionomic theory of finance, social interactions—in which people engage with one another—cause social reactions. People are social creatures by nature, and as a result of these interactions, collective reactions are produced that might range from optimism to pessimism. In the end, these investor sentiment waves determine whether general market behavior is bullish or bearish.

Consequently, it is believed that the economy is the culmination of these social networks (Nofsinger, 2005; Rasheed *et al.*, 2021), and the behavior of financial markets is a reflection of societal attitudes. The general state of society has an impact on the financial projections used to make investment decisions. Positive attitudes can be linked to overestimated financial expectations and vice versa. A shift in the overall attitude of society stems from shifts in the mood of stockholders, which are communicated through various channels (Nofsinger, 2005; Rasheed, 2021). In contrast to other economic scenarios where the influence of public sentiment takes time to materialize, the stock market exhibits instantaneous outcomes. Socionomic theory states that one can use social mood to forecast changes in the stock market. According to Frost, Prechter, and Collins (1999), abrupt changes in social disposition might be related to either positive or negative data. Market waves show a consistent pattern that allows for probabilistic forecasts. They trail five discrete patterns that can be categorized into the impulse and corrective phases. Socionomic theory states that social mood—which is influenced by a range of emotional and social factors—leads to an overall sentiment in the market and determines stock market predictability by leading to these phases. Therefore, investor sentiments are expected to have variable associations across various economic trends and stock markets; hence, the current study will also validate these theoretical inferences by quantitatively testing the impact of investor sentiments across stock markets in various cultural settings.

2.3 Cognitive factors and market predictability

This segment of the study looks at how behavioral factors affect stock return behavior to determine the behavioral components that back up optimistic and pessimistic investor sentiment in the capital market. Conventional finance theories suggest that social mood and market conduct should be significantly efficient if the majority of investors are rational. But the existence of return predictability says otherwise, suggesting that a significant fraction of investors act irrationally and fuel the market's optimism or pessimism. In the field of behavioral finance, irrational behavior is attributed to elements that can produce the psychological phenomenon known as social mood, which is a group of illogical emotions. The study conducted by Dhingra *et al.* (2024) summarizes various behavioral factors that can influence investors' emotional states leading to suboptimal financial choices (Gul & Akhtar, 2016; Kirchler, Maciejovsky, & Weber, 2005; Rasheed *et al.*, 2018). There is also a strong connection between different behavioral components, suggesting that when one bias is present, an investor is more likely to apply additional biases (Kudryavtsev, Cohen, & Hon-Snir, 2013). The current study will follow Shefrin's classification of these factors into three categories: framing effects, heuristics, and biases. Within each category, the most frequently used and significant behavioral factors will be used, namely the disposition effect, availability heuristic, and overconfidence bias.

The first behavioral element to be taken into account is overconfidence bias, which occurs when investors erroneously overestimate their skills and knowledge (Rasheed *et al.*, 2020; Shefrin, 2007). Overconfident investors can make poor decisions and cling to irrelevant information, which would result in an excessive amount of trading activity in stock markets (Gervais & Odean, 2001; Glaser & Weber, 2007; Odean, 1998). Similar investigations were established via empirical evidence in favor of the theory that overconfidence bias affects stock market investors' financial decisions (Adiputra, Rahardjo & Hadrian, 2021; Ahmad & Shah, 2020; Allen & Evans, 2005; Gul & Akhtar, 2016).

Similarly, another branch of behavioral traps is called the availability heuristic, which causes investors to make irrational decisions by depending on information that is easily accessible rather than doing thorough and thoughtful research (Kliger & Kudryavtsev, 2010; Tversky & Kahneman, 1973). Existing research validates the significant impact of availability heuristics on the decision-making approaches of investors (Chen, Cheng, Lin, & Peng, 2017; Kudryavtsev *et al.*, 2013; Rasheed *et al.*, 2018; Waweru *et al.*, 2008). When relying on this heuristic, investors run the risk of overreacting to new information, which leads to poor and illogical decision-making that diverts markets from efficiency (Marcus & Goodman, 1991; Rasheed *et al.*, 2018).

Lastly, depending on how information is presented to them, investors can deviate from reason due to a framing effect called the disposition effect. Those who are vulnerable to the disposition effect usually take longer to acknowledge losses and realize profits (Chen, Kim, Nofsinger, & Rui, 2007; Rasheed, 2021). Various explorations on the topic, including Chen *et al.* (2007), Jonsson, Söderberg, and Wilhelmsson (2017), Jordan and Diltz (2004) and Kirchler *et al.* (2005), reported a noteworthy influence of the disposition effect on investors in the stock market. The efficient market assumption of rapid adjustment is contradicted by this conduct, which leads to the inefficiency and predictability of the stock market. Investors cling to failing equities and trade winning stocks quickly.

According to the study, these behavioral characteristics are the primary causes of departures from market efficiency and have a substantial impact on the predictability of the stock market. To shed light on the complex implications of behavioral components on stock return behavior, the goal is to recognize and investigate contextualized distinctions among the various markets under discussion based on the framework provided in the figure below (see Figure 1).

3. Data and methodology

The current study relies on the data of trading volume and index return from the period of 2012 to 2023. Given that the topic of this investigation is stock market inefficiency, which is better illustrated by collective indices than by a single stock, a sample of ten indexes were chosen from around the globe. MSCI market classification system is used to select the sampled countries and their representative stock indices from around the globe. MSCI categorizes stock markets into four categories namely developed, emerging, frontier, and standalone markets, which are further divided into three geographical categories, i.e. Americas, EMEA (Europe, Middle East, and Africa), and APAC (Asia Pacific). A single country and an index from each country were chosen based on data availability. The final selection of the 10 indexes is presented in Table 1 below.

3.1 Operationalization of variables

This section covers the measurement of variables and the proxies used to assess their impact. The return stock market index (SMR) is the main variable of interest in the model because the

Classification	Region	Sample	Index
Developed	America	USA	S&P 500
	EMEA	Germany	GDAXI
	APAC	Japan	Nikkei 225
Emerging	America	Brazil	BOVESPA
	EMEA	Saudi Arabia	TASI
	APAC	China	SSCEI
Frontier	America	None	
	EMEA	Bahrain	BAX
	APAC	Pakistan	KSE-100
Standalone	America	Jamaica	JSE
	EMEA	Palestine	PLE
	APAC	None	

Source(s): Table by authors

Table 1.
Sample selection (MSCI classification)

study is centered on return autocorrelation. Dummy variables, like the disposition bias (DE), bearish and bullish sentiments of investor (IS), overconfidence (OB), availability bias (AH), and technology adoption (TA), are used to compare how the stock market behaves with and without them. Table 2 below lists the variables, their measurements, and the research sources that impacted the creation or application of these proxies.

3.1.1 Stock market return. A stock market index serves as a quantitative representation of a specific segment of the market, providing insights into the broader market's performance. In this study, our primary interest lies in analyzing stock indices and the ability to predict future returns. To ensure a consistent scale for index values, we intend to utilize logarithmic transformations. These transformed values will be employed as the dependent variables for assessing the autocorrelation patterns. To effectively capture the temporal dependencies, we will determine the optimal number of lags to include as independent variables based on the Akaike Information Criterion (AIC). The immediate lagged return will be our variable of interest for explaining the current-day return, and the remaining lagged returns from previous periods will act as control variables. This comprehensive approach aims to enhance the accuracy of our analysis by accounting for potential confounding factors and temporal dynamics in the market data.

3.1.2 Post-COVID-19 technology adoption. The COVID-19 pandemic has had a profound impact on global societies, leading to the emergence of new norms and cultural shifts across various aspects of life, including financial markets. To comprehensively investigate the effects of the pandemic on stock markets, a "dummy variable" has was adopted in this recent study. This approach serves as a tool to analyze and compare market behavior before and after the onset of COVID-19.

The dummy variable in question takes on a value of "1" to denote the period following the commencement of the COVID-19 pandemic. Before this pivotal event, the dummy variable retained a value of "0." By employing this dummy variable, researchers aim to systematically explore and quantify the changes in stock market dynamics and investor behavior that can be attributed to the pandemic. This methodological approach allows for the identification of distinct trends and patterns in stock market performance, investor sentiment, and trading activities before and after the pandemic's outbreak. It provides a structured framework to assess the extent to which the COVID-19 pandemic has influenced stock market fluctuations, investor decision-making processes, and overall market volatility. Through the utilization of the dummy variable, researchers seek to gain deeper insights into how the pandemic has

Variables	Measurement	References
SMR	Lagged Index Rt = log P_t/P_{t-1}	Nofsinger (2005), Rasheed *et al.* (2021), Xue and Zhang (2017)
TA	Dummy 2012–2019 = 0 2019–2023 = 1	Khan *et al.* (2017)
IS	Dummy rt $>$ MA5 = 1rt $\leq$ MA5 = 0	Rasheed (2021), Rasheed *et al.* (2021), Xue and Zhang (2017)
OB	Dummy $r_{t-1} > r_{t-2} \rightarrow V_t > V_{t-1}$ Otherwise = 0	Gervais and Odean (2001), Odean (1998), Rasheed (2021)
AH	Dummy $r_{t-1} > r_{t-2} \rightarrow V_t > V_{t-1}$ $r_{t-1} < r_{t-2} \rightarrow V_t > V_{t-1}$ Otherwise = 0	Marcus and Goodman (1991), Rasheed (2021), Tversky and Kahneman (1974)
DE	$r_{t-1} > r_{t-2} \rightarrow V_t > V_{t-1} r_{t-1} < r_{t-2} \rightarrow V_t < V_{t-1}$ Otherwise = 0	Odean (1998), Rasheed (2021)

Source(s): Table by authors

Table 2.
Variables measurement

transformed the landscape of financial markets, offering a quantitative basis for understanding the shifts in market behavior and helping market participants, policymakers, and analysts to make informed decisions in response to these changes. This approach contributes to a more precise and data-driven understanding of the pandemic's lasting effects on the global financial ecosystem and its implications for the future.

3.1.3 Investors sentiments. Market or investor sentiment, often referred to as crowd psychology, denotes the collective behavioral tendencies of investors within the stock market. As previously mentioned, our study revolves around utilizing investor sentiment as a surrogate for behavioral elements impacting stock market indices. Past research has employed trading volume as an indicator of investor sentiment, often creating a high-low volume variable (Mazviona, 2015) to differentiate between bullish and bearish sentiments. Specifically, when trading volume surpasses the preceding five-day average, it signals a bullish trend (denoted as "1"), and conversely, it represents a bearish trend ("0"). However, this approach possesses a limitation in that heightened volume is linked not only to bullish sentiment but also to panic trading—a scenario was investors trade excessively. Consequently, adopting trading volume as a sentiment proxy can yield misleading outcomes by incorrectly identifying a bullish market trend. Instances of panic trading are observed globally, from the historic Wall Street crash of 1929 to the more recent financial crisis of 2008. In the context of Pakistan, echoes of panic trading can be discerned on notable trading days such as August 15, 2016, when the depreciation of the Chinese Yuan aligned with protests in Islamabad during August 2014. Similarly, on July 3rd, 2017, the release of the JIT report on the Panama Papers (Hussain, 2017) triggered significant market fluctuations. To contribute to the existing literature, our study proposes a novel approach, and instead of utilizing trading volume, it captures the purchase and sale intention via increasing or decreasing returns. It considered employing stock market returns as a more accurate proxy for investor sentiments. This alternative methodology considers returns over the previous five days: a greater-than-average return signifies a bullish market trend, while a lesser return indicates a bearish tone. Importantly, this approach remains impervious to the influence of panic trading, thereby enhancing the reliability and accuracy of sentiment analysis (Rasheed, 2021).

3.1.4 Overconfidence bias. The works of Gervais and Odean (2001) as well as Odean (1998) have laid the foundation for understanding the potential linkage between variations in trading volume and the identification of overconfidence within the stock market. Drawing insights from De Long, Shleifer, Summers, and Waldmann (1990), it becomes apparent that individuals displaying overconfidence tend to harbor a significant illusion of control over outcomes. This tendency, inherent among overconfident investors, transcends the confines of individual securities and extends to encompass the broader market behavior. The phenomenon of overconfident investor manifests in their proclivity for excessive trading, particularly in instances of achieving higher returns. This inclination is observed irrespective of whether the overall market is concurrently experiencing similar performance (Gervais & Odean, 2001). Building upon this understanding, a novel approach is proposed: the introduction of a binary variable, denoted as a dummy variable. This variable serves as an indicator of overconfidence's presence within the stock market.

The operationalization of this concept involves assessing the change in the return on the stock market index. Specifically, when the lagged change in return exhibits a positive trajectory and correlates with an escalation in trading volume, it signifies the manifestation of investor overconfidence. Consequently, the binary variable assumes a value of "1." Conversely, when these conditions are not met, signifying the absence of such overconfident behavior, the binary variable is assigned a value of "0." By adopting this methodology, the study aims to systematically probe the prevalence of overconfidence as a market-wide phenomenon, bolstering the scientific rigor and comprehensive understanding of behavioral dynamics influencing trading activity (Rasheed, 2021).

3.1.5 Availability heuristics. Investors susceptible to availability bias tend to simplify decision-making by associating a complex outcome with the most recent information, often neglecting comprehensive information. This inclination leads them to emphasize recent experiences while disregarding the broader, long-term averages that underlie decisions (Ritter, 2003). Within the framework of availability, investors can draw unjustified inferences about a company's long-term growth trajectory based solely on recent increases (Waweru *et al.*, 2008). This cognitive bias can propel investors into irrational behavior, triggering overreactions (Tversky & Kahneman, 1974). An illustrative example involves investors disproportionately favoring "hot" stocks over those that have exhibited poorer performance. Therefore, we intend to employ stock market gain or loss as a surrogate for recent and influential information. Guided by this approach, if an observed trading volume increase aligns with a corresponding stock market gain or loss, it will not only signify the prevalence of availability bias. In this context, the binary variable assumes a value of "1". Conversely, if the specified conditions are not met, the binary variable will be assigned a value of "0" (Rasheed, 2021).

3.1.6 Disposition effect. In a study conducted by Odean (1998), an investigation into trading patterns revealed a phenomenon termed the disposition effect. This effect pertains to the tendency of investors to exhibit distinct behavior when managing their investment portfolios. Notably, it was observed that investors frequently demonstrate a propensity to retain underperforming stocks while promptly divesting from stocks that have yielded gains. The stock index return trend can be reasonably regarded as a surrogate for the individual security trends in the stock markets. Given this, the disposition effect's manifestation is anticipated to be mirrored in the collective trading dynamics.

Specifically, it is hypothesized that during periods of positive stock market returns, an enhanced disposition effect will be evident. This manifestation will materialize through heightened trading volumes, attributable to a surge in investors opting to liquidate their successful stock holdings. Conversely, during periods marked by negative stock market returns, a converse scenario is anticipated. Investors are expected to exhibit a propensity to retain underperforming stocks, thereby leading to a reduction in overall trading volume. To empirically assess the presence of the disposition effect, a proposed analytical approach involves the introduction of a binary indicator variable. This variable serves to discern the occurrence of the disposition effect in the stock market context. When the confluence of a positive (negative) stock market return and an associated increase (decrease) in trading volume is observed, the dummy variable would take the value of 1, signifying the presence of the disposition effect. Otherwise, the dummy variable would assume a value of 0, indicating the absence of the disposition effect (Rasheed, 2021).

3.2 Statistical route

The sample's data for the study is time-series, Saunders, Lewis, and Thornhill (2009) Saunders, Lewis, and Thornhill (2009) define such data as data points of individual variables dispersed over time. The problem with time series data is that it does not meet the requirements for stationarity of variance and linearity of relationship. Dougherty (2011) considers the use of linear methods inappropriate for such data series. Specifically, because equity returns are asymmetric and skewed, using linear regression models is not appropriate (Bono, Blanca, Arnau, & Gómez-Benito, 2017; Tong & Lim, 1980). Furthermore, the research aims to differentiate between the two distinct behaviors that are anticipated with and without the variables included in the study. With a threshold separating each piece represented in equation (1), this paradigm enables researchers to perform piecewise linear analysis.

$$y_t = \begin{cases} \mu_1 + \theta_1(y_{t-1}) + \ldots + \mu_{1t}, if\ S_{t-k} < \gamma \\ \mu_1 + \theta_2(y_{t-1}) + \ldots + \mu_{2t}, if\ S_{t-k} \geq \gamma \end{cases} \quad (1)$$

For this reason, the current study uses a non-linear model similar to the other nonlinear regression models used in the investigations of Gibson and Nur (2011), Kuang, Huang, Hong, and Yan (2019), McMillan (2004), Tong (2011) and Xue and Zhang (2017). To determine the autoregression lags for which the AIC value is taken into account comes before hypothesis testing (Liew, 2004). Ten lags were employed, with an emphasis on the first lag and the remaining lags as control variables. The unit root test is also used to examine the data and check whether stationarity exists before moving on to the final analysis. Lastly, E-Views are used to apply the threshold regression model for hypothesis testing. The investigation comprised a threshold value based on dummy variables for investors' emotions, representative heuristics, overconfidence, and the framing effects. The validity and distinguishedness of this variation in coefficients between regimes are then ascertained by applying the Wald test.

4. Findings and discussion

This section presents the findings about the threshold influence of post-COVID technology developments, investor attitudes, and behavioral factors, such as biases, heuristics, and framing effects, on the presence of stock return predictability. The results in the given sections are divided based on these variables of the study and subsequently the market classification. The reported results primarily focused on the impact of the first lag and its connection to current profit in both threshold regimes. To determine if the results of lower and higher thresholds are distinguished or similar, the results of the Wald test also reported. Lastly, a discussion on the regional comparison of the results is also reported and discussed.

4.1 Post-COVID-19 technological advancement

This section presents the outcomes of a threshold analysis evaluating the impact of post-COVID-19 technological advancements on various markets, organized according to the MSCI market classification. Let's first delve into the findings concerning developed markets in Table 3. Notably, in the United States, these advancements have led to heightened market predictability. Surprisingly, before the pandemic, the US markets exhibited limited return predictability. The Wald statistics underscore a substantial shift in investor behavior at the S&P 500, emphasizing the distinction between pre- and post-pandemic periods. These results harmonize with the behaviorist school of thought, which posits that despite access to comprehensive information, investors' decisions might not always align with rationality, challenging the notions of efficient markets.

The representative German stock market, the analysis reveals a resemblance in the behavior of German investors both before and after COVID. Strikingly, their behavior lacked significant return predictability. These findings align with the traditional rational paradigm, suggesting that German investors' rational behavior remains unaffected by the presence or absence of information. The non-significance of the Wald test echoes this sentiment.

Lastly in the Japanese stock exchange, the threshold analysis shows that before the COVID pandemic, a noteworthy negative autocorrelation existed, indicating corrective investor behavior due to market overreactions. However, post-pandemic, this predictability faded. These insights imply that pre-pandemic investors displayed significant irrationality, which evolved toward rationality after the pandemic, rendering the market notably efficient.

The second part of the classification is emerging economies, now shifting the focus to emerging markets, namely Brazil, Saudi Arabia, and China, where a similar pattern emerges.

Table 3. Threshold autoregression (Post-COVID technology adoption)

Countries	Threshold variable (technology) Low (0)	High (1)	Wald-test
USA	−0.021	−0.117***	
	(−0.702)	(−4.769)	(2.554) **
Germany	−0.001	−0.009	
	(−0.021)	(−0.312)	(0.216)
Japan	−0.053**	0.029	
	(−2.219)	(0.876)	(−1.995) **
Brazil	−0.004	−0.158***	
	(−0.171)	(6.649)	(4.032) ***
Saudi Arabia	0.152***	0.093**	
	(6.649)	(2.801)	(1.478)
China	0.048**	0.015	
	(2.219)	(0.371)	(0.709)
Bahrain	0.069**	0.107***	
	(2.697)	(3.788)	(−0.992)
Pakistan	0.167***	0.093**	
	(6.836)	(3.114)	(1.931) *
Jamaica	−0.044*	0.033	
	(−1.926)	(0.961)	(−1.864) *
Palestine	0.188***	0.123***	
	(7.932)	(3.829)	(1.630)

Note(s): * = Value significant at (p < 0.1)
** = Value significant at (p < 0.05)
*** = Value Significant at (p < 0.01)
Parenthesis ( ) = t-statistics
Threshold values = Threshold regression coefficient of Return (t−1)
Source(s): Table by authors

Brazil's results mirror those of the USA, with negative predictability implying price corrections. While pre-covid results were insignificant, post-COVID predictability gained significance. The Wald comparison underscores a significant shift toward irrational behavior. On examining Saudi Arabia, the threshold analysis signals considerable irrationality and predictability in both pre- and post-COVID eras. However, post-COVID behavior appears less irrational, as evident from regression coefficients and the Wald test. These findings suggest that despite a predisposition to irrationality, post-COVID technological advancements aided investors in rationalizing decisions. Lastly, transitioning to China, an Asian Pacific emerging economy, the results signify rational investor behavior at the stock exchange. Market behavior adheres to a random walk with insignificant return predictability, a contrast to pre-COVID behavior. Nevertheless, the Wald test reveals an insignificant disparity in behavior before and after COVID.

When considering frontier economies like Bahrain and Pakistan, the analysis demonstrates significant return autocorrelation in both pre-and post-COVID-19 periods. Notably, the differences between these periods lack statistical significance for Bahrain and Pakistan. While the regression coefficients suggest that COVID-19 technologies facilitated more rational decisions among Pakistani investors, a substantial return autocorrelation remains.

Lastly, focusing on standalone stock markets—Jamaica and Palestine—the findings showcase that post-COVID-19 behavior in Jamaica shifted toward randomness with insignificant return autocorrelation, in contrast to pre-COVID-19 behavior. However, Palestine exhibits significant return autocorrelation in both scenarios. The Wald test results failed to discern significant changes in either country.

As a whole, this analysis highlights the complex effects of post-COVID-19 technical developments on different markets, with a range of results from improved predictability to changes in investor behavior and efficient markets. The bulk of market results are consistent with the hypothesis of data overload, which holds that investors would act irrationally even when they have access to all relevant information (He *et al.*, 2023; Jansen *et al.*, 2020; Kirchler *et al.*, 2005; Li *et al.*, 2019; Rasheed, Ali, & Khan, 2023; Shiller, 1995; Yuan, 2022). In addition, the Wald test's results indicate that stock market forecasting exists independent of information availability and technical improvements. While some countries like the USA and Germany indicated otherwise, their behavior is more likely to be aligned with the traditional theorists like Rosenberg, Reid, and Ronald (1985) and Fama (1970).

4.2 Investors sentiments

Market sentiment reflects the collective behavior of investors and serves as a representation of their prevailing attitudes. These sentiments are typically categorized as bearish or bullish trends. Bearish trends involve a propensity for price reduction, while bullish trends entail an inclination toward price increases. The present study employs a return-based proxy to differentiate between these states, aiming to elucidate their dynamics across various stock markets.

The findings for representative developed stock markets worldwide are summarized in the subsequent Table 4. The initial index pertains to the USA, revealing discernible variations in investor behavior between bearish and bullish trends. The Wald statistics accentuate a noteworthy distinction between investors' bearish and bullish behaviors within

Countries	Threshold variable (sentiments) Low (0)	High (1)	Wald-test
USA	−0.017	−0.129***	
	(−0.583)	(−5.278)	(2.955) **
Germany	0.0473	−0.036	
	(1.639)	(−1.441)	(2.167) **
Japan	0.025	−0.071**	
	(0.849)	(−2.681)	(2.414) **
Brazil	−0.021	−0.092***	
	(−0.719)	(−3.672)	(1.863) *
Saudi Arabia	0.267***	0.035	
	(9.678)	(1.440)	(6.304) ***
China	0.131***	−0.027	
	(4.412)	(−1.106)	(4.067) ***
Bahrain	0.112***	0.065**	
	(3.974)	(2.535)	(1.237)
Pakistan	0.188***	0.092***	
	(6.541)	(3.697)	(2.506) **
Jamaica	−0.071**	0.041	
	(−2.685)	(1.449)	(−2.873) **
Palestine	0.151***	0.176***	
	(5.352)	(6.769)	(−0.651)

Note(s): * = Value significant at ($p < 0.1$)
** = Value significant at ($p < 0.05$)
*** = Value Significant at ($p < 0.01$)
Parenthesis ( ) = *t*-statistics
Threshold values = Threshold regression coefficient of Return (t−1)
Source(s): Table by authors

Table 4. Threshold autoregression (investors sentiments)

the S&P 500. Notably, during bearish trends, there is an absence of significant return autocorrelation, suggesting a cautious approach and adherence to traditional rationality and market efficiency. However, during bullish trends, investors tend to exhibit significant irrationality, leading to return autocorrelation. These patterns resonate with the prospect theory, which contends that investors inherently display irrational behaviors, deviating significantly when faced with losses and gains.

In the representative German stock market, the outcomes indicate surprising rationality among German investors during both bearish and bullish trends. Despite this, discernible shifts in their behavior are evident during these phases, as highlighted by the Wald test. These findings align with the traditional rational paradigm in literature, suggesting that German investors cautiously consider all available information during both bullish and bearish periods. Lastly, regarding the third developed index, the Japanese stock exchange, the threshold results indicate the presence of significant negative autocorrelation during bullish trends, implying corrective investor behavior due to market overreactions. However, this predictability becomes insignificant during bearish trends. These results suggest that investors exhibit significant irrationality during bullish trends but exercise greater caution and rationality during bearish trends, thus enhancing market efficiency.

Moving on to the emerging stock markets, including Brazil, Saudi Arabia, and China. Brazil's results mirror those of the USA, with negative predictability indicating price corrections. The predictability during bearish trends is insignificant, while during bullish trends, it becomes significant. Nonetheless, the Wald comparison fails to identify a significant shift in behavior. Among these emerging markets, the behavior of Saudi investors stands out. The threshold analysis highlights considerably irrational and predictable stock market behavior during bearish periods. Conversely, during bullish periods, this irrationality diminishes significantly, as indicated by regression coefficients and the Wald test. These findings suggest that despite investors' inclination for irrationality during bearish trends, which could result in panic trading, Saudi investors approach positive periods more cautiously, leading to careful and rational investment choices and subsequently insignificant predictability.

Turning to China's results, they resemble those of Saudi Arabia. Investors in the Chinese stock exchange behave rationally, and markets follow a random walk with insignificant return predictability during bullish trends, in contrast to bearish trends. The difference in behavior is also substantial, as indicated by the Wald test.

As in the previous sections, the frontier economies of Bahrain and Pakistan, are considered. The reported results reveal significant return autocorrelation during both bearish and bullish trends for both countries. Notably, the differences between bearish and bullish trends are statistically insignificant for Bahrain but significant for Pakistan. Regression coefficients indicate that investor behavior varies significantly between both regimes. These findings align with the behavioral school of thought, indicating irrational behavior regardless of the market's state. Lastly, turning to standalone stock markets, namely Jamaica and Palestine, the results indicate that compared to bearish behavior, bullish behavior becomes more random, featuring insignificant return autocorrelation. There exists a significant difference between these two phases, characterized by a negative autocorrelation and minimal coefficient. In contrast, Palestine displayed significant return autocorrelation during both conditions. The Wald test failed to detect any significant changes in Palestine.

In conclusion, this analysis underscores the interplay of market sentiments across diverse markets, revealing patterns of behavior ranging from heightened rationality to pronounced irrationality, often influenced by the market's state. These findings support the study's perspective and are consistent with the body of current research including Boussaidi (2013), Brown and Cliff (2004), Chen and Haga (2021), Ni, Wang, and Xue (2015), Rasheed *et al.* (2021), Waweru *et al.* (2008), and Xue and Zhang (2017).

4.3 Behavioral factors

The existing literature indicates that the existence of stock market predictability can be predetermined through the existence of behavioral factors. As reported and discussed in the earlier section, there exists a significant return autocorrelation during different phases of stock markets across the globe. In this section, we will test behavioral factors as significant determinants of stock market inefficiency in the form of return predictability. The current study selected behavior based on the categorization made by Shefrin (2007) and selected the most commonly utilized behavioral pitfalls from bias heuristics and framing effects.

4.3.1 Overconfidence bias. The findings of the overconfidence bias analysis for developed stock markets across the globe are presented in the ensuing table. This section reports results for representative developed stock markets, commencing with the US index. Notably, the behavior of investors in the US exhibits limited variation, a conclusion supported by the Wald statistics. In the absence of overconfidence bias, a noteworthy return autocorrelation is evident, indicating that personality-related behavioral biases do not significantly drive return autocorrelation within the S&P 500. Even during overconfidence periods, while overconfidence does exist in the US stock market, it does not emerge as a significant contributor to return autocorrelation. These findings harmonize with the prospect theory, which posits that investors' responses to losses and gains deviate significantly despite their inherent rationality.

The subsequent market under scrutiny is the German stock market. Results reveal a pronounced overconfidence orientation among German investors, leading to stock return predictability. In contrast, in the absence of this biased behavior, such predictability diminishes. This behavioral distinction is notably significant, as underscored by the Wald test. These observations align with the irrational behavioral paradigm in the existing literature, highlighting that overconfidence among German investors leads to market inefficiency. Turning to the last developed market under consideration, i.e. the Japanese stock exchange, the threshold results unveil an intriguing dynamic. In the absence of overconfidence bias, a significant negative autocorrelation is evident, indicative of corrective investor behavior driven by market overreactions. However, when overconfidence bias is introduced into the market trend, these predictability shifts to become positively and significantly autocorrelated. These findings suggest that Japanese investors tend to overreact or underreact to available information, thereby contributing to stock market autocorrelation. Notably, the presence or absence of biased behavior induces significant variation in behavior.

The subsequent Table 5 also details the results for emerging stock markets, encompassing Brazil, Saudi Arabia, and China. Brazil's outcomes once again mirror those of the USA, with significant negative predictability indicating price corrections during the absence of overconfidence bias. Conversely, during the overconfidence wave, predictability becomes significant. The Wald comparison underscores a substantial shift in behavior leading to contradictory and irrational trends.

Among emerging markets, Saudi Arabia merits scrutiny. The threshold analysis points to significantly irrational and predictable stock market behavior both in the presence and absence of overconfidence bias. Notably, the insignificant difference between these thresholds implies a similar behavioral pattern in both regimes. Despite this consistency in investor irrationality, in the presence of biased behavior, Saudi investors contribute to heightened significant predictability in the market whereas, China's results fall in line with the expectations of behavioral theories. Investors in the Chinese stock exchange display rational behavior, resulting in markets adhering to a random walk with insignificant return predictability in the absence of behavioral biases. This pattern contrasts with their behavior under the influence of such biases. The substantial disparity in behavior, as indicated by the Wald test, further accentuates this point.

Table 5.
Threshold autoregression (overconfidence bias)

Countries	Threshold variable (biases) Low (0)	High (1)	Wald-test
USA	−0.096***	−0.057	
	(−4.672)	(−1.197)	(−0.737)
Germany	−0.033	0.093*	
	(−1.598)	(1.936)	(−2.386) **
Japan	−0.079***	0.234***	
	(−3.660)	(5.067)	(−6.073) ***
Brazil	−0.134***	0.223***	
	(−6.555)	(4.697)	(−6.833) ***
Saudi Arabia	0.119***	0.206***	(−1.792) *
	(5.489)	(4.874)	
China	−0.026	0.271***	
	(−1.195)	(6.617)	(−6.249)***
Bahrain	0.077***	0.132**	(−1.114)
	(3.639)	(3.052)	
Pakistan	0.065**	0.329***	
	(2.913)	(8.483)	(−5.795) ***
Jamaica	−0.012	−0.071	
	(−0.542)	(−1.583)	(1.183)
Palestine	0.175***	0.112**	
	(8.061)	(2.611)	(1.294)

Note(s): * = Value significant at ($p < 0.1$)
** = Value significant at ($p < 0.05$)
*** = Value Significant at ($p < 0.01$)
Parenthesis ( ) = *t*-statistics
Threshold values = Threshold regression coefficient of Return (t−1)
Source(s): Table by authors

Results for frontier economies—Bahrain and Pakistan—are also outlined. Notably, both countries exhibit significant return autocorrelation during both the presence and absence of overconfidence bias. While these thresholds differ significantly for Pakistan, they remain statistically insignificant for Bahrain. The regression coefficients emphasize substantial variability in investor behavior during both regimes. These findings align with behavioral theories, underlining irrational behavior independent of market conditions.

Lastly, the outcomes of the analysis for selected standalone economies, Jamaica and Palestine, are detailed. For the Jamaican index, behavior during the presence and absence of overconfidence bias fails to yield significant return predictability. This indicates that behavioral biases are not a significant source of stock market predictability among Jamaican investors. In contrast, Palestine displayed significant return autocorrelation under both conditions. The Wald test, however, fails to discern any noteworthy change for both Jamaica and Palestine.

In summary, this analysis underscores the role of overconfidence bias across diverse markets, revealing intricate patterns of behavior that either exacerbate or mitigate stock market predictability, depending on the market context and investor tendencies. These results are aligned with our initial expectations and in line with the body of current literature of Boussaidi (2013), Chen *et al.* (2007), Chuang and Lee (2006), Gul and Akhtar (2016), Rasheed *et al.* (2020), Tekçe and Yılmaz (2015) and Trejos, van Deemen, Rodríguez, and Gómez (2019). This led to the conclusion that stock market participants are significantly impacted by the overconfidence bias.

4.3.2 Availability heuristic. The threshold results of availability heuristics for developed stock markets across the globe are presented in the following Table 6. The first stock market

Countries	Threshold variable (heuristics) Low (0)	High (1)	Wald-test
USA	−0.194***	0.066**	
	(−8.038)	(2.251)	(−6.852) ***
Germany	−0.114***	0.223***	
	(−5.010)	(6.882)	(−8.512) ***
Japan	−0.145***	0.157***	
	(−5.851)	(5.166)	(−7.702) ***
Brazil	−0.182***	0.066**	
	(−7.427)	(2.245)	(−6.464) ***
Saudi Arabia	0.040	0.231***	(−5.031) ***
	(1.556)	(8.238)	
China	−0.039	0.161***	
	(−1.538)	(5.517)	(−5.135) ***
Bahrain	0.068**	0.104***	(−0.965)
	(2.660)	(3.718)	
Pakistan	0.015	0.237***	
	(0.545)	(9.057)	(−5.880) ***
Jamaica	−0.046*	0.015	
	(−1.853)	(0.478)	(−1.545)
Palestine	0.131***	0.202***	
	(5.018)	(7.346)	(−1.873) *

Note(s): * = Value significant at ($p < 0.1$)
** = Value significant at ($p < 0.05$)
*** = Value Significant at ($p < 0.01$)
Parenthesis ( ) = *t*-statistics
Threshold values = Threshold regression coefficient of Return (t−1)
Source(s): Table by authors

Table 6. Threshold autoregression (availability heuristics)

index reported is for the USA. It can be observed from the given results that in the USA, investor behavior does vary significantly, as indicated by the Wald statistics. The results in the presence of availability heuristics suggest a significant positive return autocorrelation, indicating that experience-related behavioral biases are a noteworthy determinant of return autocorrelation in the S&P 500. Conversely, the results in the absence of availability heuristics indicate that despite their existence in the US stock market, there is also a significant negative predictability for return autocorrelation. These results align with the behavioral school of thought, indicating that investors are inherently irrational and their reactions to losses and gains deviate significantly. The second developed market for analysis is the German stock market. The results indicate that German investor behavior is significantly influenced by heuristics, leading to stock return predictability in the market. In the absence of biased behavior, this predictability becomes negatively significant, indicating a price-correcting behavior. This behavioral difference also exhibits significant variations during these phases, as indicated by the Wald test. These results align with the paradigm of irrational behavior in the literature and indicate that experience-related heuristics play a significant role in market predictability in Germany.

Lastly, the third developed index for analysis is the Japanese stock exchange. The threshold results are similar to the other two developed nations, where the absence of availability heuristics leads to a significant negative autocorrelation. This suggests that investors tend to correct market overreactions, but in the presence of this heuristic-driven behavior, predictability becomes positive and significant. These results indicate that Japanese investors tend to overreact or underreact to available information, causing stock market autocorrelation. The difference in behavior with and without biased behavior is also significant.

Moving on to stock market indices from emerging economies, including Brazil, Saudi Arabia, and China, the results for Brazil once again resemble those for the USA, with a negatively significant predictability indicating price correction. The results in the presence of availability heuristics are significant, but in their absence, they are negatively significant. Wald comparison results indicate a significant shift towards irrational behavior. The second country considered for analysis among emerging markets is Saudi Arabia. The threshold analysis indicates that stock market behavior is significantly irrational and predictable in the presence of heuristic-driven biases. In the absence of such biases, the behavior is significantly less irrational, as indicated by the regression coefficients and the Wald test. These results suggest that the tendency of Saudi investors to rely on availability heuristics significantly influences stock market predictability. Lastly, the results for China are reported. The results for China indicate that investors operating on the stock exchange behave similarly to Saudi investors. Investors act rationally, and markets follow a random walk with insignificant return predictability in the absence of heuristic-driven biases. In contrast, during their presence, significant return autocorrelation exists. The difference in behavior is also significant, as indicated by the Wald test.

The results of frontier markets indicate that Bahrain shows significant return autocorrelation both in the presence and absence of availability bias. The differences between these thresholds are statistically insignificant for Bahrain but significant for Pakistan. In Pakistan, investors appear to follow a rational paradigm and a random walk-in stock price. The regression coefficients indicate that investor behavior varies significantly during both regimes in Pakistan. The behavior of both these markets aligns with the behavioral school of thought, indicating irrational behavior.

The results for the Jamaican index indicate that behavior in the presence and absence of availability heuristics lacks significant return predictability, suggesting that behavioral biases are not a significant cause of stock market predictability among Jamaican investors. In contrast, for Palestine, there was a significant return of autocorrelation in both conditions. The Wald test for both also fails to identify any significant change for both Jamaica and Palestine.

The majority of these findings are also consistent with the body of current research and literature, including Abdin, Farooq, Sultana, and Farooq (2017), Boussaidi (2013), Khan, Naz, Qureshi, and Ghafoor (2017), Kliger and Kudryavtsev (2010) Parveen, Satti, Subhan, and Jamil (2020), Rasheed *et al.* (2018), and Tversky and Kahneman (1973) concluded that investors in the stock market have heuristic biases that affect their capacity for rational behavior.

4.3.3 Disposition effect. The threshold analysis of disposition effects on developed stock markets globally has yielded insightful results, which are detailed in Table 7 below. Beginning with the USA stock market, the findings underscore the significant variation in investor behavior, as indicated by the Wald statistics. The presence of the disposition effect correlates with a noteworthy negative return autocorrelation, signifying that behavioral biases stemming from information-related factors substantially influence return autocorrelation in the S&P 500. In the absence of the disposition effect, it is notable that despite the persistence of availability heuristics in the US market, a significant negative predictability of return autocorrelation persists. These outcomes harmonize with the principles of behavioral economics, underscoring the inherent irrationality of investors. Shifting the focus to the German stock market, the research highlights the profound impact of the disposition effect on investor behavior. This effect contributes to the negative predictability of stock returns, and its absence leads to a shift toward positive predictability, indicative of overreaction tendencies. This disparity in behavior is statistically significant, further reinforcing the role of behavioral factors in shaping market predictability. These findings align with the prevailing paradigm of irrational behavior among investors and underscore the potency of information-driven biases in influencing

Table 7. Threshold autoregression (disposition effect)

Countries	Threshold variable (framing effects) Low (0)	High (1)	Wald-test
USA	−0.037	−0.153***	(3.112) **
	(−1.384)	(−5.738)	
Germany	0.064**	−0.076**	
	(2.353)	(−2.989)	(3.738) ***
Japan	−0.011	−0.038	
	(−0.401)	(−1.365)	(0.687)
Brazil	−0.099***	−0.032	
	(−3.808)	(−1.167)	(−1.767) *
Saudi Arabia	0.146***	0.121***	(0.653)
	(5.237)	(4.759)	
China	−0.049	0.084***	
	(−1.582)	(3.471)	(−3.383) ***
Bahrain	0.117***	0.069**	(1.241)
	(4.428)	(0.011)	
Pakistan	0.080**	0.174***	
	(2.927)	(6.780)	(−2.508) **
Jamaica	0.028	−0.085**	
	(1.065)	(−2.987)	(2.922) **
Palestine	0.208***	0.124***	
	(7.645)	(4.672)	(2.222) **

Note(s): * = Value significant at ($p < 0.1$)
** = Value significant at ($p < 0.05$)
*** = Value Significant at ($p < 0.01$)
Parenthesis ( ) = *t*-statistics
Threshold values = Threshold regression coefficient of Return (t−1)
Source(s): Table by authors

market dynamics among German investors. In contrast, the Japanese stock exchange presents a distinctive scenario. Here, the disposition effect, or lack thereof, appears to have limited influence on investor behavior, with both conditions yielding insignificant autocorrelation. This suggests that Japanese investors do not heavily rely on the disposition effect to drive inefficiencies in stock markets. Moreover, the behavioral variation between the two conditions is statistically insignificant, indicating consistent investor behavior irrespective of the presence of the disposition effect.

Turning attention to the emerging economies. Brazil demonstrates that the presence of the disposition effect yields inconsequential return predictability, whereas its absence is linked to a significant negative predictability. The Wald comparison suggests a significant shift toward irrational behavior. In the context of emerging markets, the analysis of the Saudi Arabian stock market reveals pronounced irrational behavior and predictability, both in the presence and absence of information-driven biases. However, the Wald test indicates that the disparity in behavior between the two conditions is statistically insignificant. This underscores that while information-driven biases play a role in market predictability among Saudi investors, they are not the sole determinant. Examining China, the results corroborate the rational behavior posited by the behavioral school of thought. In the absence of the disposition effect, insignificant return predictability prevails, while its presence leads to a substantial return autocorrelation. The considerable difference in behavior, as indicated by the Wald test, underscores the significance of the disposition effect in shaping stock return predictability among Chinese investors.

In frontier markets, namely Bahrain and Pakistan, significant return autocorrelation is evident in both the presence and absence of the disposition effect. The disparity between these thresholds is statistically insignificant for Bahrain but holds significance for Pakistan. Notably, regression coefficients indicate marked divergence in investor behavior between the two regimes in Pakistan, underscoring the pivotal role of the disposition effect in shaping stock return predictability in the country.

Lastly, focusing on standalone economies, specifically Jamaica and Palestine, the analysis suggests that the disposition effect significantly contributes to stock market predictability among Jamaican investors. This effect is conspicuous through significant return autocorrelation during its presence, whereas the absence of availability heuristics in Jamaica leads to a lack of significant return predictability. In Palestine, significant return autocorrelation persists in both conditions. The Wald test confirms noteworthy changes in behavior for both Jamaica and Palestine.

In summary, the threshold analysis of various developed and emerging stock markets underscores the multifaceted interplay between behavioral biases and market predictability. These findings provide substantial insights into the rationality of investor behavior, with the disposition effect emerging as a key determinant across diverse market contexts. Additionally, these outcomes concur with the behavioral justifications offered in the research of Barberis and Xiong (2009), Gärling, Blomman, and Carle (2017), Jonsson *et al.* (2017), Jordan and Diltz (2004), Kaustia (2004), Kirchler *et al.* (2005), Shen and Shen (2022) and Trejos *et al.* (2019).

4.4 Regional comparison

In this section, the study endeavors to delve into and comprehend the regional disparities highlighted by the final research outcomes. The subsequent Table 8 presents a comprehensive overview of the study's findings. The results concerning post-COVID technological advancements unveil intriguing patterns. Firstly, the influence of these advancements appears to be less pronounced in developed economies. This phenomenon can be ascribed to the premise that these economies are inherently technology-driven, rendering the pandemic's impact on their technological uptake less significant compared to less developed markets.

A second noteworthy observation pertains to countries where the dependence on behavioral biases was more pronounced. Such nations exhibited a reduction in their reliance on behavioral factors in the aftermath of the pandemic, consequently diminishing market predictability, or even rendering it insignificant. Conversely, a reverse trend was observed in cases where reliance on behavioral factors was initially lower. This duality of outcomes brings to the fore a nuanced perspective: while traditionalists often linked the advent of technology with enhanced market efficiency, the instances where reliance on these behavioral factors was previously limited witnessed an augmentation in market predictability during the post-pandemic period, thereby lending support to the behaviorist stance on market dynamics.

A plausible explanation for this phenomenon could be attributed to the decreased reliance on behavioral factors in economies that are predominantly collectivist, such as those in the Middle East and Asia. These economies leveraged technology to access pertinent information that was hitherto unavailable, consequently fostering more rational decision-making. Conversely, economies witnessing an escalation in return predictability tend to be individualistic, such as those in America and Europe. In these regions, advanced technology and easy access to relevant information are already prevalent. The post-pandemic period here merely exacerbated the socialization through social media channels, leading to an inundation of information and subsequently contributing to a deviation from rationality in investor decisions.

Furthermore, an examination of investor sentiments underscores a relatively subdued presence of return predictability within American and developed markets. Notably, the

Table 8.
Regional comparison

Americas		Low	High	EMEA	Low	High	APAC	Low	High
ÙSA	Sentiments	_−0.017_	_−0.131***_	Germany	_0.047_	_0.036_	Japan	_0.025_	_−0.071***_
	Bias	−0.096***	−0.057		_−0.033_	_0.093*_		_−0.079***_	_0.234***_
	Heuristics	_−0.194***_	_0.066**_		_−0.114***_	_0.223***_		_−0.145***_	_0.0663**_
	Framing	_−0.034_	_−0.153***_		_0.067**_	_−0.076**_		−0.011	−0.038
	COVID	_−0.021_	_−0.117***_		−0.001	−0.009		_−0.053**_	_0.029_
Brazil	Sentiments	_−0.021_	_−0.090***_	Saudi Arabia	_0.270***_	_0.035_	China	_0.131***_	_−0.028_
	Bias	_−0.133***_	_0.223***_		_0.119***_	_0.206***_		_−0.027_	_0.271***_
	Heuristics	_−0.182***_	_0.066**_		_0.040_	_0.231***_		_−0.040_	_0.162***_
	Framing	_−0.099***_	_−0.032_		0.146***	0.122***		_−0.049_	_0.084***_
	COVID	_−0.004_	_−0.158***_		0.152***	0.093**		0.048**	0.152
Jamaica	Sentiments	_−0.071**_	_0.041_	Bahrain	0.112***	0.065**	Pakistan	_0.188***_	_0.092***_
	Bias	−0.012	−0.071		0.078***	0.132***		_0.065**_	_0.329***_
	Heuristics	−0.046*	0.015		_0.068***_	_0.105***_		_0.015_	_0.237***_
	Framing	_0.028_	_−0.085**_		0.117***	0.697**		_0.080**_	_0.174***_
	COVID	_−0.044*_	_0.033_		0.069**	0.107***		_0.167***_	_0.093**_
				Palestine	_0.151***_	_0.176***_			
					0.175***	0.112**			
					_0.132***_	_0.202***_			
					_0.208***_	_0.124**_			
					0.188***	0.123***			

Note(s): * = Value significant at ($p < 0.1$)
** = Value significant at ($p < 0.05$)
*** = Value Significant at ($p < 0.01$)
Parenthesis ( ) = t-statistics
Threshold values = Threshold regression coefficient of Return (t−1). The italic values denote the significant difference among thresholds based on Wald statistics
Source(s): Table by authors

behavior of these markets diverges in response to different sentiments. Within American stock markets, a marked negative return autocorrelation is evident, signifying a reverberating impact across both market regimes. Contrarily, German investors appear to be influenced by market sentiments; however, these sentiments do not serve as the fundamental driver of market predictability. Middle Eastern markets, on the other hand, prominently exhibit a significant causal link between investor sentiments and market predictability, irrespective of bullish or bearish trends. Meanwhile, the Asia Pacific region similarly reveals a significant relation between investor sentiments and market behavior, yet the behavior during optimistic and pessimistic trends showcases substantial disparities.

Regarding outcomes tied to behavioral factors, it is apparent that coefficients in developed countries' contexts are relatively lower. This suggests a comparatively diminished reliance on behavioral factors compared with their less mature counterparts. Moreover, a closer examination of these results exposes that the intrinsic rationales behind stock market return predictability in the American region are characterized by negative predictability coefficients, displaying lesser predictive influence across various behavioral factors in comparison to analogous counterparts in different regions. European stock markets also mirror this trend, exhibiting a reduced propensity for market predictability. Contrastingly, markets represented by stock indices in Saudi Arabia, Bahrain, and Palestine, representative of the Middle Eastern region, showcase much higher levels of stock return predictability and a more pronounced dependence on behavioral factors. Notably, in this region, behavioral factors alone do not exclusively underpin the existence of stock return predictability, as evidenced by its persistence even in their absence.

Furthermore, outcomes about the Asia Pacific region underscore a shared market behavior characterized by significantly greater reliance on behavioral factors. A disaggregated analysis of these behavioral biases reveals a prevailing reliance on experience-driven cognitive shortcuts, i.e., heuristics, across nearly all stock markets. Investors in the American region display a heightened inclination towards the disposition effect, whereas their counterparts in the Asia Pacific region demonstrate a proclivity for biases tied to personality traits. These discernible patterns align logically, suggesting that more confident investors are less susceptible to the sway of information dissemination, instead adhering to their independent analyses.

Taken collectively, these findings substantiate the existence of an intricate interplay between assorted traditional and behavioral factors, collectively shaping stock markets and causing stock return predictability. The imperative lies in delving into these variations to foster a more comprehensive comprehension of the underlying dynamics governing the market.

5. Conclusion

This study is the first attempt to investigate contextual differences in the behavior of the global stock market using a simple but powerful threshold regression technique. Its examination of the effects of technology improvements on information availability and the ensuing impact on investors' choices is a significant and pioneering contribution. The study found the opposite tendency to the widely held belief that greater information availability, made possible by technical advancement and the adoption of digital communication methods after COVID-19, would result in less predictability. This result implies that, regardless of the amount of information that is available, investor irrationality and emotionally driven irrational behavior continue to play a major role in the inefficiency of the stock market, except in developed and American stock markets, where individualistic traits explain this kind of behavior.

The study also uses a behavioral finance lens, which emphasizes how important it is to understand human behavior in the financial domain, especially in light of developing computer technology. Even though advances in technology have facilitated the obtaining and analysis of a substantial quantity of financial data, human judgment is still needed to understand these data. The incorporation of distinct perspectives from markets with varied characteristics and dynamics within the study contributes to an investigative aspect. These discoveries might be the starting point for additional development and verification using deterministic models and techniques.

The study's conclusions suggest that even in a setting with technology tools and processes to reduce information asymmetry, behavioral and cognitive elements remain the main determinants of stock return predictability. As a result, the study emphasizes how important it is for financial decision-makers to combine technology innovations with a deep comprehension of human behavior. The study claims that this synergy provides a mechanism for analysts, investors, and academics to improve financial choices, minimize the effects of biased behavior, and combat market inefficiencies. In summary, this study supports a multidisciplinary approach to finance that takes behavioral insights and technical advancements into account.

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