The Economics and Finance Letters
2026 Vol. 13, No. 1, pp. 114-131
ISSN(e): 2312-430X
ISSN(p): 2312-6310
DOI: 10.18488/29.v13i1.4786

Federal reserve interest rates, investment behavior, and arbitrage in exchange traded-funds

Pegah Sobati[1+]
Ayben Koy[2]
Andac Batur Colak[3]

[1]*Istanbul Ticaret University, Turkey.*
Email: sobatipegah@gmail.com
[2]*Faculty of Economics, Administrative and Social Sciences, Fenerbahce University, Turkey.*
Email: ayben.koy@fbu.edu.tr
[3]*Faculty of Computer and Information Sciences, Department of Information Systems and Technologies, Nigde Omer Halisdemir University, Turkey.*
Email: bcolak@ohu.edu.tr


(+ Corresponding author)

Article History
Received: 31 July 2025
Revised: 6 January 2025
Accepted: 27 January 2026
Published: 16 February 2026

Keywords
Arbitrage mechanism
Exchange traded funds
Federal reserve policy
Interest rate
Investment behavior.

JEL Classification:
G10; G11; G15.

ABSTRACT

This study investigates the influence of U.S. Federal Reserve interest rate policy on investor behavior, liquidity, and arbitrage efficiency in 29 iShares exchange-traded funds (ETFs) spanning large-, mid-, and small-cap benchmarks from 2013 to 2024. Using weekly data and econometric techniques combining time-series and panel approaches, the analysis incorporates key macroeconomic indicators, interest rates, the U.S. dollar index, economic activity measures, and market volatility to assess their combined effect on ETF market dynamics. Findings show that interest rate shifts significantly influence asset allocation, sector preferences, and risk tolerance, with higher rates often strengthening the dollar and increasing the appeal of fixed-income assets. Active trading is associated with narrower bid–ask spreads through enhanced liquidity, while passive investment widens spreads. ETF volatility is positively related to spreads, reflecting increased uncertainty and transaction costs in turbulent markets. The results provide empirical evidence on the behavioral channels linking monetary policy, market conditions, and trading efficiency, offering implications for policymakers, asset managers, and market participants. The major contribution of the study is to the empirical finance literature by integrating time-series and panel econometric methods to quantify the joint effects of interest rate policy, macroeconomic indicators, and investor sentiment on ETF market microstructure. Findings offer statistically robust insights into liquidity formation, volatility transmission, and arbitrage efficiency in diversified ETF markets.

Contribution/Originality: This study uniquely integrates time-series and panel econometrics to evaluate how interest rate policy, macroeconomic factors, and investor behavior shape ETF market efficiency. The findings extend current literature by linking monetary policy shifts to liquidity, volatility, and trading behavior across diverse ETF categories from 2013 to 2024.

1. INTRODUCTION

The Federal Reserve's role in shaping U.S. monetary policy has evolved significantly since the Banking Act of 1935, which centralized policy decisions while preserving the corporate structure of Reserve Banks. The 1951 Treasury–Fed Accord marked a turning point, giving the Federal Reserve greater independence to manage inflation and economic stability. Interest rate adjustments have since been a central tool for influencing market conditions, with periods of expansionary policy often lowering rates to stimulate growth and tighter policy aimed at controlling inflation. While a centralized framework supports stable price levels, its effectiveness depends on the central bank's ability to withstand political pressure and manage inflation expectations, thereby maintaining investor confidence.

Low-interest-rate environments, especially in the aftermath of the global financial crisis, have raised the question of whether such conditions encourage greater investor appetite for risk, often described as the "search for yield." This phenomenon can facilitate monetary policy transmission by channeling capital toward higher-yielding investments, but it also carries potential risks for financial stability. If investor confidence falters, the same conditions that once stimulated growth may amplify market volatility, underscoring the need for careful policy calibration. However, if the central bank fails to regain investor confidence, it also poses a challenge to financial stability, requiring greater caution and oversight. Policymakers and investors have emphasized the importance of the search for yield (Bernanke, 2013; Rajan, 2013; Stein, 2013).

In addition to macroeconomic forces, a growing body of research emphasizes the role of behavioral factors in shaping investment decisions. Almansour (2015) and Kartini and Nahda (2021) highlight that emotional biases, social influences, and individual risk perceptions often lead to suboptimal choices. Investors may begin with a risk-averse stance but adjust their tolerance depending on market signals (Hossain & Siddiqua, 2024; Wildavsky & Dake, 2018). Risk perception is dynamic; heightened perception can lead to more frequent trading but lower participation in equity markets. Herding behavior, as observed by Ahmad (2024), Cho and Lee (2006) and Lather, Jain, and Anand (2020), further influences trading patterns, including investors mimicking the actions of others in uncertain environments, such as emotional biases, social influences, risk perception, and personality traits.

Calvet, Célérier, Sodini, and Vallée (2016) note a rise in discretionary investors those entering the market opportunistically, enabled by the liquidity and flexibility of modern financial instruments. ETFs, in particular, offer investors rapid convertibility to cash, broad diversification, and access to both risky and risk-free assets. These features, coupled with their exchange-traded nature, make ETFs highly responsive to shifts in sentiment, liquidity conditions, and macroeconomic indicators. Prior research (Clark-Murphy & Soutar, 2004; Cohen & Kudryavtsev, 2012) indicates that such responsiveness amplifies the influence of both market fundamentals and behavioral biases on ETF pricing and liquidity.

While numerous studies have examined the macroeconomic determinants of asset prices (Fama, 1965; Lintner, 1965) and the psychological drivers of investment behavior (Hassan & Anood, 2009), few have directly linked monetary policy shifts, particularly interest rate changes to ETF market microstructure outcomes. The interplay between interest rates, the U.S. dollar index, economic activity measures, and investor sentiment remains underexplored, especially in the context of bid–ask spreads, liquidity formation, and volatility transmission. Moreover, understanding how active versus passive trading behavior influences these dynamics is critical for policymakers and portfolio managers seeking to anticipate market responses.

The ETF industry has evolved into a mature market that encompasses a wide range of sectors and asset classes, offering increasingly complex and diversified products. Many of these funds are structured to mirror the performance of specific benchmark indices. This research assesses the performance of 29 iShares ETFs in relation to several benchmark categories over the period 2013–2024, using weekly data. It also explores how Federal Reserve interest rate policy, weekly U.S. economic activity, movements in the U.S. dollar, and investor sentiment interact. Through this analysis, the study examines the extent to which investor sentiment affects ETF liquidity, volatility, and arbitrage efficiency, applying integrated time-series and panel econometric techniques in Stata.

The research contributes to the literature by providing empirical evidence on how monetary policy and macroeconomic indicators interact with behavioral factors to shape ETF market microstructure. It advances understanding of the channels through which interest rate changes affect trading behavior, bid–ask spreads, and volatility, offering insights relevant to policymakers, portfolio managers, and scholars of behavioral finance.

The remainder of the paper is structured as follows: Section 2 discusses the theoretical foundations, literature on ETFs, investor behavior, and arbitrage mechanisms; Section 3 presents the research methodology, results, and discussion.

2. LITERATURE REVIEW

2.1. Interest Rate

An interest rate is the price of borrowing or the return on savings and investments, expressed as a percentage of the principal amount. It represents the compensation for the use of money over some time and has a significant impact on economic activity by influencing consumer spending, business investment, borrowing, and central bank monetary policy.

2.1.1. Monetary Policy, Asymmetric Information, and Interest Rate Dynamics

In numerous models of central bank behavior, it is shown that asymmetric information plays a key role in policy effectiveness and dynamic inconsistency (e.g., (Barro, 1976; Barro & Gordon, 1983; Canzoneri, 1985; Cukierman & Meltzer, 1986; Sargent & Wallace, 1975)). Asymmetric information between the Federal Reserve and the public is often associated with puzzling empirical phenomena. Monetary policy theories suggest that tightening monetary policy temporarily raises short-term interest rates by increasing real interest rates, but lowers them in the long run by reducing inflation. Researchers have found that "changes in interest rates generally have no effect on risk-taking," but this is only true under certain conditions, such as when interest rates are positive and stable. According to Lugo (2008) when interest rates are high, a negative relationship between investment and real bank interest rates is to be expected. The higher interest rates incentivize individuals to save rather than invest, as savings yield more profit. The expectations theory of the term structure of interest rates suggests that tighter monetary policy lowers long-term bond rates. However, Cook and Hahn (1989) found that the Federal Reserve's contractionary open market operations generally led to rising interest rates across all maturities.

2.1.2. Interest Rates and Stock Market Performance

If changes in the Federal Reserve discount rate affect the stock market's return and volatility, it has been studied by many researchers (Chen, Mohan, & Steiner, 1999). Some other studies examine how interest rates affect stock returns. Tran (2013) show that the stock market does not only follow a random walk. According to the research, long-term interest rates have a crucial impact on stock returns, especially after the 2008 financial crisis. In addition, the result of Gu, Zhu, and Wang (2022) shows the controversy where some people believe that interest rates are inversely related to stock returns, while others do not. Under conditions of economic uncertainty, surprise interest rate changes are more likely to occur. Thus, a rise or fall in interest rates is expected to be associated with negative or positive volatility for US equities.

2.1.3. Investment Behavior, Market Characteristics, and Decision

Investment behavior encompasses the decisions and actions a person takes when navigating the financial markets, and one of the most important influencing factors is Federal Reserve policy (interest rates). High inflation in an economy can create uncertainty, prompting investors to reassess their portfolios, shift toward safer assets, or delay new investments for a period. In the decision-making process, investors use information not only on their available resources but also on prevailing market conditions (Mathews, 2005). Examining how changes in the federal funds rate influence sector-specific returns, Garg (2008) reported that adjustments in Federal Reserve policy generate varying levels of volatility across the eleven sectors of the U.S. equity market. To achieve optimal returns, decision-makers require a deep understanding of market dynamics (Candian, 2015; Kester, Griffin, Hultink, & Lauche, 2011).

An important factor not mentioned in this section is market characteristics, personal risk profile, data, and profit and loss statements. According to Baker and Haslem (1973), a study by Lee and Tweedie (1977) showed that in the United States, the public pays attention to the annual financial reports of publicly traded companies but has difficulty understanding the format of these types of financial reports.

2.2. Exchange Traded Funds

2.2.1. Overview and Market Importance of Exchange-Traded Funds (ETFs)

According to ETFs are among the most effective financial instruments for managing investment risk. Financial markets can quickly shift from upward momentum to downward or negative trends, largely depending on investor sentiment, whether overly optimistic or pessimistic. In periods of optimism, demand for ETFs tends to rise; however, during times of heightened risk, investors often become more risk-averse, leading to higher sales and withdrawals from ETFs. This selling pressure can reduce ETF share prices. The variety, market relevance, and overall scale of ETFs have expanded considerably, driving greater interest among both traders and long-term investors (Yang & Chi, 2023). In discussing the ETF market, Shank and Vianna (2016) suggest that its prominence and the emphasis placed on it by investors make it a prime example of financialization, contributing to its notable growth in recent years.

2.2.2. Performance and Pricing Behavior of ETFs

Charupat and Miu (2013) examined the performance of leveraged exchange-traded funds, which are financial innovations that aim to generate multiple positive or negative returns compared to a benchmark index. They tend to be more attractive to retail investors who can only hold positions for very short periods and whose net asset value is low on average. Ivanov (2013) analyzed very high-frequency price data, recorded at one-minute intervals, for three major U.S. exchange-traded funds: DIA, SPY, and QQQ. The study found that the prices of DIA and QQQ frequently traded below their net asset value, indicating negative price divergence (discount), whereas SPY often traded above its net asset value, showing positive price divergence (premium). These discrepancies highlight the presence of potential arbitrage opportunities in the market.

Maluf and Albuquerque (2013) examined the efficiency of the Ishare Ibovespa stock valuation process on its net asset value using high-frequency time series analysis. The results showed that there was no excess return after launch and also indicated that investors could not generate abnormal returns based on the divergence between the ETF stock value and the corresponding index. Sentana and Wadhwani (1992) developed a model of investor behavior that provides a testable implication by using daily data of US stock market indices from 1885 to 1988 with generalized autoregressive conditional heteroscedasticity (GARCH) models proposed by Bollerslev (1986).

Madura and Richie (2010) found that ETFs are generally less prone to overreaction effects compared with individual stocks within a portfolio. Nevertheless, the liquidity and tradability of ETFs can sometimes exert unusual downward pressure on their prices, creating potential arbitrage opportunities for feedback traders.

2.2.3. Investor Behavior and Arbitrage in ETF Markets

Kallinterakis and Khurana (2009) studied the NIFTY Be ES ETF, the oldest ETF in the Indian market, and analyzed the behavior of two types of investors: rational investors, who base decisions on fundamental analysis, and noise traders, who make investment choices primarily in response to positive or negative market news. One of the most important variables in the study to consider is arbitrage, i.e., the difference between the bid and ask price, and how investor sentiment can influence this variable. The difference between the bid and ask price and investor sentiment, the price difference that creates and eliminates arbitrage opportunities, which arise from buying and selling ETFs during normal trading hours. Mispricing is easily recognizable and can be bought and sold by all investors, with high trading volume indicating high activity and investor interest in buying or selling stocks or financial assets

(Adicandra & Desmiza, 2022). Furthermore, Finnerty, Reisel, and Zhong (2025) state that arbitrage opportunities are not limited to APs because other market participants can engage in arbitrage without creating or redeeming ETF shares. When the ETF price is above its net asset value, the intensity of investment activity also increases. Conversely, when the ETF price falls below its net asset value, the intensity of redemption activity increases, and authorized market participants can continue to take advantage of relative mispricing during times of stress. As a result of the transaction, the investor is exposed to several costs, including fixed issuance/redemption fees and costs associated with the underlying security transactions. Petajisto (2017) notes that the fixed costs of creating or redeeming ETF shares range from $500 to $3,000 per transaction, regardless of the number of shares. By trading the underlying securities and ETFs, investors can capitalize on the price difference by buying the cheaper asset and shorting the more expensive asset.

2.2.4. ETF Pricing Efficiency and Liquidity

Engle and Sarkar (2006) and Ackert and Tian (2000) examine the volatility of ETF mispricing or tracking errors relative to their underlying index and emphasize the creation/redemption mechanism of ETFs, which allows investors to trade ETFs with the underlying index shares through expiration. Daily orders result in less mispricing than mutual funds, which do not have this option. Active trading in ETFs increases liquidity, narrows bid-ask spreads, and reduces transaction costs, which improves the efficiency of arbitrage opportunities.

3. DATA AND METHODOLOGY

When comparing ETFs with other financial products that allow trading in baskets of assets, ETFs and futures emerge as the preferred instruments for indexing due to their liquidity advantages. The financial crisis has also highlighted the primary limitation associated with total returns, drawing increased attention from investors. Table 1 presents our sample, which includes weekly closing prices for 29 passively managed ETFs and three major U.S. market indices. The selected ETFs were paired with their corresponding iShares benchmark indices and classified into three categories: iShares U.S. Large Cap, iShares U.S. Mid Cap, and iShares U.S. Small Cap. For all selected ETFs, data were collected for the period from January 1, 2013, to December 15, 2024, using sources such as iShares.com, MSCI.com, Investing.com, Yahoo Finance, MarketWatch.com, the U.S. Treasury Resource Center, and Morningstar.com.

Table 1. Listed the names of ETFs.

Sector	NO.	TICKER	ETF NAME	F.LDATE	Exchange	Benchmark
U.S large-cap	1	IVV	IShares Core S&P 500	15.5.2000	N.Arca	S&P500 Index
U.S large-cap	2	HDV	IShares Core High Dividend	29.03.2011	N.Arca	MDY
U.S large-cap	3	DGRO	IShares Core Dividend Growth	6.10.2014	N.Arca	MSCDIVG
U.S large-cap	4	USMV	IShares MSCI USA Min Vol Factor	18.10.2012	Cboe BZX	MSCIUM
U.S large-cap	5	ILCG	IShares Morningstar Growth	28.06.2004	N.Arca	MULCBG
U.S large-cap	6	OEF	IShares S&P 100	23.10.2000	N.Arca	S&P100 Index
U.S large-cap	7	SUSA	IShares MSCI USA ESG Select	24.01.2005	N.Arca	MSCIESG
U.S large-cap	8	DSI	IShares MSCI KLD 400 Social	14.11.2006	N.Arca	MSCIK400
U.S large-cap	9	IVW	IShares S&P 500 Growth	22.05.2000	N.Arca	S&P500G
U.S large-cap	10	IVE	IShares S&P 500 Value	22.05.2000	N.Arca	S&P 500 V
U.S mid-cap	11	IJK	IShares S&P Mid-Cap 400 Growth	24.07.2000	N.Arca	MIDG
U.S mid-cap	12	IJH	IShares Core S&P Mid-Cap	22.05.2000	N.Arca	MIDV400
U.S mid-cap	13	IJJ	IShares S&P Mid-Cap 400 Value	24.07.2000	N.Arca	MIDV
U.S mid-cap	14	IMCB	IShares Morningstar Mid-Cap	28.06.2004	N.Arca	MUMC

Sector	NO.	TICKER	ETF NAME	F.LDATE	Exchange	Benchmark
U.S mid-cap	15	IMCG	IShares Morningstar Mid-Cap Growth	28.06.2004	N.Arca	MUMBG
U.S mid-cap	16	IMCV	IShares Morningstar Mid-Cap Value	28.06.2004	NASDAQ	MUMCBV
U.S mid-cap	17	IWR	IShares Russell Mid-Cap	17.07.2001	N.Arca	RMCC
U.S mid-cap	18	IWP	IShares Russell Mid-Cap Growth	17.07.2001	N.Arca	RMCCG
U.S mid-cap	19	IWS	IShares Russell Mid-Cap Value	17.07.2001	N.Arca	RMCCV
U.S small-cap	20	IJR	IShares Core S&P Small-Cap	22.05.2000	N.Arca	SPCY
U.S small-cap	21	IWM	IShares Russell 2000	22.05.2000	N.Arca	RUT
U.S small-cap	22	IWO	IShares Russell 2000 Growth	24.07.2000	N.Arca	RUO
U.S small-cap	23	IWN	IShares Russell 2000 Value	11.12.2001	N.Arca	RUJ
U.S small-cap	24	IJT	IShares S&P Small-Cap 600 Growth	24.12.2000	NASDAQ	SPCY
U.S small-cap	25	IJS	IShares S&P Small-Cap 600 Value	24.07.2000	N.Arca	SPCY
U.S small-cap	26	ISCB	IShares Morningstar Small-Cap	28.06.2004	N.Arca	MUSCEX
U.S small-cap	27	ISCG	IShares Morningstar S-Cap Growth	28.06.2004	N.Arca	MUSCBG
U.S small-cap	28	ISCV	IShares Morningstar Small-Cap Value	28.06.2004	N.Arca	MUSCBV
U.S small-cap	29	IWC	IShares Micro-Cap	12.08.2005	NASDAQ	RMIC
The total number of stocks by May 2024 from www.ishares.com						

The research part consists of two models that explain the hypothesis. In the first step, we calculate and analyze the volatility rate and liquidity for all ETFs, create a time series table for the first model, and use the ARCH models of Engle (1982) to understand the different types of variables as they may affect investment sentiment. In the second model, investment sentiment will be an independent variable. For reliable results, the behavior of investors should be analyzed according to different situations caused by Federal Reserve policy. Subsequently, panel data regression models with various dependent variables are prepared to identify which main factors most effectively influence the bid-ask spread. The main tests used are unit roots, fixed effects, and random effects (Hausman test, LM test, and F-test), and GEE models (Zeger & Liang, 1986) to apply between three regressions to determine their relationships and the influence of all variables on each other in Stata.

Hypothesis one: Federal Reserve policy can affect the variables of the U.S. economy, which in turn influence the U.S. dollar. According to model one, which of these variables can more effectively impact investment behavior?

1. $USIS_t = \alpha_i + \beta_1 VIX_t + \beta_2 IR + \beta_3 USWEI_t + \beta_4 US - D + \varepsilon_{it}$

- $USIS_t$ = Investment Sentimental Index.
- IR_t = Fed Interest Rate.
- $USWEI_t$ = US Weekly Economic Index.
- DXY = Dolar Index.
- VIX= Market Volatility Index.

2. $SPD_{it} = \alpha_i + \beta_1 BenchmarkR_{it} + \beta_2 Liq_{it} + \beta_3 USIS_{it} + \beta_4 VOL_{it} + \varepsilon_{it}$

- SPD_{it} = Bid/Ask Spread.
- Liq_{it} = Liquidity.
- VOL_{it} = ETFs Volatility.

Hypothesis two: By estimating model one, how can investment behavior affect exchange-traded funds trading (SPD), depending on their volatility and liquidity?

We examine the extent to which traded prices deviate from net asset values (NAVs), representing both costs and arbitrage opportunities for investors. To this end, we calculate the frequency distribution using closing prices for the difference between price and NAV in dollars and the percentage return, expressed as the dollar difference divided by the NAV.

3.1. ETF Volatility

The volatility of ETFs refers to the extent to which the price of an ETF fluctuates over time. During periods of high volatility, there may be mispricing between the ETF and its NAV, usually offset by arbitrage transactions. Where the return variance around the average return is represented by VAR and the risk of the ETF portfolio is represented by SD. The study also focuses on the costs and trading characteristics of ETFs. These include (i) assets, (ii) bid-ask spread, and (iii) volatility. A useful method for comparing option prices, especially between strike prices and maturities, is to express the implied volatility of each option (IV). The volatility and (vi) the turnover of the ETFs.

Step 1. The following equation is used to determine the price volatility of ETF in Equation 1.

$$VOl_t = \frac{(H_i - L_i)}{CP_i} * 100 \qquad (1)$$

Where vol_t is the intraday volatility of the ETF; H_i and L_i are ETF intraday price of the ETF (highest and lowest price), while cp_i is the closing price of the ETF.

3.2. Bid/Ask Spread

APs and institutional traders monitor spreads and exploit discrepancies between the market price of an ETF and its NAV. Wider spreads may indicate inefficiencies in the arbitrage mechanism, especially in volatile markets, while spreads tend to narrow during periods of stable markets due to increased trading activity and reduced uncertainty. A wider bid/ask spread increases the cost of buying or selling an ETF and therefore acts as a hidden fee.

Step 2. We calculate Bid/Ask Spread by the following (Roll, 1984) in Equation 2.

$$SPD_i = \frac{s}{\sqrt{(A_i - B_i)}} \qquad (2)$$

Where *'s'* represents the ask/bid quotes difference. A_i represents the ETF holder's selling price and B_i represents the ETF holder's buying price.

3.3. ETF Liquidity

Liquidity can be understood through several aspects. One key element is the cost of executing a trade, typically measured by the bid-ask spread. Another aspect is the price impact, which reflects the adverse price movements that may occur when executing large orders. Immediacy, or the ability to quickly sell an asset without resorting to a significantly reduced price, is also an important component. In contrast, illiquidity can be partly assessed by the discount below market value that a seller must accept when a rapid sale is necessary.

Step 3. A perfectly liquid asset would not incur a discount for illiquidity and is calculated by Equation 3.

$$\text{Illiquidity} = \sum_{i=1}^{t} |R_t| / DVOL_t \qquad (3)$$

$$\text{Liquidity} = \frac{1}{\sum_{i=1}^{t} |R_t| / DVOL_t}$$

Here $|R_t|$ stands for an absolute value of the closing price in each ETF price. Then vol here means each ETF volume*open price.

4. EMPIRICAL RESULTS AND ANALYSIS

The econometric challenge is to specify how the information is used to predict the mean and variance of returns that depend on past information. Descriptive statistics are important in academic techniques as they allow researchers to summarize and describe the data collected for research purposes (Aguinis, Gottfredson, & Joo, 2013). Table 2 shows the total number of observations and the standard error (95% confidence interval), which provides information for each variable (mean, CD test).

Table 2. Descriptive statistics of the sample.

Variables	Mean	Max.	Min.	Std.Dev	CD-Test
USIS	0.003	0.044	-0.431	0.016	0.0000
USWEI	0.1903	1.187	-1.145	0.292	0.0000
DXY	0.095	0.112	0.079	0.007	0.0001
IR	1.613	5.198	0.042	1.743	0.0000
VIX	0.179	0.740	0.094	0.068	0.0024
SPX 500	0.309	0.603	0.146	0.114	0.0000
SPCY	0.096	0.153	0.047	0.028	0.0002
MIDG	0.012	7.878	-0.04	0.315	0.0012
MIDV	0.018	3.211	-4.22	0.971	0.0000
RUT	0.182	0.270	0.109	0.038	0.0000
RUJ	0.099	0.169	0.049	0.029	0.0001
MUMC	1.337	4.11	0.116	0.776	0.0026
MUMCBV	7.566	6.96	-0.44	6.160	0.0000
MUMCBG	0.022	0.111	-0.256	0.074	0.0000
MDY	0.008	6.906	-6.89	0.800	0.0000
MULCBG	11.62	2.778	0.172	11.07	0.0000
MSDIVG	0.009	1.696	-1.67	0.102	0.0000
RUO	0.182	0.270	0.109	0.038	0.0003
SPX 100	0.140	0.296	0.066	0.056	0.0041
MSCIUM	0.002	0.116	-0.162	0.022	0.0000
MSCIESG	1.006	1.959	0.010	0.276	0.0000
MSCI KILD 400	1.737	4.176	0.011	0.900	0.0001
SP500G	0.0002	0.038	-0.039	0.009	0.0000
RMCCV	0.001	0.149	-0.172	0.029	0.0000
RMCC	2.06	3.22	1.193	0.465	0.0000
RMIC	5.87	9.912	2.130	1.598	0.0012
RMCCG	-0.002	0.123	-1.399	0.083	0.0000
SPD	0.017	0.098	-0.089	-2.231	0.0003
VOL	0.055	11.88	-0.387	0.009	0.0000
LİQ	0.880	2.284	-0.777	24.05	0.0000

Several methods have been developed to test for cross-sectional independence in panel data models. An early approach was proposed by Moran (1948), who introduced a test for spatial independence in pure cross-sectional models. Later refinements of Moran's test are discussed by Anselin (2001) and (Anselin, 1988). However, this method relies on the choice of a spatial weight matrix and may not be appropriate for many economic and financial panels where spatial relationships are not inherently defined. An alternative is the Lagrange multiplier (LM) correlation test developed by Breusch and Pagan (1980). In this study, we applied both the Pesaran CD test and the Breusch-Pagan LM test to assess cross-sectional dependence. Pesaran's CD test evaluates whether the units in a panel are interdependent. Based on the results, the p-value is 0.000, leading us to reject H_1 and accept H_0, indicating that the variables exhibit significant cross-sectional dependence, as summarized in Table 2.

4.1. Unit Root Test

After demonstrating the cross-sectional dependence in the model, we must select one of these tests to examine the panel unit root: here, we choose the Augmented Dickey and Fuller (1979) and Kwiatkowski, Phillips, Schmidt, and Shin (1992).

Augmented Dickey and Fuller (1979): We use the Augmented Dickey-Fuller t-statistic, where the number of lagged terms (p) is determined by minimizing the Schwartz-Bayes information criterion or the Akaike information criterion, or by removing lags until the last lag is statistically significant. The null hypothesis of the Augmented Dickey-Fuller t-test is.

$H_0: \theta = 0$ (i.e., the data needs to be differenced to make it stationary).

versus the alternative hypothesis of

$H_1: \theta < 0$ (i.e., the data is stationary and doesn't need to be differenced).

Kwiatkowski et al. (1992): The Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test was introduced by Kwiatkowski et al. (1992). Unlike the ADF test, which focuses on detecting unit roots, the KPSS test is designed to assess the stationarity of a time series. It operates under the assumption that the series consists of a deterministic trend, a random walk component, and a stationary error term. The hypotheses for the test are then as follows:

H_0: The time series is trend stationary.

H_1: The time series contains a unit root.

According to Table 3, we see in all variations that both test results are acceptable since we reject H_0 and accept H_1. This means that we do not have a unit root between the variables.

Table 3. Unit root test.

Variables	(Augmented Dickey-Fuller)			Variables	(Kwiatkowski-Philips-Schmidt-Shine)		
	Test statistic	Prob.	Integrated order		Test statistic	Prob	Integrated order
USIS	-4.396	0.0021*	I(0)	USIS	0.21	0.0712***	I(2)
USWEI	-3.8452	0.0149**	I(0)	USWEI	0.739	0.0755***	I(0)
DXY	-0.7211	0.0001*	I(0)	US-D	0.216	0.0905***	I(0)
IR	-3.5962	0.0309**	I(0)	IR	0.216	0.1378	I(0)
VIX	-3.5001	0.0411**	I(0)	VIX	0.739	0.1831	I(1)
SPX 500	-3.2481	0.0761***	I(1)	SPX 500	0.739	0.1649	I(1)
SPCY	-25.511	0.0000*	I(1)	SPCY	0.739	0.2987	I(1)
MIDG	-3.2714	0.0720***	I(2)	MIDG	0.739	0.3383	I(2)
MIDV	-24.747	0.0000*	I(0)	MIDV	0.739	0.1944	I(0)
RUT	-3.4407	0.0000*	I(1)	D(RUT)	0.216	0.0729***	I(2)
RUJ	-3.6489	0.0274**	I(1)	RUJ	0.216	0.0647***	I(1)
MUMC	-3.4406	0.0000*	I(1)	MUMC	0.739	0.0576***	I(1)
MUMCBV	-9.0520	0.0000*	I(1)	MUMCBV	0.216	0.1625	I(1)
MUMCBG	-5.1940	0.0001*	I(1)	MUMCBG	0.216	0.0962***	I(1)
MDY	-7.4321	0.0000*	I(0)	MDY	0.739	0.0605***	I(0)
MULCBG	-4.0175	0.0087***	I(0)	MULCBG	0.739	0.2339	I(0)
MSDIVG	-7.4298	0.0000*	I(0)	MSDIVG	0.739	0.0605***	I(0)
RUO	-6.6098	0.0000*	I(1)	D(RUO)	0.216	0.0709***	I(1)
SPX 100	-3.4001	0.0532***	I(1)	SPX 100	0.216	0.0854***	I(1)
MSCIUM	-26.339	0.0001*	I(0)	MSCIUM	0.216	0.0543***	I(0)
MSCIESG	4.2614	0.0000*	I(0)	MSCIESG	0.739	0.4937	I(1)
MSCI KILD	-15.678	0.0000*	I(1)	MSCI KILD	0.216	0.0722***	I(2)
SP500G	-14.073	0.0000*	I(0)	SP500G	0.739	0.1310	I(1)
RMCCV	-13.572	0.0002*	I(0)	RMCCV	0.739	0.2310	I(0)
RMCC	-11.572	0.0000*	I(0)	RMCC	0.739	0.0412**	I(0)
RMIC	-24.540	0.0000*	I(1)	RMIC	0.216	0.0781***	I(1)
RMCCG	-30.148	0.0000*	I(0)	RMCCG	0.739	0.3339	I(0)
SPD	-42.139	0.0000*	I(1)	SPD	0.739	0.3282	I(1)
VOL	-40.367	0.0005*	I(1)	VOL	0.739	0.2322	I(1)
LİQ	-40.119	0.0021**	I(1)	LİQ	0.216	0.1450	I(1)

Note: *0.01, **0.05, ***0.10.

4.2. The First Model (Time-Series), ARCH Model

Volatility persistence refers to a situation where, although successive shocks in a time series are uncorrelated, they exhibit serial dependence over time. Engle (1982) introduced the autoregressive conditional heteroscedasticity (ARCH) class of models to capture this behavior and model time-varying volatility. In this study, we analyze the first model using ARCH/GARCH-type specifications.

Step 4. The ARCH (q) model can be expressed as Equation 4.

$$\varepsilon_t = Z_t \sigma_t \qquad (4)$$
$$Z_t \sim i.i.d\, D(0,1)$$
$$\sigma_t^2 = \sigma^2(\varepsilon_{t-1}, \varepsilon_{t-2}, \dots t, x_t, b)$$

Where ε_t is the prediction error at time t, x_t is a vector of lagged exogenous variables, b is a vector of parameters, and D_0 is the distribution. The conditional variance of εt as a function of the information at time *t-1* is σ_t^2.

Step 5. Many possibilities are proposed in the literature for the parameterization of this variance. In its original form, ARCH can be written as Equation 5.

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \dots + \alpha_q \varepsilon_{t-q}^2 \qquad (5)$$

Using $\sum$ operator equation.

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \, \varepsilon_{t-i}^2$$

The ARCH model can describe volatility clustering through the following mechanism: if ε_{t-1} was large in absolute value, σ_t^2 and thus ε_t is expected to be large in absolute value as well. Even if the conditional variance of an ARCH model is time-varying, the unconditional variance is ε_t constant provided that.

$\alpha_0 > 0$ and $\sum_{i=1}^{q} \alpha_i < 1$ Conditional variance σ_t^2 has to be positive for all t. Sufficient conditions are when $\alpha_0 >$ 0 and $\alpha_i \geq 0$. It has been shown that a high ARCH order must be chosen to capture the dynamics of the conditional variance.

Table 4. (ARCH 1,1).

Variance equation				
Variables	**Co-efficient**	**Std-err**	**T-test**	**P-value**
Arch(1)	0.569	0.112	5.07	0.000
Garch (1)	0.139	0.083	1.68	0.094
Garch(2)	0.087	0.084	1.023	0.303
USWEI	1.040	0.198	5.25	0.000
DXY	5.03	2.197	2.29	0.022
Rf	0.236	0.035	6.59	0.000
VIX	-3.389	0.955	-3.54	0.000
-Cons	0.802	0.177	5.12	0.000
*Sample (Adjusted): January 3, 2013 to December 25, 2024.				

***Note:** Dependent Variables: USIS.

In Table 4, ARCH (1,1) variance equation, most variables are significant, but Garch (2) is not (p = 0.303) and Garch (1) is borderline (p = 0.094). The Garch (2) term has a positive coefficient (0.087) but is statistically insignificant, and while the sign is consistent with the persistence of volatility shocks, where past variance at a two-period lag tends to increase current volatility, the lack of significance suggests that in this sample, the more distant lag contributes little additional explanatory power beyond the immediate past captured by the Garch (1) term. This aligns with standard volatility clustering theory, yet the results indicate that the market responds primarily to more recent shocks, rendering the second lag less relevant. For the borderline Garch (1) coefficient (0.139, p = 0.094), the positive sign matches theoretical expectations in financial econometrics, indicating that volatility is persistent over short horizons. Although not significant at the conventional 5% level, its magnitude and direction remain consistent with the idea that recent volatility transmits into current volatility through investor behaviors such as herding and gradual information absorption. The remaining significant variables also follow expected economic logic: a positive USWEI coefficient suggests that stronger weekly economic performance increases investor optimism and trading activity, leading to greater sentiment variability; a positive DXY indicates that a stronger dollar, often associated with tighter financial conditions for U.S. multinationals, can heighten sentiment volatility. Although the DXY variable is statistically insignificant in its relationship with the Investment Sentiment Index, its positive coefficient can be interpreted in the context of global capital flows and investor sentiment dynamics. A stronger U.S. dollar often reflects relatively robust U.S. economic conditions or higher interest rate differentials, which can attract foreign investment into U.S. financial markets and, in turn, boost certain aspects of investor confidence. This can create upward pressure on sentiment measures, especially among internationally diversified investors who perceive dollar strength as a signal of macroeconomic stability. However, the insignificance of the relationship in this sample suggests that the dollar's influence on sentiment is not consistent across all periods and may be conditional on broader market regimes. A positive R_f (Fed interest rate) reflects how higher rates may alter risk perceptions and prompt portfolio rebalancing, thereby increasing sentiment swings; and a negative VIX shows that higher market volatility typically dampens investor sentiment, reducing the optimism component of the sentiment index. Overall, even for coefficients without statistical significance, the signs align with established theoretical expectations regarding volatility persistence and macro-financial linkages.

4.3. The Second Model (Panel), GEE Model

To address the second model and investigate the relationships between variables, we applied two common approaches used in the econometric modeling of panel data: the fixed-effects estimator and the random-effects estimator. In the fixed-effects approach, time-invariant and unobservable factors specific to each observational unit are either explicitly represented by dummy variables or eliminated through within-transformation.

For our analysis, we performed the Hausman test (Hausman & Taylor, 1981) and the Breusch–Pagan extended LM test for balanced panel data models. The results indicated that the fixed-effects specification is more appropriate. Specifically, the Hausman test produced a p-value of 0.000, which is less than 0.05, leading to the rejection of the null hypothesis (H_0). This confirms that the fixed-effects model is preferred. Subsequent tests and estimations were therefore conducted under the assumption that the model type is fixed effects. After testing the unit root for each variable, we rejected H_0 and accepted H_1 by creating models in Stata using the GEE (Generalized Estimating Equations) method because.

Dependent variable

- GEE is suitable for data with dependencies (correlations) between observations.
- Data is clustered within the same group.
- GEE provides more accurate estimates as this type of dependency is taken into account.

Independent variables

- Independent variables can generally consist of fixed (time-invariant) or time-varying variables.
- It is important to define these variables correctly and choose an appropriate model.

Table 5 presents the results of the first GEE regression model for the bid–ask spread. From an econometric perspective, the results indicate that both volatility and liquidity have a positive impact on the spread (SPD). However, the relationship between liquidity and SPD is not statistically significant (Fraenkle, Rachev, & Scherrer, 2011). The effect of USIS (investment behavior) on SPD is negative and statistically significant at $p < 0.001$. Specifically, the estimates suggest that when the ETF return changes by one unit, the volatility ratio decreases by 0.4. The model's R^2 value of 0.78 indicates a good fit.

Table 5. GEE population-averaged model.

Variables	Co-efficient	Std-err	T-test	P-value
Liq	4.20	3.27	1.28	0.199
Vol	0.009	0.0002	35.16	0.000
USIS	-0.06	0.004	-13.99	0.000
Benchmark	-0.0001	0.0002	-9.24	0.000
-Cons	0.017	0.0008	19.68	0.001
Min	622.0			
Max	622.0			
Avg	622.0			
R-squared	0.78			
Obs	18.038			
Sample (adjusted): January 3, 2013 to December 25, 2024.				

Note: Dependent Variables: SPD

During periods of high market volatility, bid–ask spreads often widen due to increased uncertainty and risk for market makers, even when trading volume an indicator of liquidity is high (Fung, Hwang, & Leung, 1998). High trading volume does not necessarily imply lower costs for market makers. When they face high costs or elevated risks in maintaining liquidity for underlying securities, they may maintain wider spreads to compensate. An ETF is an investment instrument whose units are traded on exchanges at market-determined prices. Most ETFs resemble traditional index funds, comprising a portfolio of securities that aim to track the performance of market indices or benchmarks as closely as possible. According to Goltz and Schröder (2011), ETFs enable investors to gain broad exposure to equity, fixed-income, and alternative investment markets with minimal effort and at low cost.

There is also a negative relationship between investment behavior and bid–ask spreads for ETFs, which may vary depending on how investment behavior is defined. Increased trading activity reduces the cost of matching buyers and sellers, leading to narrower spreads. Conversely, when investors are passive, engage in limited trading, or prefer to hold positions for the long term, ETF liquidity decreases. In such cases, lower trading volume leads to wider spreads because market makers bear greater risk and cost in providing liquidity. Based on step 4 of the GEE method and the observed positive relationship between volatility and the bid–ask spread, the EPD is also expected to increase as volatility rises. Higher volatility reflects more frequent price fluctuations, increasing the risk for market makers when providing liquidity (Ben-David, Franzoni, & Moussawi, 2014). For example, a market maker may purchase at the bid price but experience a decline in the ETF's value before selling at the ask price, resulting in a loss.

Table 6. Test of Assumption.

Models	Heteroscedasticity	Autocorrelation	VIF	Skewness	Kurtosis
Model(1)	0.0063	Lag(1) 2.04	1.82	0.1757	2.8241
Model(2)	0.0000	Lag(1) 2.79	1.22	0.0012	0.0000
Hypothesis	H_0=Homoscedasticity	H_0: p>2	VIF<5	H_0: S=0	H_0: K=3
	H_1=Heteroscedasticity	H_1: p<2	5<VIF<10	H_1: S≠0	H1: K≠3
Model1:	USISt= $\alpha_i + \beta_1 VIX_t + \beta_2 IR + \beta_3 USWEI_t + \beta_4 US-D + \varepsilon_{it}$				
Model2:	$SPD_{it} = \alpha_i + \beta_1 BenchmarkR_{it} + \beta_2 Liq_{it} + \beta_3 USIS_{it} + \beta_4 VOL_{it} + \varepsilon_{it}$				

After examining the relationships between the main factors, we conducted several key diagnostic tests. First, we applied White (1980) general test for heteroscedasticity, which is a specific case of the Breusch–Pagan test. The Stata documentation notes that White's test is typically very similar to the first term of the Cameron–Trivedi decomposition. As shown in Table 6, the p-values from White's test are less than 0.05 for both models, indicating rejection of the null hypothesis (H_0) and the presence of heteroscedasticity. Next, we calculated the Baltagi and Wu (1999) Durbin–Watson statistic to test for autocorrelation. If the Durbin–Watson value is less than 2, autocorrelation is present. For Model (1), the initial statistic was below 2; however, after including a lag, it increased to 2.04, allowing us to reject the alternative hypothesis (H_1). For Model (2), autocorrelation was also detected initially, but after examining a lag of one period, the statistic rose to 2.79, leading to the rejection of H_1. To test for multicollinearity, we calculated the Variance Inflation Factor (VIF). For Model (1), the mean VIF was 1.82 (< 5), and for Model (2), it was 1.03 (< 5), both indicating no multicollinearity among the independent variables. Finally, we assessed the normality of residuals using the Jarque and Bera (1987) test, Kuiper (1960) test, and the skewness and kurtosis measures proposed by D'agostino, Belanger, and D'Agostino Jr (1990). In Model (1), the skewness value of 0.175 (> 0) suggests a slight right skew in the residuals, while the kurtosis value of 2.82 (< 3) indicates that the null hypothesis of normality cannot be rejected. Model (2) exhibits a similar pattern, with kurtosis values below 3, suggesting the residual distribution is slightly flattened but still consistent with the null hypothesis of normality.

5. DISCUSSION

The results of the first hypothesis (model one) indicate that interest rates, particularly those influenced by the Federal Reserve, are crucial in shaping the behavior of financial markets and the US economy. Changes in interest rates can impact the volatility of market indices such as the S&P 500, Dow Jones, and Nasdaq, as well as weekly economic indicators. For instance, the relationship between the dollar index and investment behavior depends on interest rates (federal policy), which are perceived as signals of economic strength or higher interest rates in the US. This perception can lead to positive sentiment for dollar investments or make fixed income investments more attractive when interest rates rise. In this context, the dollar index and interest rates serve as important macroeconomic indicators that influence investor behavior by affecting asset allocation, sector preferences, and risk tolerance. Asset prices and interest rates reflect an investor's ability to adjust their portfolio structure between stocks and bonds. Malkiel (1982) and Modigliani and Cohn (1979) argue that interest rates are among the most significant determinants of stock prices. However, empirical evidence suggests a positive rather than a negative relationship between interest rates and stock prices. Understanding these relationships helps investors and policymakers anticipate market reactions and economic trends. After examining four main factors in the financial market (IR, USWEI, DXY, and VIX) to find out how they affect investor behavior, in the second hypothesis (model two), I included investors' feelings as independent variables to determine how their major decisions influence the bid-ask spread. The rise of behavioral economics has been evident throughout finance and economics over the last three decades. Arbitrage involves buying or selling commodities to exploit differences in effective prices across different trading venues. In perfect markets, arbitrage opportunities are limited by risk aversion and trading risks (De Long, Shleifer, Summers, & Waldmann, 1991). Ritter and Warr (2002) point out that the mispricing of interest rates due to shifting inflation trends led to long bull and bear markets in the US. The effectiveness of arbitrage depends on "smart" investors who act rationally and avoid irrational mispricing of profit opportunities. According to the statistical data in the methodology sections, there is a negative relationship between USIS and SPD, so the relationship between investment behavior and ETF bid-ask spread may vary depending on the definition of "investment behavior." In general, however, an inverse (negative) relationship may exist under certain conditions. Increased trading reduces the cost of matching buyers and sellers and allows for tighter (narrower) bid-ask spreads. As Bohl and Siklos (2008) have demonstrated, the behavior of investors in emerging markets appears to be influenced by arbitrage opportunities. Active investment behavior results in higher liquidity and a narrower bid-ask spread. Conversely, when investors are less active or prefer to hold long-term positions, the ETF experiences lower liquidity and trading volumes, leading to wider spreads due to increased risks and costs faced by market makers in providing liquidity. Passive investor behavior is associated with reduced liquidity and wider bid-ask spreads. An additional significant variable affecting the spread (SPD) is ETF volatility, which, according to our findings in Table 5, is positively correlated with SPD. The positive relationship between ETF volatility and bid-ask spreads stems from the fact that higher volatility elevates uncertainty and risk for market participants. Elevated volatility often causes rapid price fluctuations, complicating the efforts of market makers to efficiently match buy and sell orders, thereby increasing transaction costs and widening spreads. In volatile markets, arbitrage becomes riskier and less efficient, resulting in discrepancies between the ETF price and the net asset value, which can further widen spreads.

6. CONCLUSIONS

Central bank intervention in foreign exchange markets has long been a significant area of research and continues to draw scholarly attention to central bank behavior. The management of foreign exchange reserves, particularly in countries with flexible exchange rates, as well as the accumulation of reserves, plays a key role in monetary policy in both emerging and developed economies. In modern financial markets, analytical decision-making offers significant advantages over relying solely on intuition. Human intuition, shaped by evolutionary environments, often provides limited guidance for complex decisions in contemporary markets and large economies. Over the past three decades, the field of behavioral finance has had a growing influence on financial markets and economic research. Investment decisions are often complex and challenging even for experienced financial professionals. Exchange-traded funds (ETFs) are well-diversified, passively managed instruments designed to track underlying indices, thereby offering exposure to different market segments (Shank & Vianna, 2016; Yang & Chi, 2023). Compared to actively managed investments such as mutual funds, ETFs provide greater control for investors, allowing them to trade either actively or passively while retaining oversight of their capital. ETFs also offer high liquidity, enabling investors to convert holdings into cash efficiently and at low cost. For risk-averse investors, ETFs provide a flexible way to manage volatility and move capital as needed. Additionally, ETFs facilitate instant diversification across assets, including stocks, bonds, or commodities, making them an attractive option for investors seeking broad market exposure.

This study examines the impact of behavioral factors on the bid-ask spread of U.S. large-cap, mid-cap, and small-cap ETFs, focusing specifically on how these factors influence investment decisions in financial markets.

Future research directions: Further work could explore the interaction between interest rate policy and investor behavior using higher-frequency intraday data to capture short-lived volatility spikes and liquidity shocks. Expanding the scope to include ETFs in emerging and developed non-U.S. markets would enable cross-country comparisons of behavioral effects. Additionally, integrating sentiment analysis from news and social media could offer a richer understanding of how qualitative factors influence bid–ask spreads and arbitrage efficiency. Examining the role of algorithmic and high-frequency trading in shaping ETF liquidity under different monetary policy regimes also represents a promising avenue for research.

Policy implications: The results suggest that U.S. Federal Reserve interest rate decisions have direct and measurable effects on investor asset allocation, trading activity, and market liquidity in ETFs. Policymakers should recognize that rate hikes can shift investor preferences toward fixed-income instruments and strengthen the dollar, potentially tightening liquidity in equity-linked ETFs, especially during periods of elevated volatility. Market regulators could use these insights to anticipate potential widening of bid–ask spreads and prepare measures to maintain market efficiency during policy transitions. For asset managers, understanding behavioral responses to monetary policy can inform portfolio rebalancing strategies and liquidity management, reducing transaction costs and minimizing exposure to adverse spread movements.

Funding: This study received no specific financial support.
Institutional Review Board Statement: Not applicable.
Transparency: The authors state that the manuscript is honest, truthful, and transparent, that no key aspects of the investigation have been omitted, and that any differences from the study as planned have been clarified. This study followed all writing ethics.
Data Availability Statement: The corresponding author can provide the supporting data of this study upon a reasonable request.
Competing Interests: The authors declare that they have no competing interests.
Authors' Contributions: All authors contributed equally to the conception and design of the study. All authors have read and agreed to the published version of the manuscript.

REFERENCES

Ackert, L. F., & Tian, Y. S. (2000). Arbitrage and valuation in the market for standard and poor's depositary receipts. *Financial Management, 29*(3), 71-87.

Adicandra, G. R., & Desmiza, D. (2022). Analysis of differences in share return, trading volume activity, and bid-ask spread of share before and after the announcement of emergency community activities restrictions enforcement (PPKM): study on transportation sector companies listed on the Indonesia Stock Exchange. *IDEAS: Journal of Management & Technology, 2*(1), 53-62.

Aguinis, H., Gottfredson, R. K., & Joo, H. (2013). Best-practice recommendations for defining, identifying, and handling outliers. *Organizational Research Methods, 16*(2), 270-301. https://doi.org/10.1177/1094428112470848

Ahmad, M. (2024). The role of cognitive heuristic-driven biases in investment management activities and market efficiency: A research synthesis. *International Journal of Emerging Markets, 19*(2), 273-321. https://doi.org/10.1108/IJOEM-07-2020-0749

Almansour, B. (2015). The impact of market sentiment index on stock returns: An empirical investigation on Kuala Lumpur Stock Exchange. *Journal of Arts, Science & Commerce, 6*(3), 1-28.

Anselin, L. (1988). *Spatial econometrics: Methods and models*. Dordrecht, Netherlands: Kluwer Academic Publishers.

Anselin, L. (2001). Spatial effects in econometric practice in environmental and resource economics. *American Journal of Agricultural Economics, 83*(3), 705-710. https://doi.org/10.1111/0002-9092.00194

Baker, H. K., & Haslem, J. A. (1973). Information needs of individual investors. *Journal of Accountancy, 136*(2), 64-69.

Baltagi, B. H., & Wu, P. X. (1999). Unequally spaced panel data regressions with AR (1) disturbances. *Econometric Theory, 15*(6), 814-823. https://doi.org/10.1017/S0266466699156020

Barro, R. J. (1976). Rational expectations and the role of monetary policy. *Journal of Monetary Economics, 2*(1), 1-32. https://doi.org/10.1016/0304-3932(76)90002-7

Barro, R. J., & Gordon, D. B. (1983). Rules, discretion and reputation in a model of monetary policy. *Journal of Monetary Economics, 12*(1), 101-121. https://doi.org/10.1016/0304-3932(83)90051-X

Ben-David, I., Franzoni, F., & Moussawi, R. (2014). *Do ETFs increase volatility?* NBER Working Paper No. 20071. National Bureau of Economic Research.

Bernanke, B. S. (2013). *Monitoring the financial system*. Paper presented at the 49th Annual Conference on Bank Structure and Competition, Sponsored by the Federal Reserve Bank of Chicago, Chicago, Illinois (Speech No. 621). Board of Governors of the Federal Reserve System.

Bohl, M. T., & Siklos, P. L. (2008). Empirical evidence on feedback trading in mature and emerging stock markets. *Applied Financial Economics, 18*(17), 1379-1389. https://doi.org/10.1080/09603100701704280

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics, 31*(3), 307-327. https://doi.org/10.1016/0304-4076(86)90063-1

Breusch, T. S., & Pagan, A. R. (1980). The Lagrange multiplier test and its applications to model specification in econometrics. *The Review of Economic Studies, 47*(1), 239-253. https://doi.org/10.2307/2297111

Calvet, L., Célérier, C., Sodini, P., & Vallée, B. (2016). Financial innovation and stock market participation. *Finanzinnovation und Aktienmarktbeteiligung, 1*, 35–50.

Candian, G. (2015). *Information frictions and real exchange rate dynamics. Working paper, Boston College*. Retrieved from http://ecomod.net/system/files/Candian_JMP_latest.pdf

Canzoneri, M. B. (1985). Monetary policy games and the role of private information. *The American Economic Review, 75*(5), 1056-1070.

Charupat, N., & Miu, P. (2013). The pricing efficiency of leveraged exchange-traded funds: Evidence from the U.S. markets. *Journal of Financial Research, 36*(2), 253-278. https://doi.org/10.1111/j.1475-6803.2013.12010.x

Chen, C. R., Mohan, N. J., & Steiner, T. L. (1999). Discount rate changes, stock market returns, volatility, and trading volume: Evidence from intraday data and implications for market efficiency. *Journal of Banking & Finance*, *23*(6), 897-924. https://doi.org/10.1016/S0378-4266(98)00118-6

Cho, J., & Lee, J. (2006). An integrated model of risk and risk-reducing strategies. *Journal of Business Research*, *59*(1), 112-120. https://doi.org/10.1016/j.jbusres.2005.03.006

Clark-Murphy, M., & Soutar, G. N. (2004). What individual investors value: Some Australian evidence. *Journal of Economic Psychology*, *25*(4), 539-555. https://doi.org/10.1016/S0167-4870(03)00056-4

Cohen, G., & Kudryavtsev, A. (2012). Investor rationality and financial decisions. *Journal of Behavioral Finance*, *13*(1), 11-16. https://doi.org/10.1080/15427560.2012.653020

Cook, T., & Hahn, T. K. (1989). *The credibility of the Wall Street Journal in reporting the timing and details of monetary policy events*. FRB Richmond Working Paper No. 89-5.

Cukierman, A., & Meltzer, A. H. (1986). A theory of ambiguity, credibility, and inflation under discretion and asymmetric information. *Econometrica*, *54*(5), 1099-1128. https://doi.org/10.2307/1912324

D'agostino, R. B., Belanger, A., & D'Agostino Jr, R. B. (1990). A suggestion for using powerful and informative tests of normality. *The American Statistician*, *44*(4), 316-321. https://doi.org/10.1080/00031305.1990.10475751

De Long, J. B., Shleifer, A., Summers, L. H., & Waldmann, R. J. (1991). The survival of noise traders in financial markets. *The Journal of Business*, *64*(1), 1-19. https://doi.org/10.1086/296523

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association*, *74*(366a), 427-431. https://doi.org/10.1080/01621459.1979.10482531

Engle, R. F., & Sarkar, D. (2006). Premiums-discounts and exchange traded funds. *The Journal of Derivatives*, *13*(4), 27-45. https://doi.org/10.3905/jod.2006.635418

Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica*, *50*(4), 987-1007. https://doi.org/10.2307/1912773

Fama, E. F. (1965). The behavior of stock-market prices. *The Journal of Business*, *38*(1), 34-105. https://doi.org/10.1086/294743

Finnerty, J. D., Reisel, N., & Zhong, X. (2025). ETFs, creation and redemption processes, and bond liquidity. *Journal of Financial and Quantitative Analysis*, *60*(4), 1891-1924. https://doi.org/10.1017/S0022109024000346

Fraenkle, J., Rachev, S. Z., & Scherrer, C. (2011). Market impact measurement of a VWAP trading algorithm. *Journal of Risk Management in Financial Institutions*, *4*(3), 254-274. https://doi.org/10.69554/DKWI2810

Fung, H.-G., Hwang, C.-Y., & Leung, W.-K. (1998). The relationship among volatility, volume, bid-ask spread and number of brokers: Evidence from intra-day data on the Hong Kong stock market. *Review of Pacific Basin Financial Markets and Policies*, *1*(3), 303-320. https://doi.org/10.1142/S021909159800020X

Garg, K. (2008). The effect of changes in the federal funds rate on stock markets: A sector-wise analysis. *Undergraduate Economic Review*, *4*(1), 1-38.

Goltz, F., & Schröder, D. (2011). Passive investing before and after the crisis: Investors' views on exchange-traded funds and competing index products. *Bankers, Markets & Investors*(110), 1–12.

Gu, G., Zhu, W., & Wang, C. (2022). Time-varying influence of interest rates on stock returns: Evidence from China. *Economic Research-Ekonomska Istraživanja*, *35*(1), 2510-2529. https://doi.org/10.1080/1331677X.2021.1966639

Hassan, A.-T. H. A., & Anood, B. K. A. (2009). Financial literacy and investment decisions of UAE investors. *The Journal of Risk Finance*, *10*(5), 500-516. https://doi.org/10.1108/15265940911001402

Hausman, J. A., & Taylor, W. E. (1981). Panel data and unobservable individual effects. *Econometrica*, *49*(6), 1377-1398. https://doi.org/10.2307/1911406

Hossain, T., & Siddiqua, P. (2024). Exploring the influence of behavioral aspects on stock investment decision-making: A study on Bangladeshi individual investors. *PSU Research Review: An International Journal*, *8*(2), 467-483. https://doi.org/10.1108/PRR-10-2021-0054

Ivanov, S. I. (2013). High-frequency analysis of exchange traded funds' pricing deviation. *Managerial Finance, 39*(5), 509-524. https://doi.org/10.1108/03074351311313834

Jarque, C. M., & Bera, A. K. (1987). A test for normality of observations and regression residuals. *International Statistical Review / Revue Internationale de Statistique, 55*(2), 163-172. https://doi.org/10.2307/1403192

Kallinterakis, V., & Khurana, S. (2009). *NIFTY BeES: Refuge for rational or noise traders.* Mumbai, India: National Stock Exchange (NSE) of India Research Papers Series.

Kartini, K., & Nahda, K. (2021). Behavioral biases on investment decision: A case study in Indonesia. *The Journal of Asian Finance, Economics and Business, 8*(3), 1231-1240. https://doi.org/10.13106/jafeb.2021.vol8.no3.1231

Kester, L., Griffin, A., Hultink, E. J., & Lauche, K. (2011). Exploring portfolio decision-making processes. *Journal of Product Innovation Management, 28*(5), 641-661. https://doi.org/10.1111/j.1540-5885.2011.00832.x

Kuiper, N. H. (1960). Tests concerning random points on a circle. *Indagationes Mathematicae (Proceedings), 63*, 38–47. https://doi.org/10.1016/S1385-7258(60)50006-0

Kwiatkowski, D., Phillips, P. C. B., Schmidt, P., & Shin, Y. (1992). Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root? *Journal of Econometrics, 54*(1-3), 159-178. https://doi.org/10.1016/0304-4076(92)90104-Y

Lather, A., Jain, S., & Anand, S. (2020). The effect of personality traits on cognitive investment biases. *Journal of Critical Reviews, 7*(2), 221-229.

Lee, T. A., & Tweedie, D. P. (1977). *The private shareholder and the corporate report: A report to the Research Committee of the Institute of Chartered Accountants in England and Wales.* London, UK: Institute of Chartered Accountants in England and Wales.

Lintner, J. (1965). Security prices, risk, and maximal gains from diversification. *The Journal of Finance, 20*(4), 587-615. https://doi.org/10.2307/2977249

Lugo, O. A. M. (2008). *The differential impact of real interest rates and credit availability on private investment: evidence from Venezuela.* Paper presented at the Participants in the Meeting.

Madura, J., & Richie, N. (2010). *Overreaction of exchange-traded funds during the bubble of 1998–2002. In Handbook of Behavioral Finance.* Cheltenham, UK: Edward Elgar Publishing.

Malkiel, B. G. (1982). *US equities as an inflation hedge, The Stock Market and Inflation.* Homewood, Illinois: Dow Jones-Irwin.

Maluf, Y. S., & Albuquerque, P. H. M. (2013). Empirical evidence: Arbitrage with exchange-traded funds (ETFs) on the Brazilian Market. *Revista Contabilidade & Finanças, 24*(61), 64-74. https://doi.org/10.1590/S1519-70772013000100007

Mathews, J. A. (2005). Strategy and the crystal cycle. *California Management Review, 47*(2), 6-32. https://doi.org/10.2307/41166293

Modigliani, F., & Cohn, R. A. (1979). Inflation, rational valuation and the market. *Financial Analysts Journal, 35*(2), 24-44. https://doi.org/10.2469/faj.v35.n2.24

Moran, P. A. P. (1948). The interpretation of statistical maps. *Journal of the Royal Statistical Society, Series B (Methodological), 10*(2), 243–251. https://doi.org/10.1111/j.2517-6161.1948.tb00012.x

Petajisto, A. (2017). Inefficiencies in the pricing of exchange-traded funds. *Financial Analysts Journal, 73*(1), 24-54. https://doi.org/10.2469/faj.v73.n1.7

Rajan, R. (2013). A step in the dark: Unconventional monetary policy after the crisis, Andrew Crockett Memorial Lecture. In (pp. 1–16). Basel, Switzerland: Bank for International Settlements.

Ritter, J. R., & Warr, R. S. (2002). The decline of inflation and the bull market of 1982–1999. *The Journal of Financial and Quantitative Analysis, 37*(1), 29-61. https://doi.org/10.2307/3594994

Roll, R. (1984). A simple implicit measure of the effective bid-ask spread in an efficient market. *The Journal of Finance, 39*(4), 1127-1139. https://doi.org/10.1111/j.1540-6261.1984.tb03897.x

Sargent, T. J., & Wallace, N. (1975). "Rational" expectations, the optimal monetary instrument, and the optimal money supply rule. *Journal of Political Economy, 83*(2), 241-254. https://doi.org/10.1086/260321

Sentana, E., & Wadhwani, S. (1992). Feedback traders and stock return autocorrelations: Evidence from a century of daily data. *The Economic Journal, 102*(411), 415-425. https://doi.org/10.2307/2234525

Shank, C. A., & Vianna, A. C. (2016). Are US-Dollar-Hedged-ETF investors aggressive on exchange rates? A panel VAR approach. *Research in International Business and Finance, 38*, 430-438. https://doi.org/10.1016/j.ribaf.2016.05.002

Stein, J. C. (2013). *Overheating in credit markets: Origins, measurement, and policy responses.* Paper presented at the Symposium on Restoring Household Financial Stability After the Great Recession, Federal Reserve Bank of St. Louis, St. Louis, MO, USA.

Tran, H. T. (2013). *Relationship between interest rate and bank common stock return: Evidence from the top 10 United States banks and financial sector index (Undergraduate honors project).* Smithfield, RI, USA: Bryant University.

White, H. (1980). A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. *Econometrica, 48*(4), 817-838. https://doi.org/10.2307/1912934

Wildavsky, A., & Dake, K. (2018). Theories of risk perception: Who fears what and why?. In the Institutional Dynamics of Culture, Volumes I and II. In (243-262 ed.). London, UK: Routledge.

Yang, C., & Chi, J. (2023). Investor sentiment and volatility of exchange-traded funds: Evidence from China. *International Journal of Finance & Economics, 28*(1), 668-680. https://doi.org/10.1002/ijfe.2443

Zeger, S. L., & Liang, K.-Y. (1986). Longitudinal data analysis for discrete and continuous outcomes. *Biometrics, 42*(1), 121-130. https://doi.org/10.2307/2531248