Market predictors of European equity ETF performance

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Market predictors of European equity ETF performance

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1. Introduction

Active investing in a highly efficient market requires a complex understanding of available information, which can be challenging and time-consuming for an average investor. Fortunately, the evolution of technology has revolutionized the investment landscape, enabling investors to efficiently allocate their assets into the stock market without the constant need to interpret current market information and react accordingly. This paradigm shift has given rise to the concept of passive investing, wherein investors seek to replicate the performance of an index or a specific set of assets. The SPDR S&P 500 ETF known as the SPY is a name for an ETF which tracks the S&P 500 index, and was the first ETF introduced to the US market in 1993. To closely replicate the performance of the index, the ETF will hold the securities in equal proportion to their weighting in the index. In the last twenty years, exchange traded funds (ETFs) have undergone a remarkable surge in growth. Beginning with a modest $100 billion in assets under management in 2000, the ETF market skyrocketed to $1 trillion by 2010 and almost achieved a $10 trillion market cap in 2020. In contrast, US-based mutual funds, which have been a present in the market for nearly a century, held approximately $27 trillion in assets as of 2020. One of the reasons for such an extraordinary increase in popularity is the benefits it offered to average investors. Some of these are minimal fees associated with owning and trading securities, high liquidity while managing a large basket of stocks, diversification benefits and simple tradability.

They track a large basket of securities, usually an index and ultimately expect the same return as the index. Any amount of deviation between the two variables is called a tracking error. The ETFs performance with respect to its tracking error has attracted a great attention among scientists and practitioners (Johnson, 2009; Dorocáková, 2017; Tsalikis & Papadopoulos, 2019; Feder-Sempach & Miziołek, 2023). When the tracking error is low, it suggests that the ETF is almost perfect at copying its benchmark index, while a high tracking error indicates that the ETF deviates to its benchmark index by some extent.

In this paper, the effect of market related variables on the ETF tracking error is analyzed. While current literature mainly revolves around the American market and the ETFs and indexes analyzed are mostly American, this paper shifts attention and contributes to the literature which focuses on the European market. Hence, the analysis is done on an ETF which tracks the performance of an index composed of 50 largest companies in the Eurozone.

1.1. Objectives and contribution of the research

In this paper, close attention is paid to how tracking error correlates with market-related variables, as they hold significant importance in the research.. This study also explores how tracking error behaves during recent crisis periods. Prices of securities tend to fluctuate more in times of stress and market turmoil and hence decrease the ability of the portfolio manager to efficiently manage portfolios of the constituent ETF. The inability of the portfolio manager to balance portfolios strays the price of the ETF away from its benchmark index and hence decreases the performance of the ETF in terms of the tracking error. Conversely, actively managed ETFs aiming to outperform their benchmark index may experience a decrease in tracking error during stressful periods. This occurs when the portfolio manager successfully identifies undervalued securities and incorporates them into the portfolio, leading to superior performance compared to the index. Consequently, the primary objective of this study is to determine whether the tracking error of the Eurozone ETF, in relation to its benchmark index, decreased or increased during crisis periods encompassing the COVID-19 pandemic and the Ukrainian war.

Alongside analyzing market periods or regimes, the paper offers empirical evidence on widely used market-based measures that may impact tracking error, such as market volatility, liquidity proxy (bid-ask spread), net flow, premium or discount, and trading volume. By considering the distinctive influences of these factors across different market regimes, this paper not only presents empirical evidence and comprehensive explanations but also fills the existing gap in the analysis of Eurozone ETF performance with respect to regime switching methodology. After gathering the data, proper interpretations following economic logic will be given to explain why there may exist a relationship in the first place. This research is of significant interest to investors seeking a deeper understanding of the ETF market.

1.2. Subject of interest

There are various approaches for assessing ETF tracking error, including the historical approach, ex-post approach, and ex-ante approach all of which have their own advantages and disadvantages (G. De Rossi, 2015). Most studies have used regression analysis after obtaining the tracking error, indicating that European ETFs generally exhibit good performance in terms of tracking their benchmarks. However, there is significant variation depending on the specific ETF under analysis, the measurement of tracking error, the observed period, and the approaches employed to examine the factors influencing tracking error. Understanding these factors can assist investors in making informed decisions when selecting ETFs for their portfolios.

This study relies on the ex-ante approach, which offers the key advantage of providing a forward-looking estimate of tracking error. Unlike historical or ex-post tracking error, the ex-ante approach considers changes in market conditions and the underlying holdings of the ETF. The study uses the root of the squared residual from a simple regression of NAV returns on the benchmark returns as an indicator of daily tracking error. The focus of the research is on a Eurozone equity ETF that tracks the Euro STOXX 50 index. The STOXX 50 index is a widely recognized benchmark for the Eurozone equity market, representing the performance of fifty blue-chip companies from 18 Eurozone countries. While there are several exchange-traded funds that track the STOXX 50 index, the iShares Euro Stoxx 50 ETF is chosen due to its popularity as the largest and most liquid option, managing over 10 billion USD in assets as of May 2023. Additionally, the chosen ETF is accumulating which means that all dividends are reinvested back to the fund maximizing future returns, which is another reason for selecting it.

1.3. Data and methodology

In this study, the focus lies on examining how tracking error behaves concerning other market-related variables over a four-year timeframe. Additionally, interest is directed towards its behavior during the COVID-19 crisis and the Ukrainian War. As such, data is obtained from the Refinitiv Eikon source, covering the dates from May 27, 2019, to May 26, 2023. The investigation deals with a combination of a crisis period and a bull period, entailing nonlinear relationships between variables and nonstationary properties of these variables. Therefore, the model that is used in this study is the Markov switching model. In a Markov switching model, complex relationships between variables can be captured, which are not well explained by linear models. This is done by considering that the parameters of the model can change depending on a regime they're currently in. "Regime" in this case is the state of the market and is either bullish or bearish. Markov switching model also addresses the nonstationary property of the variables.

1.4. Thesis structure

The thesis follows a structured approach to provide a comprehensive understanding of Exchange-Traded Funds (ETFs) and their mechanics, followed by an analysis of the performance in regards to tracking error. The first section of the thesis delves into the unique characteristics of ETFs and explores the distinguishing features of ETFs. This section aims to establish a clear understanding of how ETFs differ from traditional investment options, such as mutual funds or individual stocks. The second section focuses on explaining the mechanics of ETFs. It delves into the arbitrage mechanics that play a crucial role in maintaining the relationship between an ETF's market price and its underlying assets' value. It explores the creation and redemption process, highlighting the role of authorized participants and the potential for arbitrage opportunities. Additionally, this section discusses how ETFs are indexed, including different indexing methodologies and their implications for tracking performance. The last part of the thesis sets the direction of the study, which is to analyze the effect market related variables have on the tracking error. Lastly, literature review and results of the analysis are provided followed by the interpretation.

2. The characteristics of Exchange Traded Fund investing

2.1. Background of ETFs

According to Markowitz (1952) investors should be led by actions in which they can maximize the return and minimize the variance of their portfolio. This is the foundation of modern portfolio theory. Markowitz assumed that most investors prefer less risk and are more comfortable with avoiding losses rather than seeking higher returns. Therefore, when given a choice between a riskier option with higher returns and a safer option with lower returns, most people naturally opt for the safer option, even if it means lower potential gains. Modern portfolio theory further suggests that investors can decrease the amount of volatility of their portfolio by diversifying the assets they invest in. ETFs clearly offer the benefit of diversification.

Both mutual funds and ETFs serve to reduce risk through diversification and are managed by portfolio managers. However, there are key distinctions between the two. ETFs are pooled investment vehicles that track specific indexes, mostly passively managed. With a focus on risk reduction rather than returns, ETFs have seen a significant increase in total market cap in the last two decades. This simplicity makes them attractive to retail investors. On the other hand, mutual funds lack the ability for investors to sell shares at any time and are actively managed. Fund managers strategically select stocks, aiming for higher returns than the market. One strategy involves investing in emerging markets and capitalizing on their inefficiencies. One of the ways of beating the market is investing in emerging markets and looking for its inefficiencies. However, a study from Frino and Gallagher (2001) strongly suggests that the average investor does not gain economic benefits from using actively managed equity mutual funds. The research conducted by Kaminsky, Lyons, and Schmukler (2001) suggests that mutual funds play a significant role among institutional investors as the primary channel for financial flows into emerging markets. On the other hand, the findings of Ong and Sy (2004) indicate that this phenomenon is more pronounced in the European market compared to the United States. This active management of the fund comes with greater initial and management costs as well as higher transaction costs compared to ETFs which drive retail investors toward cheaper alternatives.

Other than diversification benefits investors gain, Broman (2016) says that higher liquidity ETF shares attract investors who are not willing to invest directly into illiquid assets such as commodities, emerging markets etc.

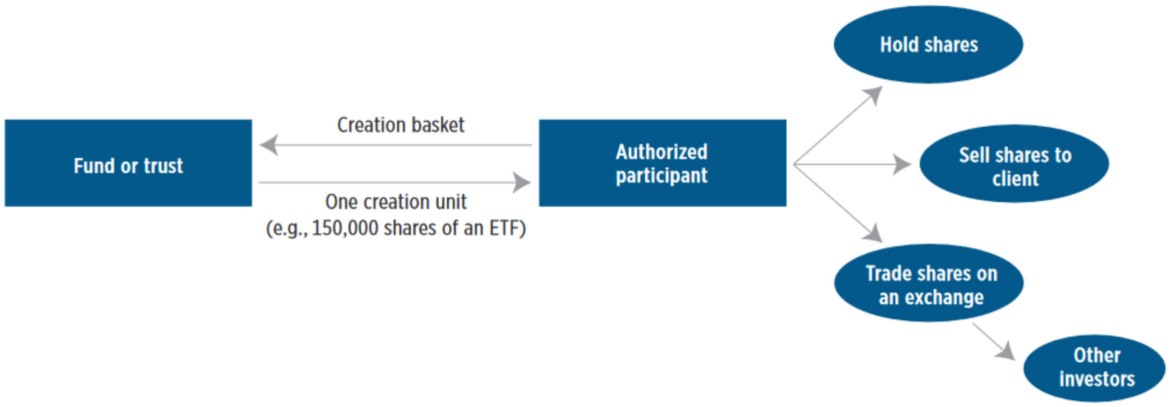
When buying ETFs from the broker, one will encounter that there are many different options of an ETF that one wants to buy. For example, when searching for iShare Euro Stoxx ETF one will see that there are different extensions at the end, for example .L, .AS, .DE, .MI which all stand for different cities or countries, London, Amsterdam, Germany and Milan respectively. An ETF from the London stock exchange will show prices in pounds, whereas on some exchanges there will be a limited number of ETFs available to be bought. Investors also want to avoid buying from multiple exchanges as there are annual fees which are charged by stock exchanges. One important factor to consider is the volume that certain instruments have on different exchanges. This is particularly important when buying ETFs because of their tracking error. If the volume and trading frequency of the ETF is low, it can exhibit bigger spreads or bid and ask prices and therefore increase the tracking error that the instrument experiences. Therefore it is smart to choose a stock exchange which displays big volume when compared to other exchanges. This paper chose the ETF from the German exchange as all variables are taken into account.

2.2. Creation and redemption mechanism of ETFs

The arbitrage mechanism is the reason for the alignment of the prices between the ETF and its underlying NAV. When prices start deviating, arbitrageurs use the opportunities to profit, and correct the prices of ETFs to match those of their NAV. To understand how arbitrageurs profit in the first place, let’s look at how ETFs trade on the market in the first place. ETFs trade on both primary and secondary markets. In the primary market the ETF shares are created or redeemed by the institutions called ETF funds/sponsors. The sponsor of an actively managed ETF has the freedom to trade securities as they see fit, similar to an actively managed mutual fund. They set the investment goal of the fund, such as outperforming a market segment or focusing on a specific sector, and build a portfolio of stocks, bonds, or other assets to achieve that objective (Antoniewicz, R., and J. Heinrichs, 2014). ETF sponsors work together with authorized participants (APs). APs are institutions, such as market makers, broker-dealers, or banks, that have contractual agreements with the ETF sponsor. These agreements allow them to directly trade with the sponsor and access the primary market, enabling them to exchange shares for ETFs and vice versa. In the case of U.S. equity ETFs, these transactions are typically conducted in-kind, meaning a basket of securities is exchanged for a creation unit of ETF shares after the trading day concludes. APs pay a creation fee for the transaction. Furthermore, APs are not legally obligated to participate in ETF primary markets. However, they have significant financial incentives to do so. Market-making APs can earn commissions and fees from customer orders, as well as potential profits from ETF-common stock arbitrage.

To understand the mechanics and the relationship between an ETF and the underlying, one must first understand the inner workings of ETFs and how they are created and redeemed in the first place. Figure 1 visualizes the relationship between the ETF sponsor and APs.

Figure 1: *Arbitrage mechanism*



The mechanism relies on arbitrage and involves transactions between the ETF sponsor and APs. This creation-redemption mechanism utilizes arbitrage to help maintain the ETF price within a specific transaction cost range (Madhavan, 2014). Mechanism facilitates the exchange of cash or a basket of securities matching the ETF's holdings. While APs can buy or sell ETF shares in the secondary market, they also have the option to directly purchase or redeem shares from the ETF itself, capitalizing on profit opportunities. The creation or redemption of ETF shares occurs at the net asset value (NAV) at the end of the trading day. Net asset value is the value of all the underlying securities in the basket. There are times in a trading day when the value of the basket (NAV) exceeds the value of the ETF and it is said that the ETF trades at a discount. This could happen if ETFs experience a large sell order, which pushes the price of the instrument downward. In contrast an ETF price can be higher than that of NAV and then ETF trades at a premium. If an ETF trades at a premium relative to the NAV of its underlying securities, APs buy the underlying securities and short the ETF in the secondary market until the two values equate. At the end of the trading day, APs deliver the accumulated underlying securities to the ETF sponsor, receiving newly created ETF shares which were shorted in the primary market and are then used to cover the short position. Conversely, if the ETF trades at a discount, APs buy the ETF and short the underlying basket of securities until the ETF price aligns with the basket of securities. These divergences are of our interest, the discount/premium concept is used as a variable in this research. At the end of the trading day, APs redeem the accumulated ETF shares for the underlying basket, using it to cover their short positions. The accuracy of ETF prices in reflecting the underlying securities' value relies on the involvement of various agents who enable arbitrage, including high-frequency arbitrageurs, hedge funds, and APs (Ben-David et al., 2017).

One important thing to consider when it comes to tracking error, is to understand how the ETFs are pegged against the index in the first place or more simply how they replicate the underlying index. They can either physically or synthetically replicate the index. A physical ETF replicates the underlying index by purchasing all of the stocks in the index, following the weights specified by the index. For example, a physical ETF tracking the S&P 500 would invest in each individual stock included in the S&P 500. In some cases, physical ETFs may use a sampling approach where they only buy a limited number of stocks from the index. This is necessary when an index is too large or when the underlying markets lack liquidity to hold every single stock. In such cases, the ETF carefully selects an optimized sample of stocks that adequately represents the index.

In synthetic replication, derivatives like swaps are utilized instead of underlying securities to replicate the index. Under this approach, the fund acquires a collateral basket of stocks that partially mirrors the underlying index. Subsequently, the fund engages in a swap agreement with a financial institution, exchanging the performance of the collateral basket for the performance of the underlying index. If the index's performance exceeds that of the assets physically held by the ETF manager, the counterparty is obligated to compensate the fund provider for the difference in performance. As a result, the fund manager can acquire additional physical assets. Conversely, if the index's performance is lower than that of the physical assets, the fund manager owes money to the counterparty. In this case, the manager sells physical assets to meet its payment obligations to the swap holder. One motivation for employing synthetic structures is cost reduction, however, they give rise to counterparty risk (Pagano et al., 2019).

In Europe, UCITS (The Undertakings for Collective Investment in Transferable Securities) regulations govern the operation of ETFs and due to their organization under the Investment Company Act of 1940 and limitations imposed on physical replication, synthetic replication is uncommon for ETFs domiciled in the United States. One notable distinction of the European market, unlike the U.S. market due to regulatory constraints, is the utilization of synthetic replication methods. Regarding how tracking error behaves with synthetic and physical ETFs, study by Chu (2013) reveals that the synthetic ETFs have higher tracking errors, however, it suggests that for the Chinese market, while Johnson et al. (2013), who analyzed ETFs from all over the world, suggests that synthetic replication produced lower tracking error. Nevertheless, synthetic replication is used to increase liquidity and therefore decrease the tracking error in emerging market ETFs as Hillard & Le (2022) point out in their study. Fund creating iShares EURO STOXX 50 ETF uses a physical replication method.

2.3. The theory and literature review

Firstly, the variables which are analyzed and compared to the tracking error are market volatility, liquidity proxy (bid-ask spread), net flow, premium or discount, and trading volume. Because of the nature of ETFs and their mechanics, the movements of tracking error can be expected to move in directions which align with the theory behind the variables. The deviation of ETF prices from their NAV is primarily maintained through the arbitrage process. Theoretically, the increase in premium/discount should invite arbitrageurs which in turn should align ETF prices better with its NAV. Moreover, ETFs that include international stocks are expected to exhibit greater deviation due to the continued trading of their shares on the domestic exchange while the market for the underlying securities in the creation basket is closed. Similarly, in theory, ETFs containing illiquid securities should experience higher deviation as the arbitrage process would require a larger deviation to compensate for the higher transaction costs associated with trading those less liquid securities. The increased trading volume impacts positively on the liquidity and bid-ask spread, while market volatility increases bid-ask spreads. Net inflows and their effect on the tracking error highly depend on the state of the market as market participants have different behaviors during each regime. To expand the theory, the examination also includes a review of what the literature suggests about the variable relationships.

Hillard & Le (2022) found that tracking errors for emerging European markets do have higher tracking error in comparison to developed Europe, and it was around 0.67% and 0.33% respectively. In his study Rompotis (2011) states that tracking error for ETFs with higher expense ratios was higher. Additionally, the study by Tsalikis & Papadopoulos (2019) confirmed that tracking error for European ETFs was on average higher than for US ETFs, while a possible explanation for the aforementioned could lie in the economies of scale and thus lower costs. Chu & Xu (2021) also found that economies of scale will improve tracking ability, while their research suggests that expense, delay in receiving dividends, the trading cost and the market risk increase the tracking error. Additionally, Elton et al. (2019) suggested that tracking error is significantly influenced by delayed reinvestments of dividend. Regardless of the tracking error measurement, higher assets under management (AUM) positively affect tracking ability. The study also finds that higher expense ratios are associated with higher tracking errors, although statistical significance is observed only for one measurement. Another study by Frino, & Gallagher (2001) presented evidence that tracking error is positively and significantly correlated with dividend payments and also that there were seasonal patterns with higher error rates in January and May, and a lower error rate in the quarters ending in March, June, September, and December. Study by Aber et al. (2009) stated that the range of daily price fluctuations was very large which indicated that active traders or arbitrageurs were more likely to profit than passive traders. Blitz et al. (2012) revealed in their study that index funds and ETFs in Europe underperform their benchmarks by larger amounts than their reported expenses, with dividend taxes explaining a significant portion of the underperformance. This highlights the need to account for dividend taxes in evaluating fund performance and measuring fund costs accurately.

Other well-known factors explaining ETFs tracking error are market volatility, trading ,, the net flow as well as premium or discount. Higher market volatility and trading volumes can lead to wider bid-ask spreads, which can increase the cost of trading and result in higher tracking errors as observed in several studies including Ben-David et al. (2019). In a study on Hong-Kong ETFs Chu & Xu (2021) demonstrate that trading volume increases the tracking error however it is not significant, while Yiannaki (2015) suggests that there is a weak correlation between tracking error and trading volumes. Dorocáková (2017) found that fluctuations in the underlying index can have a relative influence on tracking error. In the case of bid-ask spreads Delcoure and Zhong (2007) indicate a positive relation to the tracking error. Müller et al. (2012) confirm these results for the German ETF market. Osterhoff & Kaserer

(2016) and Bae & Kim (2020) have documented the positive relation between illiquidity and tracking error. Petajisto (2018) suggests that larger deviations are more present in funds which hold illiquid or international securities.

On the demand side, the net flow ETF may affect its tracking error. ETF net flow tends to increase during bull markets when investors are more optimistic and confident about the future of financial markets. Conversely, during bear markets, ETF net flow tends to decrease as investors become more risk-averse and seek to reduce their exposure to equities. According to research of Ben-David et al. (2017), tracking error is negatively related to ETF net flow. Another study by Osterhoff, & Kaserer (2016) confirmed that net flow had a significant negative effect on tracking error for small ETFs.

Divergence of ETF market prices from their net asset value, reported as premium (or discount), is yet another explaining factor of ETF tracking error. A study by Wong & Shum (2010) found that the tracking error of the examined ETFs is consistently positive in both bullish and bearish markets. This suggests that investors are willing to pay a premium for ETF investments, as ETFs provide positive returns that can cover transaction costs and potentially yield returns in different market conditions. Study published by Rompotis (2010) found tracking error to be positively affected by premium/discount. Li and Zhao (2014) found that premiums can lead to increased tracking error in ETFs that hold illiquid securities.

Study Aber et al. (2009) suggested that ETFs traded more at the premium than discount which means that the market tended to overvalue ETFs compared to their NAV. Additionally, premiums have shown to be higher for newly created ETFs shown in study by Piccotti (2018) which indicates that investors are willing to pay a premium in order to access the liquidity benefits provided by ETFs, which allow indirect access to less accessible underlying securities.

3. Empirical research

3.1. Data formulation and description

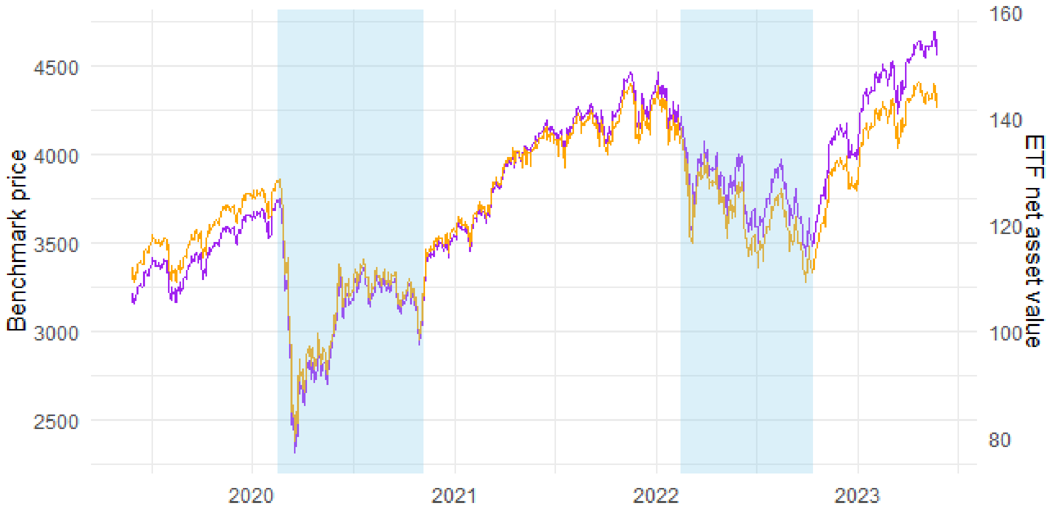
In previous studies, researchers have used both NAV returns and closing market price returns to evaluate the tracking error of ETFs compared to their benchmark index returns. However, the NAV-based measurement of tracking error is widely recognized as the preferred approach due to its advantages. NAV returns consider dividends or any income generated by the underlying assets, providing a more accurate and reliable measure of the ETF's performance in accordance with GIPS - Global Investment Performance Standards (2020).

Additionally, changes in the net asset value reflect what an investor would actually receive from holding the ETF. In contrast, closing price ETF returns may be influenced by short-term price fluctuations that do not necessarily reflect the underlying performance of the ETF. Therefore, using closing price returns to assess tracking error can be misleading. Furthermore, the difference between the ETF market prices and their respective net asset value introduces another variable known as the premium or discount. This variable will be utilized to explain the ETF tracking error. The mispricing of an ETF in relation to its net asset value creates arbitrage opportunities through the creation and redemption mechanism, which can be advantageous for investors.

The first impression of tracking error can be made by visual inspection of iShares Euro Stoxx 50 ETF net asset values and market closing prices of a benchmark Euro STOXX 50. Figure 2. uses dual scale axis for comparison and purposely shaded area covering turbulent periods of COVID crisis and Ukrainian war. Both, net asset values and closing prices are expressed in the same currency EUR, but with different scales.

Although Figure 2. clearly indicates that the ETF tracks its benchmark quite well with few disparities during a bullish regime, commenting on the ETF performance solely based on price differences is not possible; instead, return differences are considered.

Figure 2: *ETF net asset values vs benchmark index prices*



Source: *author's construction in RStudio using data provided by Refinitiv Eikon*

Before analysis continues, all variables of interest are derived from the raw data. Firstly, the tracking error is estimated following the ex-ante approach by regressing NAV returns of the ETF on a benchmark returns. The root of squared regression residual for each trading day resulted in a tracking error:

$$tracking_t = \sqrt{(Ret_t^{NAV} - 0.0109 - 0{,}9949 Ret_t^{BEN})^2} \tag{1}$$

In above expression -0.0109 and -0.9949 are constant term and slope coefficient, respectively.

Daily NAV returns of ETF and benchmark returns, used in the regression, are obtained following the same formulation:

$$Ret_t^{NAV} = \frac{NAV_t - NAV_{t-1}}{NAV_{t-1}} 100\% \quad Ret_t^{BEN} = \frac{C_t^{BEN} - C_{t-1}^{BEN}}{C_{t-1}^{BEN}} 100\%, \tag{2}$$

where NAV_t and NAV_{t-1} are ETFs net asset values at current and previous trading day, while C_t^{BEN} and C_{t-1}^{BEN} are closing prices of a benchmark index likewise.

Next, an illiquidity proxy measure is obtained as bid-ask spread with end-of-day ETF quotes towards its mid quote, by following expression:

$$iliquidity_t = \frac{2(A_t^{ETF} - B_t^{ETF})}{A_t^{ETF} + B_t^{ETF}} 100\% \tag{3}$$

ETF daily premium is also expressed in percentage as all other variables, according to:

$$premium_t = \frac{C_t^{ETF} - NAV_{t-1}}{NAV_{t-1}} 100\% \tag{4}$$

where C_t^{ETF} is closing (market) prices of ETF at day t.

Daily ETF net flow, which represents the inflow and outflow of ETF, is given by formula:

$$net\ flow_t = \frac{TNAV_t - \left(1 + \frac{Ret_{t-1}^{ETF}}{100}\right) TNAV_{t-1}}{TNAV_{t-1}} 100\% \tag{5}$$

where the total net asset value $TNAV_t$ represents a product of NAV per share and number of outstanding shares at current day. Previous day total net asset value $TNAV_{t-1}$ is corrected with the respective ETF daily return to subtract out the performance effect of the change, which is independent of capital flows.

The market volatility is measured by the official Euro Stoxx 50 volatility index (VSTOXX), which is the European version of VIX, reflecting investors sentiment as expectations of future volatility.

Summary statistics of variables of interest are reported in Table 1. All values of variables are expressed in percentages, except volatility index and trading volume. Only trading volume is transformed into logs due to a large scale and extreme variations of trading across days.

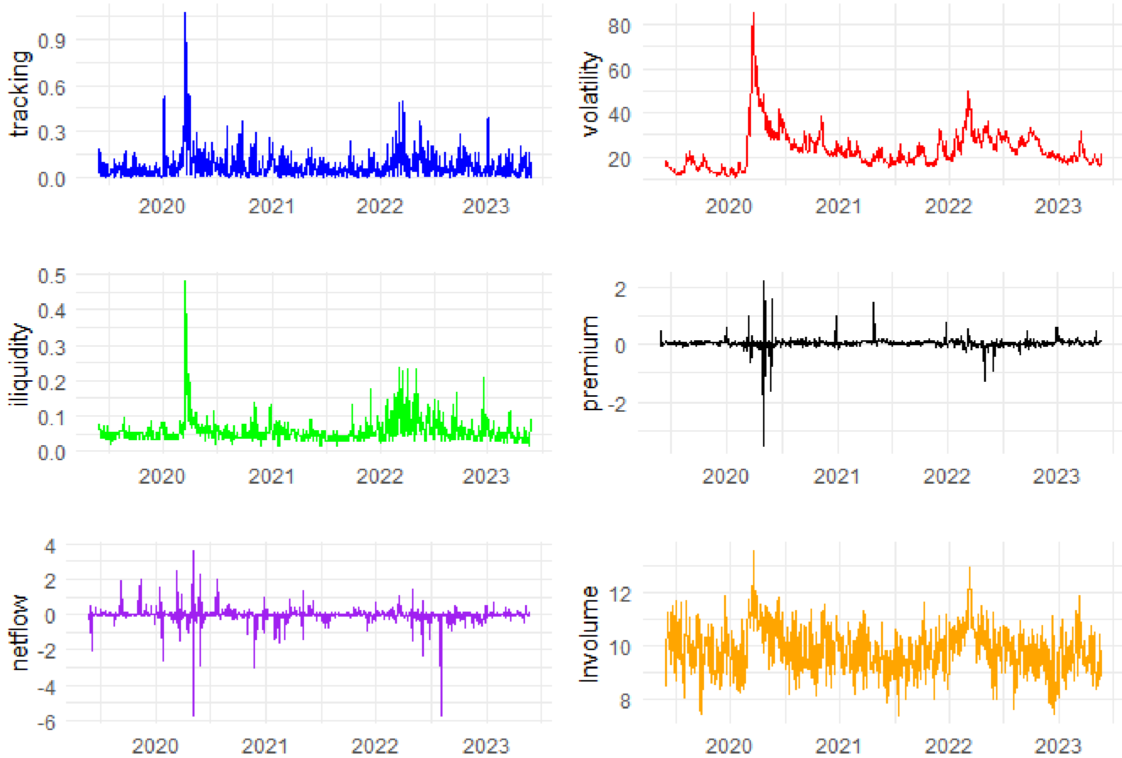
Table 1: *Descriptive statistics of iShares Euro Stoxx 50 ETF tracking error and its explanatory predictors along with ADF unit root test*

	Min	Max	Mean	SD	Median	ADF test
Tracking error	0.00	1.08	0.07	0.09	0.05	-15.1558***
Illiquidity proxy	0.01	0.48	0.06	0.04	0.05	-11.5989***
Volatility index	10.69	85.62	23.21	8.85	21.36	-13.8413***
Net flow	-5.74	3.59	-0.03	0.48	-0.01	-20.9258***
Premium/discount	-3.55	2.19	0.04	0.21	0.05	-18.7641***
Logs of volume	7.37	13.56	9.84	0.85	9.82	-13.4245***

Source: *author's calculation in RStudio using data provided by Refinitiv Eikon*

It can be seen from Table 1 that the mean and median tracking error is 0.07% and 0.05%. Maximum value of 1.08% can be expected during high market volatility and stress, when assets in the portfolio become less liquid and more difficult to optimize. The null hypothesis of Augmented Dickey-Fuller (ADF) unit root is rejected at significance level of 1%, indicating that all variables of interest are stationary. ADF in the levels is performed without trend and without drift, except for net flow and premium/discount as their mean is approximately zero, and thus a drift term is not omitted for those two variables. Stationarity of all variables is preferred to eliminate possible suspicion of the results in post-estimation phase, caused by nonstationarity issue.

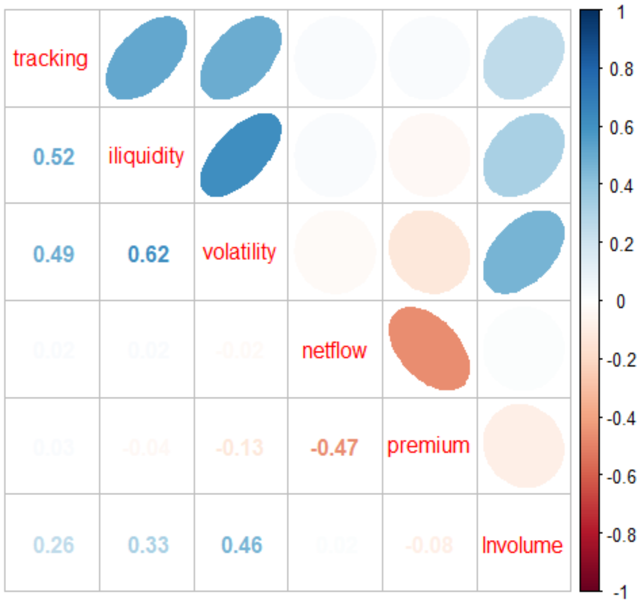
Figure 3: *Time-series of variables observed from May27, 2019 to May 26, 2023*



Source: *author's construction in RStudio using data provided by Refinitiv Eikon*

From Figure 3. the clustering of tracking error, volatility and illiquidity is evident, particularly in crisis periods which can be identified as bearish states of the ETF regime. Therefore, it is not surprising that these three variables are more correlated than other variables, indicating that illiquidity and volatility contribute to tracking error positively (Figure 4).

Figure 4: *Correlation matrix between variables*



Source: *author's construction in RStudio using data provided by Refinitiv Eikon*

3.2. Model specification

The application of Markov regime-switching (MRS) models has attracted great interest in capturing dynamics of financial time-series, primarily due to the nonlinear dependence between considered variables as well as their nonstationary property (time-varying moments). In these circumstances the main advantage of the MRS is that it allows the regression parameters to switch across multiple states or regimes, with the probabilities of switching between these states being dependent on the current state. For example, the MRS model can capture changes of the dependence between two or more variables during different economic cycles or market regimes, such as high and low volatility regimes or bearish and bullish regimes, which usually coincides with crisis and non-crisis periods.

The simple Markov switching bivariate regression model which considers two states of regime can be formalized as:

$$y_t = \alpha_{St} + \beta_{St} \cdot x_{St} + u_{St}$$

$$u_{St} \sim WN(0, \sigma_{St}^2)$$

$$\alpha_{St} = \alpha_1(2 - S_t) + \alpha_2(S_t - 1) \tag{6}$$

$$\beta_{St} = \beta_1(2 - S_t) + \beta_2(S_t - 1)$$

$$\sigma_{St}^2 = \sigma_1^2(2 - S_t) + \sigma_2^2(S_t - 1)$$

where $S_t = j$ is a discrete state variable that indicates in which regime the Markov process is. $j = 1, 2, \dots, k$. Consequently if the process is in the first regime state, then $S_t = 1$ with parameters α_1 , β_1 and σ_1^2, but if the process is in the second regime state, then $S_t = 2$ with parameters α_2, β_2 and σ_2^2. Assuming that conditional probability density function is Gaussian:

$$f(S_t) = \frac{1}{\sqrt{2\pi\sigma_{St}^2}} exp\left\{-\frac{(y_t - \alpha_{St} - \beta_{St} \cdot x_{St})^2}{2\sigma_{St}^2}\right\}, \tag{7}$$

then a log-likelihood function $lnL = \sum_{t=1}^{T} \quad ln\{f(S_t)\}$ can be maximized with respect to parameters α_1 , α_2 , β_1 , β_2, σ_1^2, and σ_2^2. However, the state variable is usually unobserved in practical applications, but it is commonly assumed that it follows a Markov chain process with a *k*-dimensional state space (Hamilton, 1989). Specificity of Markov chain process is the first-order dependence, implying that state variable at the moment t depends only on the previous state of the process at the moment $t - 1$ (Goldfeld & Quandt, 1973). Thus, for $k = 2$ the log-likelihood function takes the form:

$$lnL = \sum_{t=1}^{T} \quad ln\left[\left(\sum_{j=1}^{2} \quad \frac{1}{\sqrt{2\pi\sigma_{St}^2}} exp\left\{-\frac{(y_t - \alpha_{St} - \beta_{St} \cdot x_{St})^2}{2\sigma_{St}^2}\right\}\right) Pr(S_t = j | I_{t-1})\right]. \tag{8}$$

The probability density function (8) for each observation $t = 1,2, \dots, T$ is presented as a weighted sum of conditional probability density functions for both regime states $j = 1, 2$. The associated weights $Pr(S_t = j | I_{t-1})$ are interpreted as conditional probabilities that the process is in the state j at the moment t, conditioned on all information from previous periods up to and including the moment $t - 1$. These conditional probabilities are called *ex ante* probabilities. In order to maximize the log-likelihood function it is necessary to assume *a priori* the behavior of discrete state variable S_t. It is assumed that the state variable is generated by a first-order Markov process:

$$Pr\, Pr\, (S_{t-1}, S_{t-2}, \dots, S_1, I_{t-1}) \; = Pr(S_t | S_{t-1}) \tag{9}$$

Ex ante probabilities $Pr(S_t = j | I_{t-1})$ are generated by matrix of transitional probabilities, the so-called stochastic matrix:

$$P = [p_{11}\; p_{12}\; p_{21}\; p_{22}\,] = [p\;(1 - p)\;(1 - q)\; q\,] \tag{10}$$

The matrix of transition probabilities P is an irreducible and primitive matrix. This means that all states of the Markov chain communicate with each other, i.e. that there is a probability of transition from state i to state j, as well as a probability of transition from state j to state i. Therefore, it is assumed that all elements of the stochastic matrix are greater than zero (primitive matrix). In the matrix P the probability $p_{ij} = Pr(S_t = j|S_{t-1} = i)$ is the conditional probability that the process is in the state j at the moment t, if it was in the state i at the previous moment $t - 1$. For example, p_{12} it is interpreted as the probability of transition from the first state to the second state of the regime, and p_{22} as the probability that the process remained in the second state of the regime. The probabilities p_{11} and p_{12} are complementary, just like the probabilities p_{12} and p_{12}. The transition probabilities p and q in the stochastic matrix P are mostly parameterized using inverse logit transformation:

$$p = \frac{e^{p_0}}{1 + e^{p_0}} \; ; \; q = p = \frac{e^{q_0}}{1 + e^{q_0}} \tag{11}$$

Upon transitional probabilities $Pr(S_t = j|S_{t-1} = i)$, conditional probabilities $Pr(S_t = j|I_{t-1})$ can be generated and then the log-likelihood function can be maximized by the parameters α_1, α_2 , β_1 , β_2, σ_1^2, σ_2^2, p_0 and q_0. Since the process of maximizing the log-likelihood function is iterative, in each new iteration conditional probabilities $Pr\,Pr\,(I_{t-1})$ $t = 1, 2, \ldots, T$ are updated using Kim's smoothing algorithm or Kim's filter. Kim's (2017) smoothing algorithm can be described in two steps. In the first step, at the beginning of iteration, *ex ante* probabilities are calculated as:

$$Pr\,Pr\,(I_{t-1}) \; = \sum_{j=1}^{2} \quad Pr(S_t = j|S_{t-1} = i) Pr(S_{t-1} = i|I_{t-1}) \quad j = 1, 2. \tag{12}$$

In the second step, according to the Bayes rule, for the observed values of response variable y_t, the so-called filtered probabilities are obtained:

$$Pr\,Pr\,(I_{t-1}, y_t) \; = \frac{f(y_t|S_t = j, I_{t-1})\, Pr\,Pr\,(I_{t-1})}{\sum_{j=1}^{2} \quad f(y_t|S_t = j, I_{t-1})\, Pr\,Pr\,(I_{t-1})}\,. \tag{13}$$

However, initial probabilities need to be determined before the iterative procedure of maximizing the likelihood function can begin. For the initial probabilities, Hamilton (1989) proposed unconditional probabilities of the state of the regime, i.e. steady state probabilities:

$$\mu_1 = \frac{1 - p}{2 - p - q} \; ; \; \mu_2 = \frac{1 - q}{2 - p - q}. \tag{14}$$

Based on the transitional probabilities of the regime state, the expected duration of the process in the $j-th$ regime state can be calculated:

$$d_1 = \frac{1}{1-p}\ ;\ \ d_2 = \frac{1}{1-q}. \qquad (15)$$

In the two-state regime model, the first regime state is assumed to be a low-volatility state and the second regime state is a high-volatility state. Then the parameters π_1 and π_2 can be interpreted as the expected probabilities that the process is in the regime of low (high) volatility in the long term, while the parameters d_1 and d_2 show how long (days) the process is in the regime of low (high) volatility. Also, it is interesting to analyze how long it takes for the process to go from a state of low volatility to a state of high volatility and vice versa.

3.3. Model estimation and findings

In accordance with previously described methodology and research objectives, assuming two states of regime $k = 2$, a following MRS regression model is estimated:

$$tracking_t = \alpha_{St} + \beta_{1,St} \cdot illiquidity_{St} + \beta_{2,St} \cdot volatility_{St} + \beta_{3,St} \cdot netflow_{St}$$
$$+ \beta_{4,St} \cdot premium_{St} + \beta_{5,St} \cdot ln\, ln\, (volume)_{St} + u_{St}$$

For two states of regime 16 parameters (five coefficients, constant term and error variance for each state along with two transition probabilities) are estimated by approximate maximum likelihood method using expectation–maximization (EM) algorithm due to its convenience. For comparison purposes a single regime regression model is also estimated to verify the switching property of regression coefficients. In addition, appropriateness of MRS approach is supported by diagnostic checking of unobserved error component u_{St} which should follow a white noise process with zero mean and constant variance for each state of regime.

Table 2: *Estimates of a single regime model and two states regime model*

	Single regime model	Two states switching regime model	
		Regime 1	Regime 2
(Intercept)	0.0172	0.0165***	-0.0321***
	(0.0134)	(0.0043)	(0.0006)
Volatility index	0.0012***	0.0008***	0.0029***
	(0.0001)	(0.0002)	(0.0001)
Illiquidity proxy	1.1595***	1.0975***	1.0049***
	(0.0404)	(0.0666)	(0.0096)
Net flow	0.0522***	-0.1482***	-0.0155***
	(0.0044)	(0.0067)	(0.0014)
Premium/	-0.0424***	-0.3891***	0.0507***
discount	(0.0117)	(0.0277)	(0.0030)
Logs	-0.0051***	0.0033***	-0.0514***
of volume	(0.0015)	(0.0004)	(0.0031)
Num.Obs.	1019	1019	-
R2	0.897	0.9318	0.9925
AIC	-6536.0	-8507.4	-
BIC	-6501.5	-8365.2	-
Log.Lik.	3274.995	4265.739	-
RMSE	0.011	0.008	0.002

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Source: *author's calculation in RStudio using data provided by Refinitiv Eikon*

$$P = [0.8509\ 0.1491\ 0.4237\ 0.5762\ ]$$

For 1019 observations, the results of a single regime model and two states regime switching model are compared in Table 2. All variables are statistically significant. Increase in volatility and illiquidity increases tracking error. This is highly likely the case because their increase is associated with an increase in trading costs for arbitrageurs which decreases their ability to create and redeem ETF shares and underlying assets. The results are the same for single and two state regime models. However, tracking error increases more in the second regime (for 0.29%) than in the first regime (0.08%) with respect to 1% increase in volatility, while 1% change of illiquidity has approximately the same impact on tracking error in both regimes (it increases for 1.09% and 1.00% respectively). When comparing results from both models it is evident that parameters in a single regime case are overestimated or have spurious and unexpected signs, i.e. impact of illiquidity is overestimated, while the net flow has a misleading direction of influence. According to Ben-David et al. (2019) increases in trading volume can lead to wider bid-ask spreads which should in turn increase tracking error, while our results confirm the same but only for the bull period on the market (first state of regime). Contrary to that, in the bearish regime (second state) trading volume reduces the tracking error more than it contributes in bullish regime.

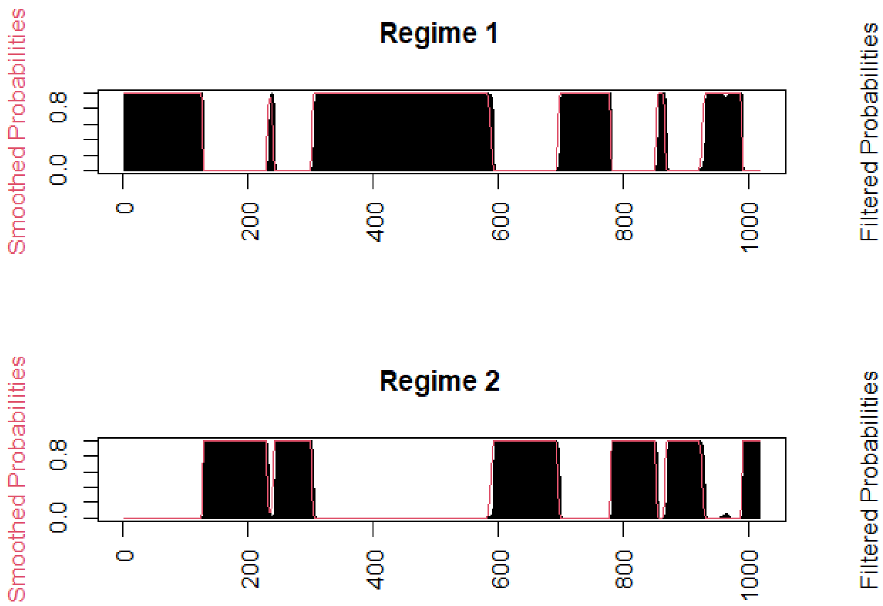
For the case of net flows, it shows a positive relationship with the tracking error only in a single regime model. The expected negative relationship was present for the two states switching model, also indicating a steeper coefficient for a bull period meaning that the effect of net flows is stronger during bull periods, i.e. tracking error reduces for 0.14% with respect to 1% increase of net flow. Furthermore, results indicate that premium/discount affect tracking error negatively in a single regime model, however, their effect is both negative and positive for bull and bear period respectively for the two states switching model. An increase in premium should, in theory, invite APs, hedge funds and arbitrageurs and hence decrease the tracking error, which is confirmed only for bull periods (-0.38%). The results for premium/discount to have a positive effect on tracking error was documented by Rompotis (2012), while this study had same results for bear periods. One explanation for the positive relationship during bear period could be the herding behavior by investors during the crisis period documented by Ferreruela & Mallor (2021). Shum & Kang (2012) found higher premiums/discounts in ETFs during crisis periods, which could indicate less activity by the arbitrageurs during turbulent times due to higher trading costs. The findings of our analysis show that the results are consistent with the economic literature for most of the variables. In two states switching regime model, the coefficients change for net flow, premium and volume, indicating a more comprehensive insight of the influential variables on the tracking error.

The transition probability matrix $P = [0.8509\ 0.1491\ 0.4237\ 0.5762\ ]$ provides information about probability transitions between to regime. The probabilities p_{11} = 0.8509 and p_{22} = 0.5762 indicate the likelihood of remaining in the first and second states of the regime, respectively. Conversely, p_{12} = 0.1491 represents the probability of transitioning from the first state to the second state, while p_{21} = 0.4237 signifies the probability of transitioning from the second state to the first state. Interestingly, it is more likely to remain in the bull state regime once the market gets to that state and approximately stays in that state for 7 trading days (week and a half). In addition, returning from bearish to bullish state of regime is 2.8 times more likely than otherwise (probability of 0.4237 against 0.1491).

Goodness of fit measures confirm appropriateness and superiority of the two states regime model over single regime model in terms of R2, information criteria's AIC and BIC, and root mean square error (RMSE). In both regimes R2 is substantially greater than in a single regime case. Likewise, RMSE indicates lower regression standard errors in both states against single state. The smaller Akaike information criteria and Bayes information criteria are observed in the Markov regime switching model, supporting its preference.

After estimation of the Markov switching model parameters, it is common to obtain filtered probabilities of the regime states, which are already calculated by Kim's filtering algorithm and therefore is a side product of the log-likelihood maximization iterative procedure. Inspection of the filtered as well as the smoothed probabilities is useful for interpretation of the switching regression coefficients associated with different time periods. From Figure 5 it is clear that regime 1 corresponds to bull regime of the market, while regime 2 corresponds to bearish regime, and more importantly, it covers crisis periods including COVID pandemic and onset of Ukrainian war.

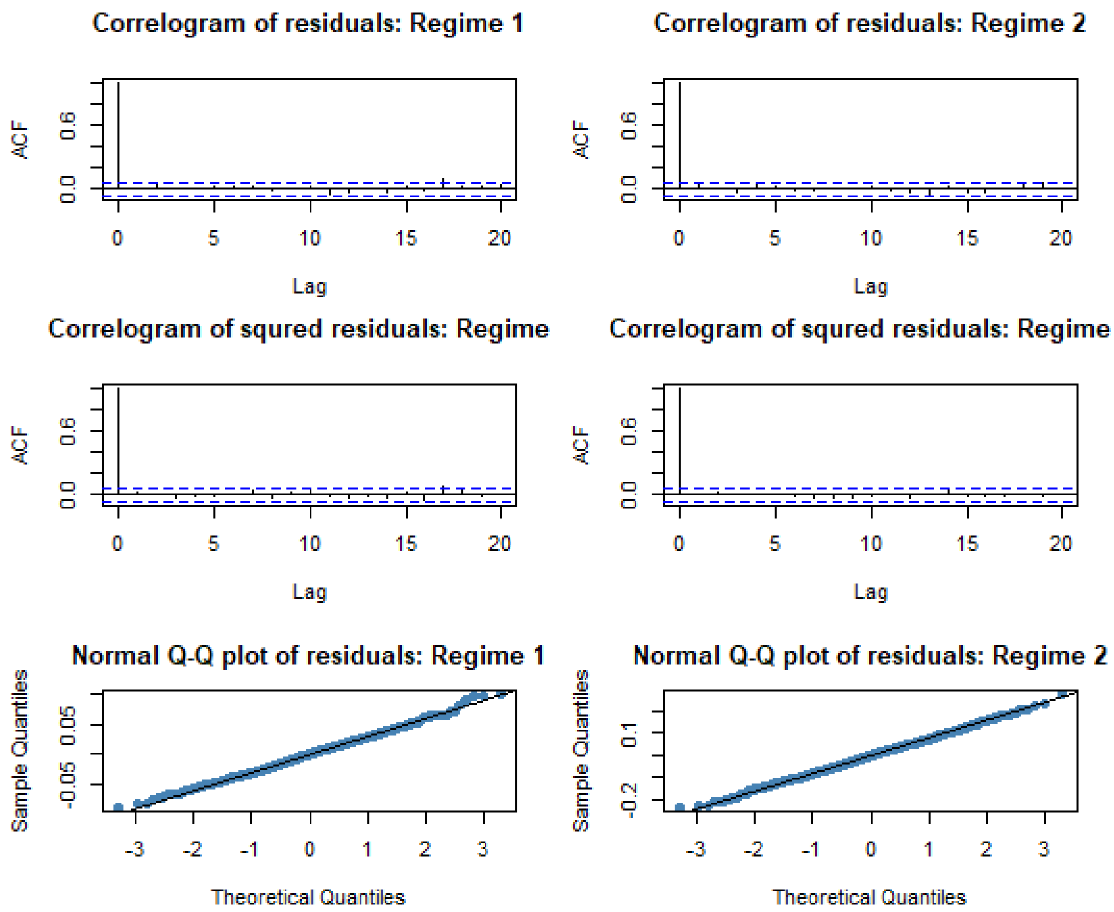
Figure 5: *Filtered and smoothed probabilities of Markov switching model*



Source: *author's construction in RStudio using data provided by Refinitiv Eikon*

Validity of the Markov switching model requires residuals checking. Two series of residuals are generated in total, by one for each state of regime. Three diagnostic plots are constructed for each residual series (normal quantile-quantile plot, correlogram of residuals and correlogram of squared residuals), whereas formal diagnostic test (Ljung-Box test, ARCH test and Jarque-Bera test) are performed for weighted residuals, i.e. linear combination of two residual series using smoothed probabilities as the weights. From Figure 6 correlograms indicate no autocorrelation of residuals in both regimes and no autocorrelation of squared residuals, confirming serial independence of the error terms as well homoscedasticity (error terms have constant variance). The same conclusion is supported by non-rejection of Ljung Box test null hypothesis with 5 and 10 time lags, and by non-rejection of ARCH test null hypothesis for autoregressive conditional heteroscedasticity at 5% significance level (Table 3). According to Jarque-Bera test, normality assumption of weighted residuals is met.

Figure 6: *Diagnostic plots of two regimes residuals*



Source: *author's construction in RStudio using data provided by Refinitiv Eikon*

Table 3: *Diagnostic checking of weighted residuals*

Test	Statistic
Ljung-Box (5)	1.8469
Ljung-Box (10)	3.7356
ARCH	20.7821
Jarque-Bera	1.3569

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Source: *author's calculation in RStudio using data provided by Refinitiv Eikon*

4. Conclusion

The primary objective of this study was to address a critical gap in the analysis of Eurozone ETF performance by specifically focusing on the European market and investigating the impact of market-related variables on ETF tracking error. The research explored how the tracking error of a Eurozone ETF, concerning its benchmark index, is influenced during crisis periods, including the COVID-19 pandemic and the Ukrainian war. By carefully examining market periods or regimes, the paper offers empirical evidence on several market-based measures, such as market volatility, liquidity proxy, net flow, premium or discount, and trading volume, to comprehensively understand their influence on the tracking error. In addition to presenting in-depth explanations and empirical evidence, this study contributes to the literature by employing a regime-switching methodology.

This paper found the following: the results support existing economic literature to some extent and highlight the importance of considering different market regimes. While all variables are statistically significant, it was found that an increase in volatility and illiquidity led to a decrease in tracking error. However, the method of switching regimes has shown that the influence of volatility on tracking error is stronger during periods of market stress than in bull periods (0.29% and 0.08% respectively), while for illiquidity the influence is the same for both regimes. When considering trading volume, the results confirm the findings from Ben-David (2019) that and increase in volume does increase tracking error, but only slightly (0.003%). The relationship holds true only for the first regime (bull period). On top of that, the study finds the influence of volume to be both, negative and stronger for periods of market stress (-0,05%).

Regarding net flows, the results surprisingly show a positive relationship with the tracking error in a single regime model. However, the use of switching regimes yields the excepted negative relationship between net flows and tracking error. To be more precise, 1% of net flow reduces the tracking error for 0.14% during bull periods and 0.01% during bearish periods. Lastly, the results show that premium/discount negatively affect tracking error using single regime model. With two state switching model, the results yield interesting results. The affect of premium/discount seems to be both positive and negative. Negative influence was expected, and it was found only during bull period of the market (-0.38%). Positive but weaker (0.05%) influence of premium/discount on tracking error was found during periods of stress and was also documented by Rompotis (2012). One of the explanations for positive influence could lie in the herding behavior exhibited by investors during periods of market stress.

Another reason could be higher trading costs which arise in periods of market stress. Higher trading costs tend make arbitration costlier. Hence, it keeps APs waiting for the price between ETF and its NAV to be further and further away, explaining the positive relationship between premium/discount and tracking error.

All these findings show researchers the importance of using two state switching methodology. It was clearly shown how the effect of variables can change with the introduction of two state switching methodology (net flow, premium, volume). Aside current variables, supplementary variables like ETF provider rebalancing frequency, benchmark index composition, and expense ratios could help in explaining the tracking error. However, obtaining this information from publicly available data is not straightforward, and the significance of these variables may be questionable due to their daily time-invariance. For example, expense ratios are typically reported as annual fees, not on a daily basis.

One limitation of the current research is the fact that only a single ETF is used in the analysis. It would be of great value if future researchers take into account ETFs with different liquidities and sizes.

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